How is cumulative seabird displacement from offshore wind farms assessed and verified, and what does current and future cumulative displacement look like?

PhD Thesis

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Abstract

The cumulative impact of offshore wind farms is likely to become one of the largest factors in delaying or preventing the construction of renewable energy. Cumulative effects assessments are carried out on a range of species and industries, but there needs to be consistency in the species that are assessed cumulatively. A critical step in understanding the impact on sensitive species is the ability to detect seabird changes in abundance through careful survey design. Minimising the displacement of birds by altering the spatial design of a wind farm is also a key factor in marine planning. Predicting future cumulative displacement using a range of displacement metrics is further required to mitigate impacts.

Environmental Statements of spatially close UK offshore wind farms were reviewed, and the species included in their cumulative assessments were compared. Red-throated diver (*Gavia stellata*) distribution data from 1979 to 2012 was used to investigate how survey design variables influenced the statistical power of being able to detect displacement. Statistical analysis was undertaken to determine whether wind farm design is a factor in seabird displacement. Furthermore, seabird distribution was overlain with 18 operational and planned wind farms, and displacement scenarios were simulated to investigate cumulative impacts on a Special Protection Areas in the southern North Sea.

This research found that numerous approaches have been taken to assessing cumulative impacts on seabirds, seemingly without standardisation, potentially leading to either underestimates or overestimates. When looking to predict and confirm displacement impacts, consideration needs to be given to alterable but costly factors, such as spacing transects and the number of surveys, and to site-specific factors, such as the density of birds. The wind farm design could be further modified, for instance, by spacing turbines further apart to minimise displacement. Cumulative displacement without mitigation may lead to massive areas of habitat loss.

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BACI	Before After Control Impact
CEA	Cumulative Effects Assessments
CReSS	Complex Region Spatial Smoother
CRM	Collision Risk Model
EIA	Environmental Impact Assessments
ES	Environmental Statement
GAM	Generalised Additive Model
GAMM	Generalised Additive Mixed Model
GLM	Generalized Linear Model
HRA	Habitats Regulations Assessment (England, Wales, and Northern Ireland) or Habitats Regulations Appraisal (Scotland)
IROPI	Imperative Reasons of Overriding Public Interest
JNCC	Joint Nature Conservation Committee
MRSea	Marine Renewables Strategic environmental assessment
SAC	Special Area of Conservation
SALSA	Spatially Adaptive Local Smoothing Algorithm
SeaMaST	Seabird Mapping and Sensitivity Tool
SNCB	Statutory Nature Conservation Body
SPA	Special Protection Area
VEC	Valued Environmental Components

Chapter 1 Introduction

Offshore wind farm development is set to rise significantly in the near future, and with it, the challenge associated with understanding the cumulative environmental impacts of developments with other projects (Goodale and Milman, 2016). The continual growth of more, larger wind farms in UK coastal waters will lead to a substantial area of the sea being used to generate renewable energy. With wind farms being situated in relative proximity to one another, the interaction of environmental impacts, or cumulative environmental impacts, is becoming an increasing concern. The environmental effects of offshore wind farms can be direct (e.g. mortality, injury) or indirect (e.g. behavioural, habitat, or prey changes). They could also be positive or negative. Individual effects can be small, but when combined with effects from other projects, they can be quite significant and surpass thresholds of reversible change (King *et al.*, 2009). This thesis is an investigation into various aspects of the cumulative effects of seabirds from offshore wind farms, focussing on the displacement of seabirds.

This chapter first describes the importance of determining the cumulative seabird displacement caused by offshore wind farms. It goes on to describe the aims and objectives of the research before providing context of how the research for this thesis has been carried out. Finally, the structure of the thesis is described.

1.1 The importance of determining the cumulative seabird displacement caused by offshore wind farms

Research has shown that there is no area of the marine ecosystem that is unaffected by the presence of humans (Halpern *et al.*, 2008). Up to 66% of the marine environment has been significantly altered and is strongly affected by more than one human activity (IPBES, 2019). An unprecedented rate of global change in nature has been observed. The drivers of this include changes in sea and land use, the exploitation of species, climate change, pollution of the air, land and water, and non-native invasive species (IPBES, 2019). The progression of climate change is subsequently the driver of the development of energy from renewable sources. Many ambitious targets have been set globally for the reduction of greenhouse gas emissions and renewable energy developments. The Paris Agreement was the first legally binding deal aiming to limit global warming to below 2°C and ideally 1.5°C. In the UK, this has been translated into law by setting the first net zero emissions law, requiring zero net emissions by 2050 (Department for Business Energy & Industrial Strategy, 2019). One aspect of reaching this target is the Offshore Wind Sector Deal (signed 2019), which aims to increase the installed capacity of offshore wind to 30GW by 2030, providing a third of the UK's electricity demand (HM Government, 2019).

However, the progression of renewable energy faces a conundrum. A driver of biodiversity change is climate change, and renewables form part of the solution. However, another driver of biodiversity change is land and sea use change, to which renewable energy development contributes. Therefore, sustainable development, which takes ecological interactions at multiple scales into account, is required.

Despite much research having been carried out on Cumulative Effects Assessments (CEAs), it is still an area that is lacking within Environmental Impact Assessments (EIAs). A large reason for this appears to be the fact that CEAs are a sub-section of EIA, yet they have very different focuses. The receptors assessed through both EIA and CEA are usually classified as Valued Environmental Components (VECs), meaning that their conservation is the main aim. However, whilst CEA puts the focus on the status of the VEC by assessing all of the factors that may affect it, EIAs simply assess the effect of a single project on the VEC and disregard other pressures. Whilst CEAs remain a sub-section of EIAs, the priority is their improvement (Duinker and Greig, 2006).

The continual growth of more, larger offshore wind farms has led to, and will continue to lead to, much of the sea being used to generate renewable energy. The cumulative impact of wind farms has become an increasing concern for regulatory authorities and statutory consultees alike (Broadbent and Nixon, 2019; Natural England, 2019). This is largely because the cumulative displacement of birds is generally unknown (Masden *et al.*, 2015). The assessment, or lack of assessment, of such cumulative impacts has led to delays in granting consent (Leigh, 2021; Raymond Stephen Pearce v Secretary of State for Business Energy and Industrial Strategy, 2021). This can have implications for the start of construction and operation. The novelty of this work largely lies in the unknowns prevailing in the cumulative environmental effects of developments. This is enhanced by the sudden expansion of wind energy developments onshore and offshore. The understanding of the environmental impacts of wind energy has lagged behind wind energy development. The cumulative effects of many developments are, therefore, even more unknown; many questions remain as to how cumulative effects occur and the scales involved (Rezaei *et al.*, 2023). The uncertainties associated with predicted individual wind farm impacts are consequently multiplied when trying to predict cumulative effects.

Further to the uncertainties surrounding environmental impacts themselves, the process of carrying out CEAs as part of the EIA varies widely across offshore wind farms. These variations exist in terms of the procedure of assessment, spatial and temporal scales, the scoping of species and the pathways between pressures and receptors, to name but a few (Willsteed *et al.*, 2018). Consideration of cumulative effects at appropriate scales for receptors is needed to better understand the implications of renewable developments, which is likely to need a transboundary approach (Busch *et al.*, 2013).

The interactions between offshore wind farms and seabirds are largely unknown. Much progress has been made with regard to the collision of birds with wind farms, both onshore and offshore. However, the movement of birds in response to the presence of offshore wind farms remains unknown. Research is required to investigate several aspects of bird movements:

- How far, spatially, do birds move?
- How long, temporally, do birds take to move to a different location?
- How long, temporally, do birds remain in a different location?
- Do birds move from this different location back towards the wind farm?
- How long, temporally, does it take to move back towards the wind farm?
- How close to the wind farms do birds move?
- Does the transition away from and/or towards the wind farm occur in one event or in stages?
- What is the availability and reliability of data to determine these topics?

The movement of birds away from offshore wind farms may effectively constitute the loss of habitat which they previously utilised (Drewitt and Langston, 2006). The area may have been used for foraging, feeding, or simply moving between other sites. This habitat loss has the potential to limit food sources, affect the quality of food sources, increase foraging time, and increase travel time. Each of these may have a consequence that affects energy acquisition and expenditure (Masden *et al.*, 2010a). Few of these effects are understood, as are the impacts on reproductive success and individual survival (Masden *et al.*, 2015). Therefore, scaling these effects to a cumulative levels, particularly for mobile species which may come into contact with multiple stressors is even less well understood, yet more important to understand (Duinker *et al.*, 2013).

Red-throated divers (*Gavia stellata*, Figure 1.1) are one of the most sensitive species to displacement from offshore wind farms. There are numerous designated areas for the species, and large areas of their habitat coincide with multiple marine industries (Furness *et al.*, 2013; JNCC, 2020a; JNCC, 2020b; Garthe *et al.*, 2023). Therefore, this thesis focuses on red-throated divers as a key species for investigating the extent of displacement, monitoring and mitigating their displacement, and predicting future cumulative displacement. Further investigation and justification for investigating red-throated divers are provided in Chapter 2.

Figure 1.1 A red-throated diver (Gavia stellata) in summer plumage, showing red colouring to the throat. Copyright Emma Hall 2020.

With many wind farms already operational and many more to be built in the future, understanding the effects and impact on sensitive species is crucial to preventing negative implications and enhancing positives. By understanding how birds are affected, efforts can be made to plan and design future developments better. This can be implemented at various levels. Accounting for interactions with seabirds at an early stage in the design process is beneficial for wind farm developers, saving time and money prior to examination by the consenting authority. Environmental consultancies providing advice and guidance at various stages of development can better inform both developers and consenting authorities with an improved understanding of ecological interactions. Consenting authorities themselves will benefit from more understanding and reduced uncertainty surrounding these interactions. This is particularly true where cumulative effects are concerned, and consenting authorities have a responsibility to ensure not-significant environmental effects whilst promoting renewable energy developments in order to meet government targets.

Adequate monitoring is required to acquire empirical evidence of seabird-wind farm interactions in order to begin understanding them. However, this is a two-way process. Without an understanding of the movements of birds away from wind farms, current monitoring programmes may not cover a sufficient study area and/or timescale to provide evidence of this interaction. Therefore, adaptive monitoring and management is a crucial aspect of validating predictions and furthering our understanding.

These uncertainties and unknowns associated with assessing, predicting, and understanding the environmental impacts of offshore wind farms are key areas where improvements need to be made, and there is much scope to do so. An area of work that links the assessment, prediction, and understanding of environmental impacts is the validation of predictions through environmental monitoring. This addresses some of the uncertainties from predicting effects and may highlight the advantages and/or disadvantages of the assessment process whilst also increasing scientific understanding. Validating predictions of cumulative effects is yet another unknown, as cumulative effects are assessed at the planning stage, along with individual wind farm impacts. However, whilst individual wind farm effects are subsequently monitored during construction and operation, this only applies to the impact of individual wind farms; cumulative effects are not monitored. There is a wealth of publicly available data collected from individual operational wind farms, yet it has not been analysed in a cumulative manner in order to try to validate predictions.

1.2 Research aim and objectives

The overall aim of this thesis is to analyse how cumulative seabird displacement from offshore wind farms is assessed and verified and to explore what current and future cumulative displacement might look like. This aim is addressed through several objectives in each chapter of the thesis.

The research objectives are as follows:

a) to review the methods used to predict cumulative seabird displacement and the empirical evidence of red-throated diver displacement from offshore wind farms;
b) to investigate which species and impacts are assessed for displacement in offshore wind farm cumulative assessments;
c) to explore how offshore wind farm design influences red-throated diver displacement;
d) to investigate how much monitoring is sufficient to detect red-throated diver displacement from offshore wind farms;
e) to determine how red-throated diver displacement changes with distance from offshore wind farms; and
f) to explore what future cumulative red-throated diver displacement from offshore wind farms might look like

1.3 Context of how the research for this thesis has been carried out

The research throughout this thesis is set within the context of when and how it was carried out. For the first 16 months, the research was undertaken full-time within the context of a PhD student at the University of Strathclyde. After this, the research was undertaken part-time whilst working full-time as a marine ornithologist at the Joint Nature Conservation Committee (JNCC). Further details of this, including a description of what I have learned through working at JNCC and how this has influenced the thesis, are provided in Appendix A.

1.4 Structure of the thesis

The thesis consists of nine chapters, each individual but also sequential. In addition to the introduction (Chapter 1) and the conclusion (Chapter 8), there are seven chapters, as shown in Figure 1.2.

In Chapter 2, entitled “Literature review of cumulative seabird displacement”, the research begins by reviewing the methods used to predict cumulative seabird displacement and the empirical evidence of red-throated diver displacement from offshore wind farms. This helps to set the scene for the current understanding of cumulative displacement.

Chapter 3, entitled “Which species and impacts are assessed for displacement in offshore wind farm cumulative assessments?” follows this by reviewing how offshore wind farm EIAs approach cumulative displacement impact assessments. It also explores how offshore wind farms interpret the outcome of other wind farms’ individual assessments. This digs deeper into how cumulative displacement is assessed within an EIA to provide a prediction of what cumulative displacement might look like. This links to the next chapter, which investigates how wind farm design influences red-throated diver displacement.

Chapter 4, entitled “How does offshore wind farm design influence red-throated diver displacement?” first reviews the parameters which can be used to quantify displacement. It goes on to determine which wind farm design parameters affect displacement and finally discusses how wind farms could be designed to minimise displacement. In order to determine the true extent of displacement, seabird distribution surveys need to be carried out. Besides the introduction and conclusion, the content of Chapter 4 is published in Environmental Impact Assessment Review (Hall and Black, 2024).

Chapter 5, “How much monitoring is sufficient to detect red-throated diver displacement from offshore wind farms?” goes on to address the ability to quantify displacement. Different red-throated diver displacement scenarios are first generated before power analyses on survey designs are run to check if they are sufficient to detect displacement. Once it is established whether or not surveys are capable of detecting displacement, the details of the extent of displacement can be explored.

Chapter 6, “How does red-throated diver displacement change with distance from offshore wind farms?” reviews the extent of displacement, both in terms of displacement rates and spatial scales. This chapter also uses evidence of displacement across distances from wind farms to generate representative displacement gradients. This aids with understanding the typical extent of displacement, but also provides evidence-based displacement rates that developers and regulators could use in wind farm displacement assessments.

Finally, knowledge from all previous chapters is brought together to hypothesise future displacement in Chapter 7, “What might future cumulative red-throated diver displacement from offshore wind farms look like?”. First, a range of typical displacement rates and maximum displacement distances are generated to explore numerous scenarios. Then, the extent of current and future cumulative red-throated diver displacement is simulated. This uses an up-to-date evidence base to assess the existing level of cumulative displacement as well as predict the potential future cumulative displacement. This gives an indication of the impact of future wind farms, which will aid the siting of these developments, thereby providing a strategic environmental assessment of red-throated diver displacement.

This chapter has provided an introduction to the research conducted throughout this thesis, including the overall aim and objectives. The next chapter will, therefore, begin describing in detail the first part of this research, a literature review of cumulative seabird displacement.

2

Literature review of cumulative seabird displacement

To review the methods used to predict cumulative seabird displacement and the empirical evidence of red-throated diver displacement from offshore wind farms

3

Which species and impacts are assessed for displacement in offshore windfarms cumulative assessments?

To review how offshore wind farm EIAs approach cumulative displacement impact assessments

To explore how offshore wind farms interpret the outcome of other wind farms' individual assessments

4

How does offshore wind farm design influence red-throated diver displacement?

To review the parameters which can be used to quantify displacement

To determine which wind farm design parameters effect displacement

To discuss how wind farms could be designed to minimise displacement

5

How much monitoring is sufficient to detect red-throated diver displacement from offshore wind farms?

To model different red-throated diver displacement scenarios and run a power analysis on survey designs to check if they are sufficient to detect such displacement

To find the lowest detectable level of displacement for a given survey design and the transect spacing and number of surveys required to detect a given displacement rate

6

How does red-throated diver displacement change with distance from offshore wind farms?

To review how displacement change with distance from wind farms

To explore how a representative displacement gradient be generated for application within impact assessments

7

What might future cumulative red-throated diver displacement from offshore wind farms look like?

To generate a range of typical displacement rates and maximum displacement distances may occur from offshore wind farms

To simulate the extent of current cumulative red-throated diver displacement

To simulate the extent of future cumulative red-throated diver displacement

Figure 1.2. Thesis structure, including the objectives addressed in each chapter.

Chapter 2 Literature review of cumulative seabird displacement

The aim of this chapter is to review the methods used to predict cumulative seabird displacement and the empirical evidence of red-throated diver displacement from offshore wind farms. This chapter begins by setting the context of seabird species within the UK, followed by the industrial setting of offshore wind farms. Subsequently, the chapter reviews the effects of offshore wind farms on seabirds, including collisions, displacement, barrier effects, and indirect effects. The chapter continues by evaluating the species most sensitive to displacement from offshore wind farms. The ecology of the most sensitive species, red-throated divers, is described, followed by a review of evidence of red-throated diver displacement from individual offshore wind farms and then from multiple offshore wind farms. The role of Environmental Impact Assessments and Cumulative Effects Assessments are then described. Finally, the methods that can be used to assess the impact of red-throated diver displacement from offshore wind farms are reviewed.

2.1 Marine birds in the UK

The UK hosts a range of bird species which utilise the marine environment, including true seabirds, divers and grebes, and waterfowl. There are 25 species of breeding seabirds in the UK; six of these species are on the UK Birds of Conservation Concern Red List, whilst 18 are on the Amber List (Eaton *et al.*, 2015). Many species have been or are currently in decline (Table 2.1) (JNCC, 2021a), with 13 seabird species declining in abundance by an average of 24% since 1986 (JNCC, 2021b). Similarly, waterbirds have been facing continual declines over the past 25 years, with the likes of greater scaup and velvet scoter seeing decreases if 68% and 59% in abundance since 1996, and 68% decline in black-throated diver since 2011 (Table 2.2) (Woodward *et al.*, 2023). Marine birds utilise a range of habitats, feed on a range of trophic levels, and often migrate large distances, which makes them good indicators of the health of the marine environment (Mallory *et al.*, 2010).

Table 2.1. Population trends in UK seabirds from 1986 to 2019, taken from the Seabird Monitoring Programme (JNCC, 2021a) and from 2000 to 2013, taken from (MacDonald et al., 2015).

	Population change (%)			
Species	**1969-70 to 1985-88**	**1985-88 to 1998-2002**	**2000 to 2019**	**2000 to 2013**
Arctic skua	+266	-37	-70	-74
Arctic tern	+50	-31	-5	+6
Atlantic puffin	+15	+19	n/a	n/a
Black guillemot	n/a	+3	n/a	n/a
Black-headed gull	+5	0	+26	+26
Black-legged kittiwake	+24	-25	-29	-61
Common guillemot	+77	+31	+60	+9
Common gull	+25	+36	n/a	n/a
Common tern	+9	-9	-3	-17
European shag	+21	-27	-40	-41
European storm-petrel	n/a	n/a	n/a	n/a
Great black-backed gull	-7	-4	-23	-24
Great cormorant	+9	+10	+16	-20
Great skua	+148	+26	n/a	n/a
Herring gull	-48	-13	n/a	-30
Leach's storm-petrel	n/a	n/a	n/a	n/a
Lesser black-backed gull	+29	+40	n/a	-48
Little tern	+58	-23	-28	-4
Manx shearwater	n/a	n/a	n/a	n/a
Mediterranean gull	n/a	+10,900	+327	n/a
Northern fulmar	+77	-3	-33	-13
Northern gannet	+39	+39	+34	n/a
Razorbill	+16	+21	+37	+13
Roseate tern	-66	-83	+125	+155
Sandwich tern	+33	-15	+5	-7

Note: Pink shaded cells indicate an increase in the species. Purple shaded cells indicate a decline in the species.

Waterbirds face a range of pressures, most notably climate change, through changes in forage fish supply and extreme weather causing mortalities (Sydeman *et al.*, 2012; Daunt and Mitchell, 2013; Daunt *et al.*, 2017). Highly Pathogenic Avian Influenza (HPAI) has most recently become a larger pressure on seabirds and mammals, with most seabird species testing positive for the disease throughout 2023. More than 25% of the only UK breeding colony of Roseate terns (*Sterna dougallii*) and 11% of great skuas (*Stercorarius skua*) were lost in the summer of 2022 (RSPB, 2023). Barnacle geese were also impacted by HPAI during 2022 and 2023 generating a loss in abundance (Woodward *et al.*, 2023).

Table 2.2. Population trends in UK waterbirds from 1996 to 2022, taken from the Wetland Bird Survey Annual Report (Woodward et al., 2023).

	Population change (%)	
Species	10-year trend (2011/12-2021/22)	25-year trend (1996/97-2021/22)
Black-throated diver	-68	-46
Great northern diver	-19	+38
Red-throated diver	-25	-4
Slavonian grebe	-40	-34
Greater scaup	-53	-68
Common eider	-26	-31
Common goldeneye	-24	-54
Common scoter	+47	+278
Velvet scoter	-63	-59
Great-crested grebe	-2	-19
Long-tailed duck	-54	-74

Note: Pink shaded cells indicate an increase in the species. Purple shaded cells indicate a decline in the species.

2.2 Offshore wind farm development

Since the first offshore wind farm, Vindeby, off the coast of Denmark, was built in 1991, there has been a rapid upscaling of the size, number, and capacity of this renewable energy technology. In 2022, there were 8.8GW of new offshore wind installations globally, yet this figure is predicted to rise to an average of 26GW annually over the next five years, meaning 130GW of new offshore wind by 2027 (Global Wind Energy Council, 2023). In the UK, as of September 2023, there are 44 offshore wind farms fully operational with a total capacity of 13,663MW, with a further eight wind farms under construction, 15 with consent to build, and 38 in the early stages of development (Figure 2.1). If all of these are built, there could be 105 wind farms with a total capacity of up to 88,984MW, more than twice the number of wind farms and over six times the capacity currently installed (The Crown Estate, 2023).

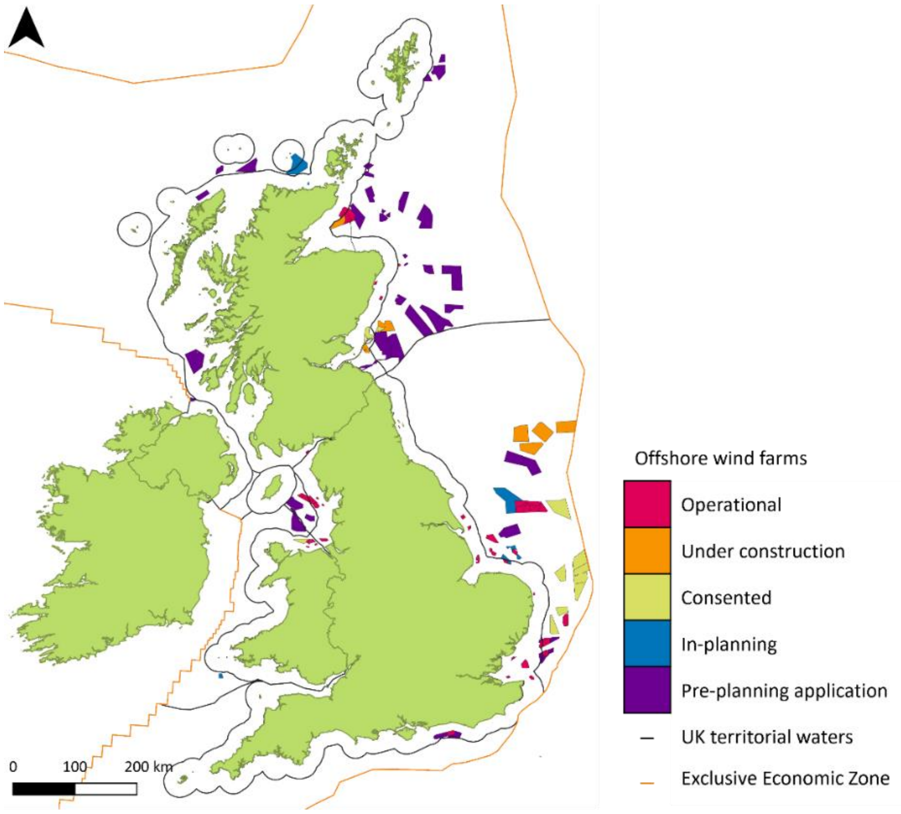

Figure 2.1. The location of offshore wind farms around the UK at different stages of development.

Data source: The Crown Estate Offshore Wind Site Agreements (England, Wales & NI), 2023.

Given the vast deployment of offshore wind required to meet climate goals, the development of such projects needs to be carefully planned from initial site selection to beginning operation. This includes accounting for the time taken to select, plan, and construct a project. In the UK, it typically takes an average of eight years from granting of a seabed lease to the start of operation for an offshore wind farm (Ireland = four years, Scotland = eight years, Wales = nine years, England = 10 years) (Global Wind Energy Council, 2022). A large part of this time scale is due to the permitting process required to gain consent to build and operate a project.

2.3 Effects of offshore wind farms on seabirds

There are numerous environmental effects associated with offshore wind farms, which occur at many stages of development and affect different species in different ways. Impacts may occur during the construction of the wind farm, such as impacts on seabed morphology and benthic species from cable installation, disturbance to birds from construction traffic, and noise disturbance to marine mammals and fish from pile driving (Dannheim *et al.*, 2019; Fliessbach *et al.*, 2019; Gill and Wilhelmsson, 2019; Nehls *et al.*, 2019; Rees and Judd, 2019). Impacts during operation can include bird collisions with turbines, displacement of birds from the wind farm area, colonisation of the turbines and scour protection by epibenthic species (Dannheim *et al.*, 2019; King, 2019; Vanerman and Stienen, 2019). The method of decommissioning will determine the impact that this has on species. For instance, the full removal of turbine structures will impact species that have colonised structures, removing their habitat and affecting species that utilise the species as a food source. Repowering turbine structures with newer technology or extending the life of the wind farm, on the other hand, may benefit these species if sub-sea structures retain this ecosystem (Hall *et al.*, 2022).

In terms of seabirds, the effects of offshore wind farms typically happen through collisions with turbines, disturbance (which can be split into displacement from habitat and barrier effects whilst flying), and indirect effects (Masden *et al.*, 2010a; Perrow *et al.*, 2011; King, 2019; Vanerman and Stienen, 2019). Birds that fly at the height of wind turbine rotors have the potential to collide with them, likely resulting in direct mortality (Band, 2012). Disturbance can generally be described as a behavioural response to an anthropogenic activity (Beale, 2007). In response to offshore wind farms, the disturbance of seabirds can be categorised into two effects: displacement and barrier effects. Based on the behaviour of an individual prior to disturbance occurring, a different physical reaction is seen. Seabirds in flight can perceive an offshore wind farm as an effective obstruction to flight; thereby, this disturbance is termed a “barrier effect” (Masden *et al.*, 2010a). The reduction in the number of birds on the water within or adjacent to a wind farm is termed “displacement” (Drewitt and Langston, 2006). Displacement can be described by two metrics: displacement rate and displacement distance. Displacement rate is the proportion of birds that are displaced from an offshore wind farm and adjacent area. Displacement distance is the distance from the boundary of an offshore wind farm that birds are displaced. Neither displacement nor barrier effects are likely to result in immediate mortality of an individual but instead may result in lost foraging habitat, foraging in less productive areas, or increased time and energy spent flying or foraging (Masden *et al.*, 2010a; Searle *et al.*, 2014; Welcker and Nehls, 2016). Direct mortality by seabird collisions is usually assessed through Collision Risk Models (CRM), which predict the number of birds at risk of collision; the well-established and commonly used CRM is the Band model (Band, 2012). Impacts that result in indirect mortality or reduced productivity, such as displacement and barrier effects, have been much harder to model (Fox and Petersen, 2019). The consequence of these types of disturbance may be changes in breeding success and survival of adults or dependants Figure 2.2. Indirect effects to seabirds may arise through changes in prey resource, for example the change in habitat and associated new life growing on turbine foundations may generate a reef effect and hence a more plentiful and diverse prey resource (Linley *et al.*, 2007). Changes in hydrodynamics may further influence prey availability (van Berkel *et al.*, 2020). Both positive and negative effects may may seen, with reef effects potentially being positive, whilst negative effects may occur due to noise produced during wind farm construction, causing injury or death to fish (Perrow *et al.*, 2011). These trophic level effects are far less understood compared to collisions and displacement, and as yet there is no standard approach to assessing the implications to seabirds.

In the UK, adverse impacts to seabirds have led to a wind farm being denied consent to build and operate and other wind farms needing to compensate for the remaining impacts that cannot be mitigated. Consent to construct and operate an offshore wind farm known as Docking Shoal was refused in 2012 due to an inability to rule out adverse effects to breeding Sandwich terns (*Sterna sandvicensis*) from nearby North Norfolk Coast Special Protection Area (SPA) due to the cumulative effects with other offshore wind farms (Department of Energy & Climate Change, 2012). As the scale of offshore wind development increases, the need for more precise information on environmental impacts in order to reduce uncertainty (and therefore reduce reliance on a precautionary approach) will become increasingly pertinent. Hornsea Three offshore wind farm was granted development consent despite the Secretary of State concluding Adverse Effect on the Integrity of the Flamborough and Filey Coast Special Protection Area (SPA), North Norfolk Sandbanks and Saturn Reef Special Area of Conservation (SAC), and the Wash and North Norfolk Coast SAC. However, upon the condition of compensatory measures for qualifying features of these designated sites (Black-legged kittiwake *Rissa tridactyla* and sandbanks slightly covered by water at all times) as well as the presence of “Imperative Reasons of Overriding Public Interest” (IROPI) and the lack of feasible, less damaging alternative solutions, meant that development consent was granted (Leigh, 2020).

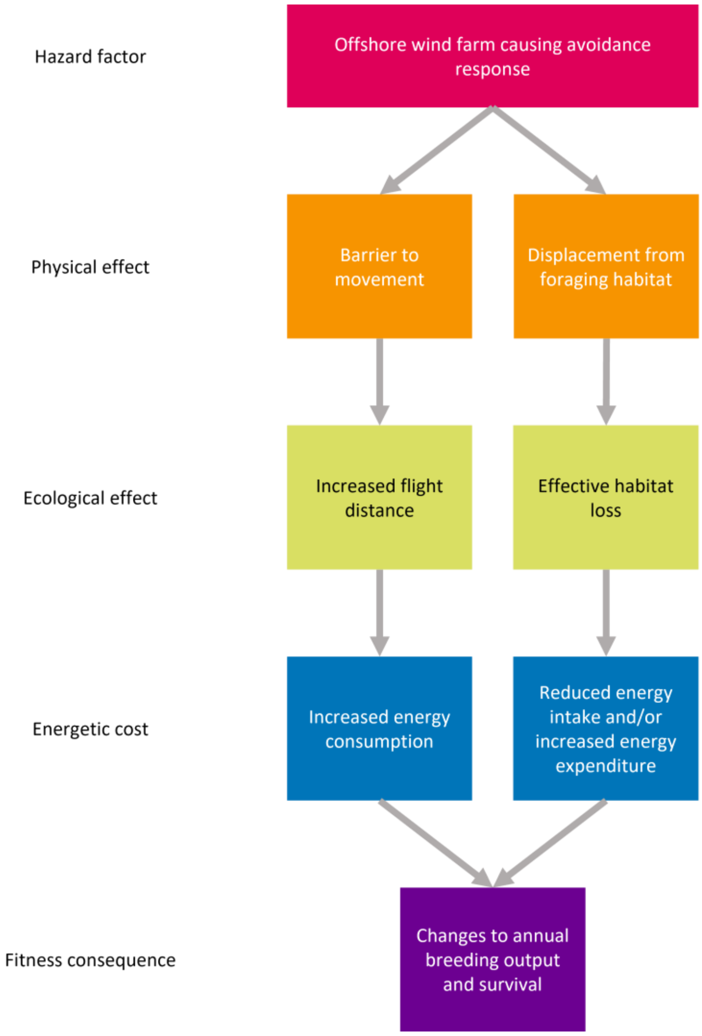

Figure 2.2. The physical effects and consequences of barrier effects and displacement to seabirds from offshore wind farms adapted from Petersen et al. (2006).

2.4 Species most sensitive to displacement from offshore wind farms

Several studies have assessed the relative sensitivity of bird species to displacement. Marques *et al.* (2021) undertook a review of the literature surrounding the displacement of all bird species to both onshore and offshore wind farms and grouped the results by bird order. The study also categorised the results by displacement rate and displacement distance. Gaviiformes (divers, sometimes called loons, including red-throated diver) had the highest average displacement rate and displacement distance of the groups studied (Figure 2.3 and Figure 2.4, respectively). Due to the vast development of onshore wind prior to the industry also moving offshore, there were many more studies of the effect of displacement as a result of onshore wind farms than offshore wind farms (Marques *et al.*, 2021).

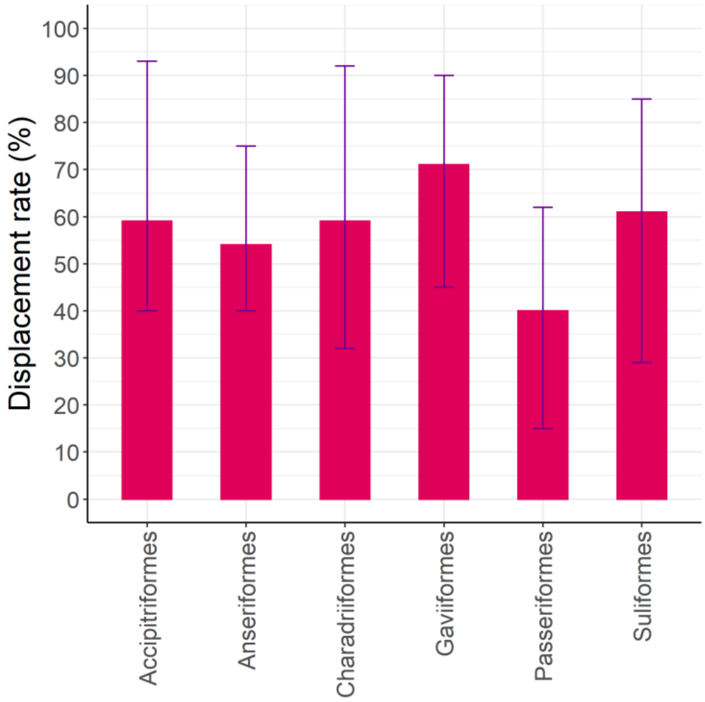

Figure 2.3. Average, minimum and maximum displacement rates of bird orders from global studies of displacement from onshore and offshore wind farms (adapted from Marques et al. (2021)).

Note: Gaviiformes include red-throated diver, the species of study within this thesis.

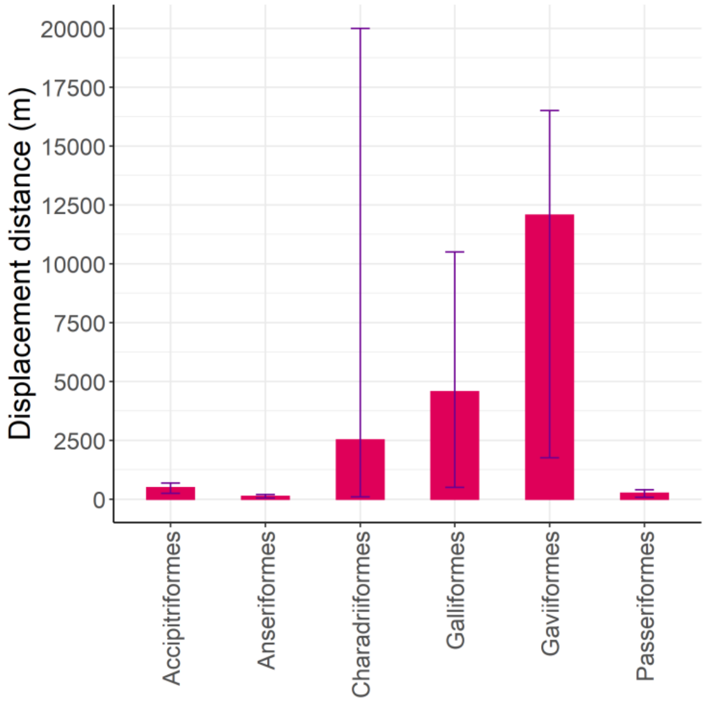

Figure 2.4. Average, minimum and maximum displacement distances of bird orders from global studies of displacement from onshore and offshore wind farms (adapted from Marques et al. (2021)).

Note: Gaviiformes include red-throated diver, the species of study within this thesis.

Several studies have quantified the vulnerability of seabird and waterbird species to displacement due to wind farms. These tend to use a combination of conservation status (such as status in the Birds Directive, adult survival rate, and percentage of the global or biogeographic population that occurs in the UK) and aspects of behaviour to provide relative scores of vulnerability. Furness *et al.* (2013) generated a disturbance score for a range of marine birds located in Scottish waters based on Equation 2.1.

$$Disturbance\ score = \frac{\mathrm{a} \times \mathrm{b} \times conservation\ importance}{10}$$

Equation 2.1. Relative disturbance of seabirds to displacement from offshore wind farms from (Furness et al., 2013).

where

a = score of disturbance by wind farm structures and ship and helicopter traffic between one and five

b = score of habitat specialisation between one and five

A collision risk score was also calculated in this study and combined with the displacement score to generate and overall species vulnerability score. The displacement calculation included the division by an arbitrary value of 10 due to the lower impact of mortality from displacement in comparison to that from collision (Furness *et al.*, 2013).

Bradbury *et al.* (2014) carried out a similar study of displacement vulnerability to offshore wind farms but expanded the species to cover those across English waters. The same equation to calculate disturbance vulnerability was used for Furness *et al.* (2013). Wade *et al.* (2016) went a step further by incorporating data uncertainty into the factors contributing to the vulnerability scores. This study also split displacement by structures and displacement by vessels and/or helicopters into two separate factors and gave more weight to displacement by structures (Equation 2.2).

$$Disturbance\ score = \frac{((\mathrm{c} \times \mathrm{b}) + \mathrm{d}) \times conservation\ importance}{10}$$

Equation 2.2. Relative disturbance of seabirds to displacement from offshore wind farms from (Wade et al., 2016).

where

b = score of habitat specialisation between one and five

c = score of displacement by structures between one and five

d = score of displacement by vessels and/or helicopters between one and five

The resulting vulnerability scores for the top five species from each of these three studies show that diver species consistently come out as the most sensitive species to displacement (Table 2.3).

Table 2.3. Bird species with the highest relative vulnerability to displacement from offshore wind farms.

Rank	Furness et al 2013	Bradbury et al. 2014	Wade et al. 2016
1	Black-throated diver	Red-throated diver	Black-throated diver
2	Red-throated diver	Black-throated diver	Red-throated diver
3	Great northern diver	Common scoter	Great northern diver
4	Common scoter	Great northern diver	Common scoter
5	Common goldeneye	Common goldeneye	Common goldeneye

Red-throated divers are often cited as one of the most sensitive seabird species to displacement from offshore wind farms (Furness *et al.*, 2013; Dierschke *et al.*, 2016; Natural England, 2016; Welcker and Nehls, 2016). Assessing the impact of displacement of red-throated divers on a local scale is important, as wind farms can act as barriers to local movements (Topping and Petersen, 2011). Careful spatial planning may reduce negative impacts on red-throated divers, for instance, by avoiding important foraging areas when placing wind farms at sea (Vilela *et al.*, 2020).

This thesis focuses on the displacement of red-throated divers due to their high sensitivity to offshore wind farms. The ecology of red-throated divers is discussed in the next section, with further detail provided on empirical evidence of red-throated diver displacement in the subsequent section.

2.5 Red-throated diver ecology

Red-throated divers are a widespread migratory species breeding and over-wintering across the northern hemisphere. They utilise both marine and freshwater environments throughout the year, breeding beside freshwater lakes during summer and foraging in both marine and freshwater ecosystems (Eriksson and Sunberg, 1991; Duckworth *et al.*, 2021), then spending the winter period entirely at sea (Duckworth *et al.*, 2022). The utilisation of the marine environment is restricted to around 9km from the coast during the breeding season (Woodward *et al.*, 2019). During the non-breeding season, they are more widespread but tend to be site-faithful (Dierschke *et al.*, 2017; Duckworth *et al.*, 2022).

Their diet often consists of a mix of prey species, from clupeids, gadoids, and mackerel to flatfish and sand lances, the proportions of which often change through the seasons, making them generalists and using an opportunistic foraging strategy (Guse *et al.*, 2009; Kleinschmidt *et al.*, 2019). Red-throated divers typically forage using relatively shallow dives (mean 5.4m), but can take deeper divers (maximum 20m), with dives being shallower in lower light conditions (Duckworth *et al.*, 2020). Foraging activities have been seen to occur for up to 60% of daylight time during autumn migration at reservoirs in Poland (Polak and Ciach, 2007), and as little as 23% of the time during the summer at lakes in Finland (Duckworth *et al.*, 2020). Estuarine fronts often seem to be predictors for red-throated diver occurrence, possibly due to these being reliable locations for food resources (Skov and Prins, 2001). During the summer, the characteristic red throat is present (Figure 1.1), which changes to white in winter.

A significant proportion occur in European waters, and recent declines in the region mean that they are listed on Annex I of the EU Birds Directive. The EU Birds Directive is legislation which requires Member States to protect all wild bird species. It also requires the protection and restoration of wild bird habitats. Species listed under Annex I have specific conservation measures implemented in order to ensure their reproduction and survival. In practice, this means spatial areas are designated, known as Special Protection Areas (SPAs). Within UK waters, the largest aggregation of wintering red-throated divers occurs in the Outer Thames Estuary SPA with 6,466 individuals based on surveys between 1989 and 2007 (JNCC, 2020a). This SPA is designated for red-throated divers during the non-breeding season, as well as for breeding little terns (*Sternula albifrons*) and common terns (*Sterna hirundo*). There are many activities and developments within the local marine environment, such as shipping, offshore wind farms, and aggregate extraction. Red-throated divers are known to be sensitive to disturbance and displacement by shipping and wind farms around wider European waters and within this SPA (Irwin *et al.*, 2019). Wintering red-throated divers are also qualifying features of the Greater Wash SPA, which abuts the northern end of the Outer Thames Estuary SPA and hosts 1,407 individuals (JNCC, 2020c), and the Liverpool Bay SPA which spans the north coast of Wales and northeast coast of England, hosting 1,171 individuals (JNCC, 2020b).

Now that the ecology of red-throated divers has been described, the next section will review empirical evidence of red-throated diver displacement from offshore wind farms.

This includes the type and extent of surveys, modelling techniques to generate abundance estimates from raw survey data, and how displacement has been calculated.

2.6 Evidence of individual and cumulative red-throated diver displacement from offshore wind farms

There is a multitude of evidence of red-throated diver displacement from offshore wind farms. Red-throated diver displacement distances are very varied; reports show diver displacement from 1km to 16km (Welcker and Nehls, 2016; Mendel *et al.*, 2019; Heinänen *et al.*, 2020). Some studies report the displacement rate observed, typically in terms of the percentage removal of birds after wind farm construction compared to pre-construction. However, many reports do not describe the displacement rate; a statistically significant removal is sometimes stated instead. With such variable displacement distances and rates, it is difficult to provide guidance on how to adequately monitor displacement and what Displacement rate might be detectable. Marques *et al.* (2021) give a range of examples of good practices for onshore and offshore displacement studies. This includes multi-year and multi-location studies to enable both a control site and natural fluctuations to be accounted for, a sufficiently large study area to encapsulate the full extent of displacement, appropriate survey techniques, and a good study design capable of providing statistically significant results where possible (Marques *et al.*, 2021).

The literature search revealed 16 studies which quantified red-throated diver displacement from offshore wind farms (see details in Appendix B). Due to the overlap in distribution of red-throated divers and operational offshore wind farms, studies have almost exclusively concentrated on the North Sea, often within Danish, German, and UK waters. The majority of studies have been carried out by either aerial or boat-based surveys, or sometimes a combination of the two. There has been a range in the spatial and temporal scale of displacement studies. Most transects were placed 2km apart from one another when covering the wind farm area, but were often spaced further apart to survey the surrounding area. The maximum distance surveyed from an individual wind farms was 32km from Horns Rev I in Denmark (Petersen *et al.*, 2006) whilst the small distance covered was 2km outside the wind farm at Thanet in English waters (Percival, 2013). On average, 16km was surveyed outside the wind farm. This distance was not always the same in any direction from the wind farm, meaning an uneven area around the wind farm was often surveyed.

The majority of studies utilised data from both pre-construction and post-construction of the wind farm in question, and therefore used either a Before-After or Before-After-Control-Impact (BACI) approach to quantifying displacement. Where this was not the case, a couple of studies undertook a comparison of the density of red-throated diver within (and sometimes around) the wind farm to the density a some distance away from the wind farm using post-construction data only (Welcker and Nehls, 2016; Burt *et al.*, 2017). Similarly, some studies modelled the potential distribution of birds without the wind farm compared to the known distribution with the wind farm, again within and outside the wind farm and using only post-construction data (Krijgsveld *et al.*, 2011; Heinänen *et al.*, 2020).

The combination of survey type and displacement analysis method appears to be spread geographically, with DAS, boat-based, and a combination of the two being used across the UK, the Netherlands, Germany, and Denmark. The method used to examine displacement was also reasonably evenly spread (Figure 2.5). The different survey methods could be partly explained by time and experience. Both boat-based surveys and DAS were carried out during these earlier studies, but boat-based surveys alone became less prevalent over time unless used in combination with DAS. It is likely that, as knowledge of red-throated diver disturbance by vessels grew, boat-based surveys were used less to limit the alteration in distribution due to the survey method. Even aerial surveys need to be planned to avoid disturbance. A review of techniques to survey seabirds using aerial methods recommended that a minimum flight altitude of 450m should be used to avoid disturbing sensitive species, preventing the survey itself from altering the distribution of birds (Thaxter and Burton, 2009).

Individual offshore wind farms may have a displacement effect on red-throated divers and other species, but seabirds may interact with multiple wind farms within the marine environment. Given the large spatial scale over which red-throated diver displacement has been observed and wind farms often built in clusters, cumulative displacement is likely to occur (Goodale and Milman, 2016; Mendel *et al.*, 2019; Garthe *et al.*, 2023). Studying over a larger spatial scale within the vicinity of a wind farm may aid in detecting effects over a larger area and also pick up where birds have moved once displaced (Mendel *et al.*, 2019). Indeed, several of the red-throated diver displacement studies considered the effect of multiple wind farms.

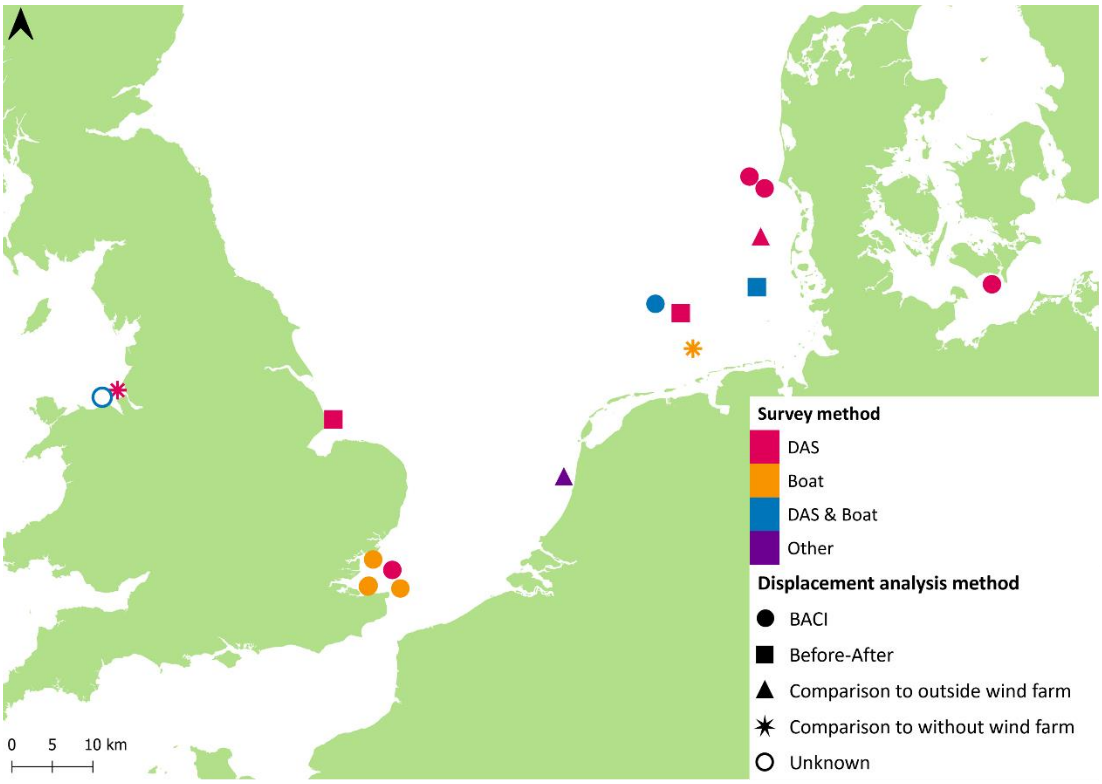

Figure 2.5. Map of the survey methods and displacement analysis methods used to study red-throated diver displacement in the literature (16 studies spanning 2006 to 2023).

To date, most studies into the cumulative effect of multiple wind farms on red-throated divers have centred on the German North Sea. This is an important wintering area for red-throated divers and has SPAs where divers are a qualifying feature (Garthe *et al.*, 2012). In addition, it is an area of extensive offshore wind farm development (4COffshore, 2023).

Vilela *et al.* (2020) studied the effect of 20 offshore wind farms across 28,625km^2 of the German North Sea. Displacement was categorised as occurring within the area that red-throated diver density was significantly lower than the mean density of the whole study area. Therefore, displacement was not attributed to wind farms individually, indeed there was no mention of whether displacement rates were different within each wind farm.

A study by Mendel *et al.* (2019) of five wind farms around the Eastern German Bight SPA used visual aerial and boat-based surveys and a before-after analysis of the survey data, and found that significant displacement occurred up to 16.5km from the wind farms. Again, displacement across the entire study area only was assessed, without mention of displacement at each individual wind farm.

Another study of the German North Sea assessed displacement at the same wind farms as in Mendel *et al.* (2019), but additionally used telemetry. The telemetry and digital aerial survey data were used separately to create two density maps, and both were used to consider the spatial extent of displacement, but only the aerial map was used to quantify the displacement rate (Heinänen *et al.*, 2020).

A wider-scale study was carried out by Vilela *et al.* (2020) covering six wind farms in and around the Eastern German Bight SPA along with 15 wind farms further southwest. Various sources of data were used collectively, mostly from wind farm monitoring but all aerial surveys. Displacement was assessed based on relative distributions across the entire study area. A before-after approach was also taken, but because the 21 wind farms were all constructed during different years, having a pre-construction phase and a post-construction phase without either category including a wind farm under construction, and potentially adding to the displacement effect, made the results less reliable.

The latest study of red-throated diver displacement in the German North Sea also used data from multiple sources, including baseline studies for EIAs, wind farm monitoring studies, the German Biodiversity Monitoring project, and various research projects (Garthe *et al.*, 2023). The surveys used visual aerial, digital aerial, and boat-based methods. A BACI approach was taken, defining the pre-construction and post-construction phases individually for five wind farm clusters. Wind farm clusters were spatially distinct from one another. The Dan Tysk cluster had just one wind farm, as did the Butendiek cluster. The Helgoland cluster contained three wind farms, the BARD/Austerngrun cluster had two wind farms, and the North of Borkum cluster included three wind farm. Displacement metrics were produced for the wind farm clusters and the study area as a whole.

A study into the cumulative effects of shipping and offshore wind farms was carried out for the north Welsh coastline (Burt *et al.*, 2017). This study used digital aerial survey data collected across the entirety of the Liverpool Bay SPA. Shipping density and locations of offshore wind farms were included as covariates in generating a model of red-throated diver distribution.

It was quite variable whether displacement rates were calculated and provided in the literature. The spatial extent over which a displacement rate was calculated was also variable, for instance in discrete 1km distance bands around a wind farm or over the entirety of the wind farm plus a 10km buffer. The quantification of displacement rates across distances are described and interrogated in more detail in Chapters 4 and 5.

An extension to the London Array offshore wind farm located in English waters of the southern North Sea was cancelled due in part to the concern over impacts to red-throated divers. The original wind farm and the proposed extension are located in a Special Protection Area (SPA), of which red-throated divers are a qualifying feature (JNCC, 2020a). Monitoring of the London Array with regard to its impact on red-throated divers was required before a decision could be made as to the effect the London Array and an extension would have upon this designated population. Time scales for collecting data, along with technical challenges, are cited as the reasons the extension did not go ahead (London Array, n.d.).

Notably, large distances over which red-throated diver displacement has been observed resulted in a recommendation that a round of seabed leases in English waters are not placed within 10km of the Greater Wash Special Protection Area (SPA) with red-throated divers as a qualifying feature. Further, it is recommended by Statutory Nature Conservation Bodies (SNCB) in the UK that a distance be maintained between the Outer Thames Estuary SPA and The Greater Wash SPA 10km (Statutory Nature Conservation Bodies, 2022a).

2.7 Environmental Impact Assessment

Environmental Impact Assessment (EIA) is a globally widespread method of assessing the potential effects of proposed developments on the environment and is often required under legislation (Morgan, 2012). The European Union mandates the implementation of EIA through the EIA Directive (2014/52/EU), which is translated into domestic law. The European Union has shaped EIA legislation in the UK since 1988, leading to the current EIA legislation, such as the Conservation of Offshore Marine Habitats and Species Regulations 2017 (as amended) and territorial equivalents, The Electricity Work (Environmental Impact Assessment) (England and Wales) Regulations 2017, and The Infrastructure Planning (Environmental Impact Assessment) Regulations 2017. This legislation remains valid in 2023 despite the exit of the UK from the European Union in 2020.

Where developments may impact EU-designated areas (Special Areas of Conservation (SAC) protecting habitats and Special Protection Areas (SPA) protecting marine birds), Habitats Regulations Assessments (HRA) are also required. Again, these are EU requirements translated into domestic law, so they remain the same as of 2023. The network of protection sites previously named “Natura 2000” sites are now named “The National Sites Network” in most nations of the UK and “European sites” in Scotland, following the UK’s withdrawal from the EU in 2020. These assessments first consider whether or not a development may have a Likely Significant Effect on the site, and if that cannot be ruled out, then an Appropriate Assessment is undertaken to determine whether the development will have an Adverse Effect on Site Integrity. The stages of HRA are specifically applicable to SACs and SPAs, with the impacts of a proposed development assessed again the conservation objectives of the designated site.

2.8 Cumulative Effects Assessment

The best practice for assessing the impacts of development is to not only do a project or plan alone assessment but also to carry out a cumulative assessment of the project or plan in combination with other pressures. This is supported by the EIA legislation mentioned in section 2.7 that bind offshore wind farm consenting, which contain a requirement to consider the cumulative effects of the project with other developments. Schedule 4 paragraph 5 of The Infrastructure Planning (Environmental Impact Assessment) Regulations 2017 states that, included within an Environmental Statement, there should be a description of the likely significant effects of the development on the environment as a result of “…the cumulation of effects with other existing and/or approved projects, taking into account any existing environmental problems relating to areas of particular environmental importance likely to be affected or the use of natural resources”.

Cumulative Effects Assessment (CEA) is often defined as a method of assessing multiple developments and pressures and their combined effect on receptors (Canter and Ross, 2010; Foley *et al.*, 2017; Willsteed *et al.*, 2017). The purpose of a CEA is to ensure that thresholds of development are not exceeded (Canter and Kamath, 1995); however, the exact metric to use as a threshold value is a matter of debate (Duinker *et al.*, 2013). Several studies have concluded that both CEA practices and research on the environmental impacts of wind farms are not sufficient to fully understand the effects and allow regulators to make informed decisions during the consenting process (Stewart *et al.*, 2007; Foley *et al.*, 2017; Willsteed *et al.*, 2018). Uncertainties about predicted environmental impacts have been cited as causes of delays in granting consent for wind farm development, which can have an adverse impact on the start of construction and operation, costing time and money (O'Hagan, 2012).

2.9 Methods of carrying out an impact assessment for red-throated diver displacement

In the UK, the method of assessing the displacement of seabird displacement is relatively simplistic, using what is known as a displacement matrix. There are three inputs to a displacement matrix: the abundance of birds at risk of displacement, a displacement rate, and a mortality rate.

The density or abundance of birds within the proposed wind farm plus a buffer is used as the basis of the assessment. The density or abundance used is calculated as the mean of the seasonal peak populations from baseline surveys. In other words, for a particular season, the peak population within each year of the survey should be used, and a mean calculated. This may overestimate the population if lower numbers are present during other periods within the season and may doubt count individuals that represent year-round. However, baseline surveys are a snapshot in time of abundance, therefore may underestimate the population.

A displacement rate is applied to the mean seasonal peak value to determine the number of birds displaced. Due to a lack of empirical evidence on displacement rates for some seabird species and ranges of rates for other species, a range of displacement rates is usually used. These displacement rates are based on the score of disturbance from ships, helicopters, and wind farms from Bradbury *et al.* (2014) (*a* in Equation 2.1). Species with the highest disturbance from ship, helicopter, and wind farm score of 5 would be assigned a displacement rate of 90% to 100%. A score of three would lead to a displacement rate range of 30% to 70%, and those with a low score of one would have a displacement rate of less than 10% applied. This is a result of a number of birds displaced from a proposed wind farm and surrounding area.

The displacement matrix then uses a mortality rate, or range of mortality rates, to the displaced birds to determine the number of mortalities due to displacement (see example for an abundance of 80 birds in Table 2.4). The range of mortality rates is based on the score of habitat specialisation; those with higher scores are less able to utilise other habitats and, therefore, more likely to be impacted by displacement. Mortality rates of between 1% and 100% are used, but in reality, between 1% and 10% mortality is more likely (Statutory Nature Conservation Bodies, 2022b). The estimate of number of mortalities is therefore calculated through Equation 2.3.

Table 2.4. Example displacement matrix to calculate the range of potential mortalities on an abundance of 80.

		Mortality rate (%)												
		1	**2**	**5**	**10**	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**	**100**
Displacement rate (%)	**10**	0.1	0.2	0.4	0.8	1.6	2.4	3.2	4.0	4.8	5.6	6.4	7.2	8.0
	20	0.2	0.3	0.8	1.6	3.2	4.8	6.4	8.0	9.6	11.2	12.8	14.4	16.0
	30	0.2	0.5	1.2	2.4	4.8	7.2	9.6	12.0	14.4	16.8	19.2	21.6	24.0
	40	0.3	0.6	1.6	3.2	6.4	9.6	12.8	16.0	19.2	22.4	25.6	28.8	32.0
	50	0.4	0.8	2.0	4.0	8.0	12.0	16.0	20.0	24.0	28.0	32.0	36.0	40.0
	60	0.5	1.0	2.4	4.8	9.6	14.4	19.2	24.0	28.8	33.6	38.4	43.2	48.0
	70	0.6	1.1	2.8	5.6	11.2	16.8	22.4	28.0	33.6	39.2	44.8	50.4	56.0
	80	0.6	1.3	3.2	6.4	12.8	19.2	25.6	32.0	38.4	44.8	51.2	57.6	64.0
	90	0.7	1.4	3.6	7.2	14.4	21.6	28.8	36.0	43.2	50.4	57.6	64.8	72.0
	100	0.8	1.6	4.0	8.0	16.0	24.0	32.0	40.0	48.0	56.0	64.0	72.0	80.0

$$e = f \times \left(\frac{g}{100}\right) \times \left(\frac{h}{100}\right)$$

Equation 2.3. Calculation of displacement mortalities through the displacement matrix

where

e = number of displacement mortalities

f = abundance of birds within the proposed wind farm plus a buffer

g = displacement rate (%)

h = mortality rate (%)

The consequences of displacement on red-throated diver populations are largely unknown, meaning there is a need to understand how populations shift (for instance, through potential biological removal (Busch and Garthe, 2016)), how individuals behave, energetics are impacted, and demography changes (for instance through individual-based models (Searle *et al.*, 2021)) following displacement. This is difficult to monitor at the scale of an individual wind farm, and strategic research is underway to try and improve understanding of the behavioural and energetic consequences of displacement (Duckworth *et al.*, 2020). Individual wind farm monitoring can, however, improve understanding of the number of individuals displaced and the distance they are displaced from a development footprint.

Comparison between predicted displacement and actual displacement at a wind farm. Using the displacement matrix approach, the number of birds displaced is based on the number of birds in the baseline environment, the area and location of the wind farm, and the displacement rate. The number of birds in the baseline may well fluctuate in the future, but the use of peak mean seasonal population and inclusion of confidence intervals helps to account for this. The location of a wind farm is not likely to change, given that seabed leases are given prior to a displacement assessment being carried out. The displacement rate may be correct or incorrect for that particular location, but as yet, there is no consensus on whether displacement rates are different in different locations and why to be able to apply site-specific rates.

The area of a wind farm may change between a displacement assessment and the building of a wind farm. A project design envelope is used at the assessment stage to predict the bounds of a wind farm's design. For the impact assessment, the worst-case scenario within the design envelope is often used to provide a precautionary approach to the assessment. This does mean that the impacts assessed may be larger than those actually occurring once the wind farm is built if the wind farm built is not the worst-case scenario, assuming the rest of the impact assessment is accurate. If assessments are more often precautionary than not, when cumulative impacts are assessed, the precaution may be compounded. There may in fact be headroom between the predicted cumulative impact and the actual cumulative impact (Womble Bond Dickinson, 2021).

However, sufficient monitoring of each wind farm's impact is needed to determine whether impact assessments were accurate. Assessments of red-throated diver displacement in UK waters have previously underestimated the extent of displacement by assuming displacement only occurred out to 4km from the wind farm boundary. A 100% displacement rate was assumed to occur across the wind farm and 4km buffer, which was a compromise between the fact that displacement may occur further than 4km but is probably less than 100% within 4km. Therefore, the number of birds displaced will be equivalent, assuming large displacement rates over a small area compared to lower displacement rates over a larger area. However, the area of lost habitat due to displacement is also an important factor in assessing the impact; therefore, assuming it only happens over 4km from a wind farm may vastly underestimate the true impact. This is important at the cumulative level, where the displacement-affected areas from multiple wind farms may overlap, potentially leading to mass areas of habitat loss.

In summary, this chapter has revealed that red-throated divers are highly sensitive to displacement from offshore wind farms and that multiple studies have investigated this effect. Such studies have varied widely in their survey method, displacement analysis, and presentation of results. Both individual wind farm displacement and cumulative displacement from multiple wind farm have been studied. With such varied approaches to displacement analysis, it is difficult to say how comparable they are, yet the consensus remains that red-throated divers are a key species for further investigation and management of effects. The overall research gap analysis found that knowledge and methods to predict, assess, and mitigate future cumulative displacement of seabirds from offshore wind farms are lacking, yet may prove to be a major factor in restricting renewable development. The next chapter will review EIAs to assess how species and impacts have been scoped into cumulative offshore wind farm assessments.

Chapter 3 How are impact assessments of cumulative red-throated diver displacement from offshore wind farms carried out?

Abstract

The continual growth of more, larger wind farms in coastal waters will lead to a substantial area of the sea being used to generate renewable energy. With wind farms being sited in relative proximity to one another, the interaction of environmental impacts, or cumulative environmental impacts, is becoming an increasing concern. Choosing which species, impacts, and other plans and projects to include in a cumulative assessment will determine the scope of the assessment. The generic approach to assessing cumulative seabird displacement was evaluated in 18 offshore wind farm Environmental Impact Assessments in the UK, and in detail using six case studies from Scottish waters. This work found that species and impacts included in individual and cumulative vary, even in spatially close wind farms. The outputs from one wind farm assessment is sometimes interpreted in different ways by other developments when considering the cumulative impact, for instance considering a low number of birds present to equal a negligible impact. Some individual wind farm impacts are quantified seasonally, whilst others are done so annually. It is unclear how these differing results have been combined across multiple wind farms. In addition, some individual wind farm assessment conclude multiple or between significance levels, such as minor/major. Again how this was treated at a cumulative level is unclear. One cumulative assessment may conclude a particular significance level, whilst another assessment conclude a different significance level, despite including the same other wind farms in the assessment. With variabilities within impact assessments, and wind farms in different locations, years, and with different design parameters, the cumulative assessment already contains large uncertainties. This is then extrapolated further when the impacts, species, and inclusion of other projects also varies widely across cumulative assessments.

3.1 Introduction to how cumulative seabird displacement is assessed for offshore wind farms

As discussed in Chapters 1 and 2, offshore wind farm development is set to rise significantly in the near future around the globe, and with it, the challenge associated with understanding the cumulative environmental impacts of developments with other projects (Goodale and Milman, 2016). The cumulative impact of wind farms has also become an increasing concern for regulatory authorities and statutory consultees alike (Broadbent and Nixon, 2019; Natural England, 2019). This is largely because the cumulative impact of developments is largely uncertain (Masden *et al.*, 2015). The assessment, or lack, of such cumulative impacts has led to delays in granting consent, such as with the redetermination of the Norfolk Vanguard wind farm (Raymond Stephen Pearce v Secretary of State for Business Energy and Industrial Strategy, 2021) and the delay to consent for the Norfolk Boreas wind farm on the grounds of cumulative effects of the two developments (Leigh, 2021). This can have implications for the start of construction and operation of an offshore wind farm.

EIA legislation, such as The Infrastructure Planning (Environmental Impact Assessment) Regulations 2017, stipulates which developments are to be included in a Cumulative Effects Assessment (CEA) by stating “existing and/or approved projects”. What developments are classed as “existing” or “approved” is ambiguous, partly because it could be argued that existing developments are already part of the baseline and so form the pre-development scenario that would be assessed against, rather than grouping them with post-development impacts. However, this may result in assessments not accounting for a shifting baseline (Pauly, 1995). Regardless, the developments to include are at least somewhat specified, whilst the species and impacts to be assessed are not specified at all, as they vary depending on the location of each wind farm. Several pieces of UK guidance suggest which species should be included in assessments (both individually and cumulatively) and methods for how to determine which species to include. This may include completing a standardised “key features” document, which assesses species in relation to their vulnerability to wind farm impacts, their designation at a protected site, and their potential for cumulative impacts (King *et al.*, 2009).

Other guidance (for onshore wind farms) has indicated that a variety of scales can be used to assess cumulative effects. However, NatureScot (previously Scottish Natural Heritage) proposes a national scale should be used, in this case restricted to Scotland (Scottish Natural Heritage, 2012). The inference is that all developments that could possibly have an effect on the same species as included in the main Environmental Impact Assessment (EIA) should be included in the CEA. The process of determining the species, impacts, and other plans and projects that are included in assessments is known as scoping.

The previous chapter reviewed the literature for empirical evidence of individual and cumulative displacement. This chapter now reviews EIAs to assess how species and impacts have been chosen for cumulative assessments in offshore wind farms. Within the overall aim of the thesis, this chapter addresses how cumulative seabird displacement from offshore wind farms is assessed. This is done by reviewing how offshore wind farm EIAs approach cumulative displacement impact assessments and exploring how offshore wind farms interpret the outcome of other wind farms' individual assessments.

This chapter begins by describing how cumulative seabird displacement has been assessed through the EIA process and analysing any differences or similarities in approaches. The results of the investigation are described with comparison across wind farms. Finally, possible reasons for diverging approaches are suggested, and the advantages and disadvantages of these approaches are discussed.

3.2 Method used to investigate how cumulative seabird displacement is assessed for offshore wind farms

In terms of investigating how cumulative seabird displacement is assessed for offshore wind farms, two things were done for this thesis:

a) Evaluate how it is done for 18 publicly available offshore wind farm EIAs across the UK
b) Evaluate in detail using six case studies from Scottish waters

3.2.1 Methods to investigate how species and impacts are scoped in for EIAs of offshore wind farms across the UK

Publicly available Environmental Statements (ES) from offshore wind farms were collated from web searches carried out in 2019. The search found 18 ESs from offshore wind farms in the UK (Table 3.1). These ESs provided a range of ages in terms of when the EIA was written and when the wind farm was consented to and became operational. Wind farms yet to be fully operational were also included. The oldest wind farm had an EIA dated 2002 and was operational in 2005, and the most recent wind farm had an EIA dated 2018 and became operational in 2023.

Table 3.1. Offshore wind farms used to investigate how cumulative seabird displacement was assessed for offshore wind farms across the UK (as of October 2023).

Location	Offshore wind farm	Year of EIA	Year of consent	Year of operation	Stage of development
England	Kentish Flats	2002	2003	2005	Operational
England	Barrow	2002	2003	2006	Operational
England	Burbo Bank	2002	2003	2007	Operational
England	Gunfleet Sands	2002	2004	2010	Operational
England	Greater Gabbard	2005	2007	2013	Operational
Wales	Gwynt Y Mor	2005	2008	2015	Operational
England	Lincs	2007	2008	2013	Operational
England	Humber Gateway	2008	2011	2015	Operational
England	Dudgeon	2009	2012	2017	Operational
England	Kentish Flats Extension	2011	2013	2015	Operational
Scotland	European Offshore Wind Development Centre	2011	2013	2018	Operational
England	Galloper	2011	2013	2018	Operational
Scotland	Beatrice	2012	2014	2019	Operational
Scotland	Moray East	2012	2014	2022	Operational
Scotland	Neart na Gaoithe	2012	2014	N/A	Construction
England	Burbo Bank Extension	2013	2014	2017	Operational
Scotland	Inch Cape	2013	2014	N/A	Consented
Scotland	Seagreen	2018	2018	2023	Operational

A series of 12 questions were generated to analyse the different ways that individual and cumulative wind farm assessments were carried out. The questions, justifications for the questions, and the possible answers to said questions are shown in Table 3.2. All EIAs from the wind farms in Table 3.1 were examined to answer the questions, and the answers were noted in a spreadsheet. The answers were then analysed to pull out themes, determine similarities and differences between wind farms, and make comparisons between approaches.

Table 3.2. Questions used to analyse EIAs of offshore wind farms in the UK to compare the different ways that individual and cumulative wind farm assessments have been carried out.

Question	Answer options	Justification for question
Is there a section dedicated to cumulative effects?	Independent section, within impact	To determine whether cumulative effects were assessed

Question	Answer options	Justification for question
	assessment section, within species section, cumulative effects not analysed, within appendix	
Was the scoping in of species the same as or different to that within the main impact assessment?	Same or different	To determine whether species were treated differently between individual and cumulative assessments
In what way was the scoping in of species different to the main impact assessment?	Free text	To determine in what ways species were treated differently between individual and cumulative assessments
Was a reason given for scoping in the species that were assessed?	Yes to all, yes to some, or no, free text	To determine why species were treated differently between individual and cumulative assessments
Was the scoping in of impacts the same as main impact assessment or different?	Same or different	To determine whether impacts were treated differently between individual and cumulative assessments
In what way was the scoping in of impacts different to the main impact assessment?	Free text	To determine in what ways impacts were treated differently between individual and cumulative assessments
Were all species scoped in and analysed with respect to every impact?	All species and all impacts, species-specific impacts, or no assessment of the species and impact	To determine whether blanket rules were applied to the assessment of impacts to species or whether species-specific approaches were taken in individual and cumulative assessments
Were potential impacts considered at different stages of the project?	List of stages which could include any or all of construction, operation, and decommissioning	To determine which stage of the process impacts were assessed at
What types of potential impacts were specified?	Free text, impacts split by stage of the project	To determine the range of impacts identified from different stages of a project
Did the assessment include displacement in the operational phase of the wind farm?	Yes or no	To determine whether a specific wind farm assessed the main impact and stage of interest to this study
If no information was available from another	Free text	To determine how wind farms dealt with missing or lack of information

Question	Answer options	Justification for question
wind farm site, what action was taken?		regarding the impact of other wind farms in cumulative assessments
What is the mechanism for calculating cumulative impacts?	Summed, synergistic (more than the sum of parts), or antagonistic (less than the sum of parts)	To determine how cumulative impacts were calculated, whether this was a simple summation or more complex modelling was involved

The species chosen for individual and cumulative assessment and the reasons for their inclusion were noted from each ES. The type of impact (for instance, collision, displacement, barrier effects) and why that impact was investigated for that species was also analysed. The species and impacts scoped in and out of assessment, and methods used for scoping, were compared across offshore wind farms to determine whether a standard approach has been taken. A comparison was also made between the scoping approach done for an individual wind farm assessment and a cumulative assessment to further investigate the level of standardisation.

3.2.2 Method of how species and wind farms are scoped in for individual and cumulative displacement assessments: Scottish case study

Case studies of planned or built wind farm EIA and CEAs in Scottish east coast waters were then studied in more detail to compare the species and impacts assessed at nearby wind farms. These wind farms were labelled A to F for ease of presenting and describing the results (Table 3.3).

Table 3.3. Scottish offshore wind farms used to investigate how species and wind farms were scoped in for individual and cumulative displacement assessments.

Offshore wind farm	Label
Beatrice	A
Moray East	B
Seagreen	C
Inch Cape	D
Neart na Gaoithe	E
European Offshore Wind Development Centre	F

The impact of specific interest was the displacement of seabirds; therefore, the result of individual and cumulative assessment in terms of displacement was noted for each wind farm and each species. The result of these assessments in an EIA context is usually described in terms of the significance of potential effects. This is determined from a combination of the magnitude of the effect and the sensitivity of the receptor. This is often presented as a matrix, such as Table 3.4.

Table 3.4. The matrix often used in EIAs to determine the level of significance, combining the magnitude of effect and the sensitivity of the receptor.

		Magnitude			
		High	**Medium**	**Low**	**Negligible**
Sensitivity	**High**	Major	Major	Moderate	Minor
	Medium	Major	Moderate	Minor	Negligible
	Low	Moderate	Minor	Minor	Negligible
	Negligible	Minor	Negligible	Negligible	Negligible

A significance matrix is a method capable of putting impacts from different developments into a standard and comparable format, providing a single value of a level of significance from negligible to major, and can be used to describe both positive and negative effects. Therefore, the level of significance was retrieved from the Environmental Statements for wind farms in Table 3.1 for both the individual and cumulative impact assessment. The wind farms that were scoped into the cumulative assessments were also noted to determine whether there was a difference between which wind farms were included or not in cumulative assessments.

3.3 Results of investigating how cumulative seabird displacement is assessed for offshore wind farms

The results of investigating how cumulative seabird displacement is assessed for offshore wind farms are split into two sections. First, the results of how species and impacts are scoped into individual and cumulative wind farm EIAs across the UK are described. This is followed by how species and wind farms are scoped for a displacement assessment for individual and cumulative assessments using a Scottish case study.

3.3.1 Results of how species and impacts are scoped into individual and cumulative wind farm EIAs across the UK

The results from a broad range of questions on scoping show that the majority of EIAs (72%) used a different set of species between the individual wind farm assessment and the cumulative assessment. For some species and wind farm, this meant more species were assessed individually than cumulatively, and for others the opposite occurred. It was often stated that impacts from wind farm alone were sufficiently small to not require assessing cumulatively. In comparison, at other wind farms the species list was expanded for the cumulative assessment to take account of effects at other wind farms. The same happened with regard to the impacts assessed individually and cumulatively but to a lesser degree. Around half of wind farms used a different set of impacts between the individual wind farm assessment and the cumulative assessment (see Figure 3.1).

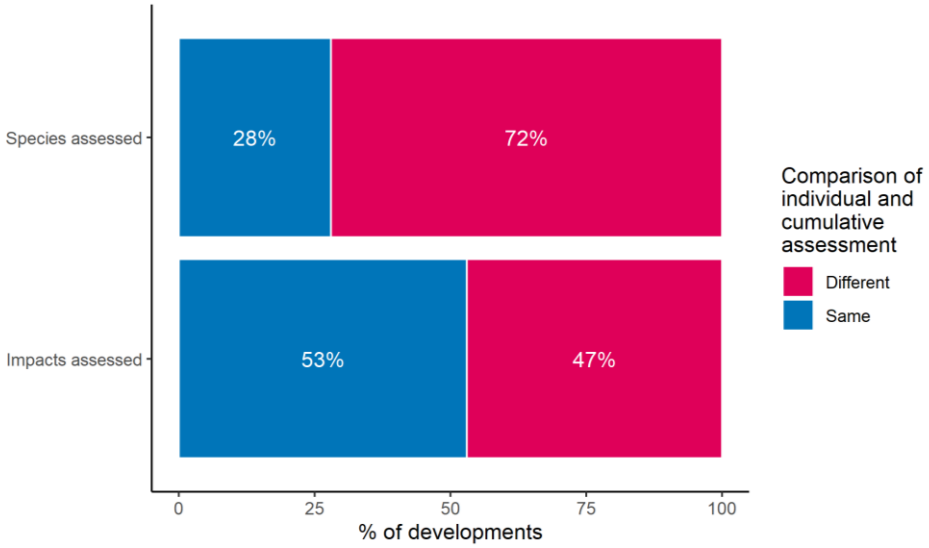

Figure 3.1. The percentage of wind farms which assessed the same or different species and impacts between individual and cumulative assessments (for the 18 offshore wind farms in the UK).

In addition, as it can be seen in Figure 3.2, the majority of cumulative effects assessments looked at species-specific impacts (61%), whilst fewer took a blanket approach and assessed all species against all impacts (22%).

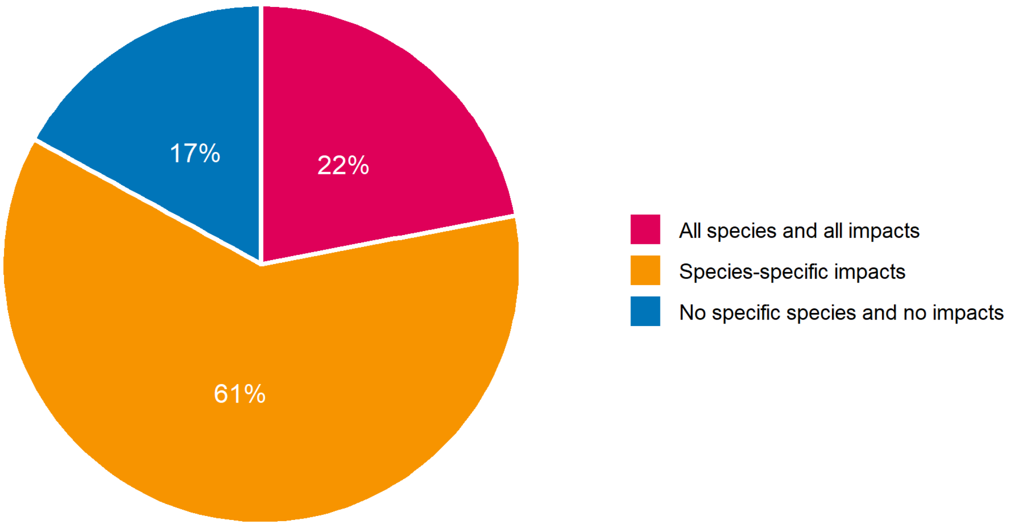

Figure 3.2. The percentage of wind farms which assessed all impacts to all species, species-specific impacts, and no impact to a specific species (for the 18 offshore wind farms in the UK).

Figures 3.1 and 3.2 both show that there is a disparity across the approaches taken by wind farms. The reasons given for why a species was scoped into a cumulative effects assessment include:

- Target species or Valued Ornithological Receptor
- Meets or exceeds 1% of the Great British population on site
- Species of high-sensitivity
- Species observed at the site
- Species present during the breeding season
- Species are at least at minor risk of impact
- Species included in the assessment at a site scoped in

Some of these directly relate to scoping for the individual wind farm assessment, such as a target species and species of national importance and were given as reasons for inclusion in the individual assessment and cumulative assessment. Others were more related to cumulative effects, such as whether a species was included in the assessment at a different site. This raises several questions:

- For what reasons should a species be scoped in for cumulative effects evaluation?
- Should species scoped in be the same for a cumulative assessment as for individual wind farm assessment?

- Should a wider range of species be assessed to take into account the broader spatial and temporal scale of cumulative effects?

Other reasons for species scoping in or out simply relate to data issues (Figure 3.3). For instance, the sparsity of environmental data when early developments were assessing cumulative effects hindered a quantitative assessment of the impact of future sites. This still exists to some extent today, with limited data on either the baseline environment of a potential site or what that site's impact might be. There have also been changes in methods of assessment used to assess different species and impacts. For instance, some species and impacts have been assessed quantitatively and others qualitatively. This was seen when a new approach was brought in for assessing bird displacement in 2015, meaning that across developments, data and results were presented in a different state, making it harder to directly compare developments using these different approaches. These factors have led to increasing uncertainty beyond what already exists as a result of data collection methods, natural variation, and the use of design envelopes. It also has the potential to increase the assessment burden of having to transform data to be used in a cumulative assessment.

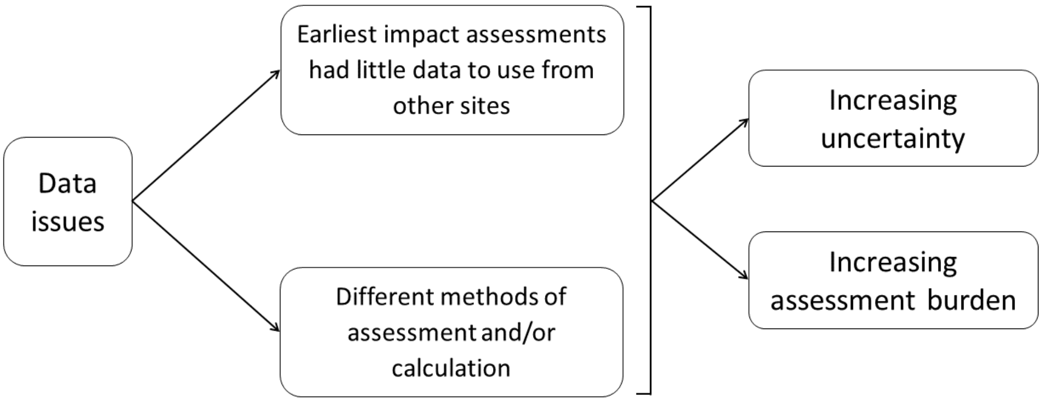

Figure 3.3. Data issues identified from reviewing offshore wind farm EIAs regarding cumulative seabird displacement assessments. Issues lead to increasing uncertainty about what cumulative impact there may be and an increasing burden upon developers to fill knowledge gaps.

The absence of data for species at a site has been dealt with in numerous ways by developers, further enhancing the disparity in approaches. For half of the sites where there was no data available from another project, that development was not included in the CEA. 25% of the time, if no quantitative data was available from another site, a qualitative assessment was made instead. Occasionally, a negligible impact was assumed where no data was available to be assessed. Infrequently, data was sourced elsewhere to enable the project to be included in the assessment.

These different actions in response to a lack of data resulted in different outcomes between individual and cumulative assessments. At an individual wind farm level, a lack of seabird data has sometimes been stated as the reason for a species not being assessed. At a cumulative assessment level, this has often resulted in the wind farm not being included in the CEA. However, there have been cases where an individual wind farm had not assessed a species because of a lack of data, but the CEA of another wind farm included the first wind farm, and a negligible effect was assumed. Other times, at an individual wind farm level, the lack of data was taken as a "negligible" effect on the species. At a cumulative assessment level, the wind farm was then included in the CEA, and a negligible impact was assumed as the result of the individual wind farm impact assessment. This is summarised in Figure 3.4.

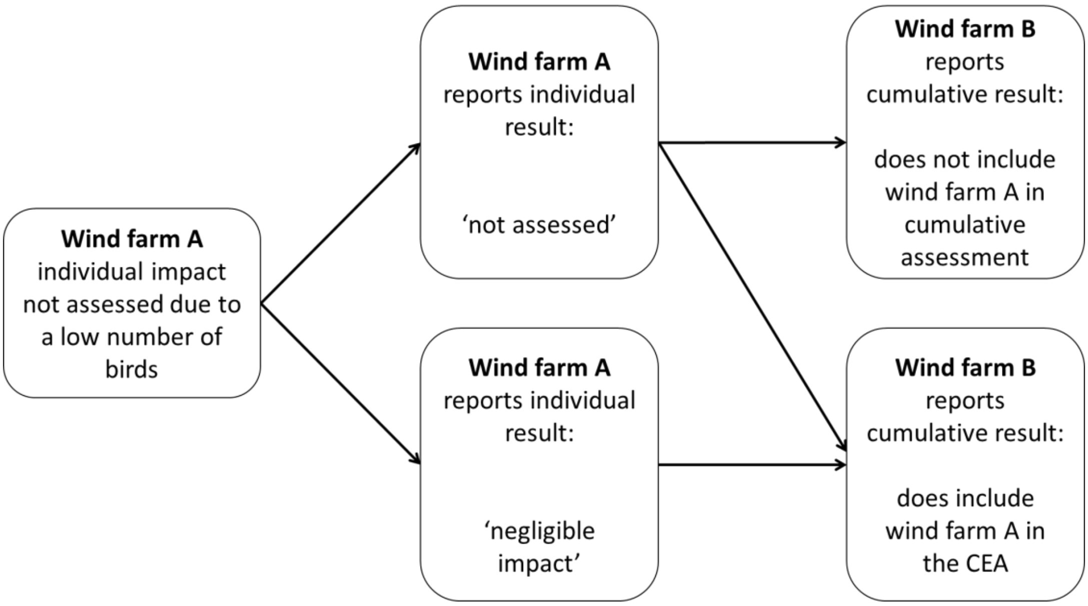

Figure 3.4. Actions by different wind farms in their cumulative assessments in response to a lack of data or assessment from other wind farms.

This raises important issues as to how CEAs should be conducted. For example, it could be argued that lack of assessment should not be stated as a negligible effect, nor should sites with a lack of data be included in other site's cumulative assessments. This research indicates that the results of individual wind farm assessments have been amended by another site's cumulative assessment (e.g. from "not assessed because of a lack of data" to "site has negligible impact") without reasoning. The suitability of amending a result, therefore, comes into question, particularly with regard to whether terms such as “not enough data for assessment” and “negligible impact” are interchangeable. If this is not the case, then the changing of terms may, in fact, generate misleading results of a cumulative assessment. Full answers to all questions are provided in Appendix C.

3.3.2 Results of how species and wind farms are scoped in for a displacement assessment for individual and cumulative assessments: a Scottish case study

The inclusion of individual species into six offshore wind farm CEAs was analysed in terms of cumulatively assessing displacement. For each wind farm, the species that were analysed for cumulative displacement were noted. A record was also made of the other wind farms that were included in the cumulative displacement of the species in question. This information was translated into a set of diagrams to visualise the conclusion of individual and cumulative assessments. Eight themes came out of this analysis:

- Theme 1: One wind farm including all other wind farms in its cumulative assessment, but none of the other wind farms including that wind farm in their cumulative assessment (section 3.3.2.1)
- Theme 2: A wind farm assessing and concluding their cumulative effect with other wind farms, whilst those other wind farms have not deemed it necessary to carry out an assessment of their own individual impact (section 3.3.2.2)
- Theme 3: A wind farm assessing and concluding their cumulative effect with other wind farms, whilst those other wind farms have not had a chance to carry out their own assessment as they are further behind in the consenting process (section 3.3.2.3)
- Theme 4: A wind farm assessing but not concluding their cumulative effect with other wind farms, whilst those other wind farms have not had a chance to carry out their own assessment as they are further behind in the consenting process (section 3.3.2.4)
- Theme 5: Wind farms concluding larger cumulative effects than their individual assessment due to comparatively large effects from other wind farms acting in combination (section 3.3.2.5)
- Theme 6: Wind farms assessing one another cumulatively but coming to different conclusions on the cumulative assessment (section 3.3.2.6)

- Theme 7: Wind farms assessing individual and cumulative effects either annually or splitting effects per season (section 3.3.2.7)
- Theme 8: Wind farms providing more than one significance level for individual and cumulative assessments (section 3.3.2.8)

Each of these themes is analysed further in the subsequent sections, with examples of species where the theme is apparent.

3.3.2.1 Theme 1: One wind farm including all other wind farms in its cumulative assessment, but none of the other wind farms including that wind farm in their cumulative assessment

The first theme when analysing individual and cumulative assessments is that one wind farm would include all other wind farms in its cumulative assessment, but none of the other wind farms included that wind farm in their cumulative assessment. This can be seen in the diagram for the northern fulmar (*Fulmarus glacialis*), as shown in Figure 3.5. In this figure, wind farm D assessed all other wind farms cumulatively, but none of those wind farms included wind farm D in their cumulative assessment.

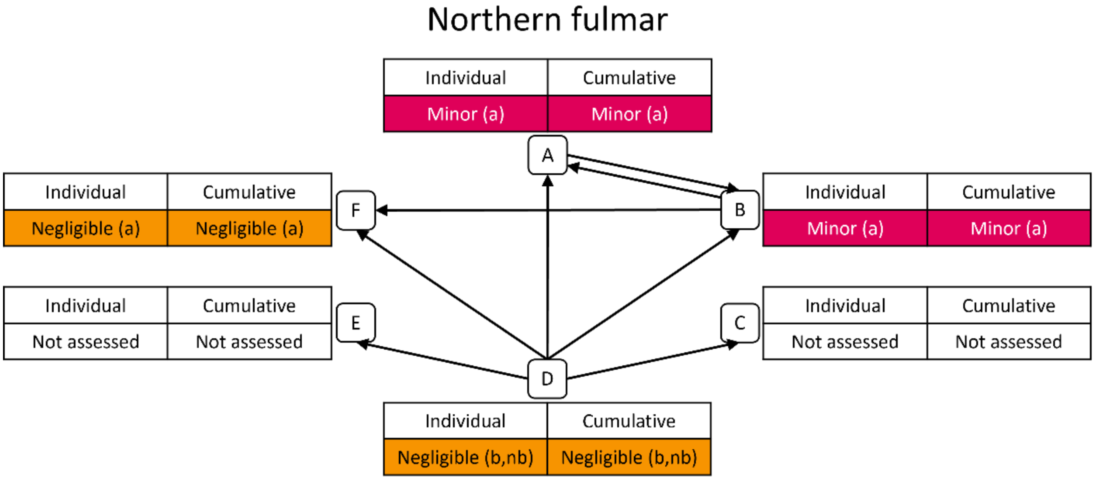

Figure 3.5. A schematic view of the result of each wind farm in the case study in terms of the individual project displacement assessment and the cumulative displacement assessment of northern fulmar.

Note: The arrow represents the wind farms included in the cumulative assessment. The origin of the arrow is the wind farm carrying out the cumulative displacement assessment. The end point of the arrow is the wind farm that was included in the origin wind farm's assessment. Where multiple results are presented in one box, this was either due to wind farms presenting two results as if unsure of the exact answer or somewhere in between the two results or as a result of the wind farm splitting impacts between the breeding season, noted by (b), and the non-breeding season, noted by (nb), or annual, noted by (a).

It is not clear why wind farm D included all other wind farms in its cumulative assessment, nor why the other wind farms did not include wind farm D in their cumulative assessments. This suggests that an inconsistent approach was taken, at least between wind farm D and the other wind farms. However, as no criteria were given for why each wind farm was scoped in or out of other wind farms, the rationale is unknown. Perhaps there was something about this species that meant different scoping results between wind farm D and all the other wind farms. Without an explanation, it is hard to say whether one method or reason for scoping is any better or worse or more or less applicable. Furthermore, there is no way to know whether these differences in scoping made a meaningful difference to the results of the cumulative impact assessment.

3.3.2.2 Theme 2: A wind farm assessing and concluding their cumulative effect with other wind farms, whilst those other wind farms have not deemed it necessary to carry out an assessment of their own individual impact

The second theme when analysing individual and cumulative assessments is that one wind farm would come to a conclusion in the cumulative assessment, which included other wind farms, but those wind farms have not assessed that species individually. This can be seen in the diagram for northern fulmar, as shown in Figure 3.5, and in the diagram for northern gannet (*Morus bassanus*), as shown in Figure 3.6. In these figures, wind farm D assessed the cumulative effect in combination with wind farm E and wind farm C, but those wind farms did not assess the species individually or cumulatively.

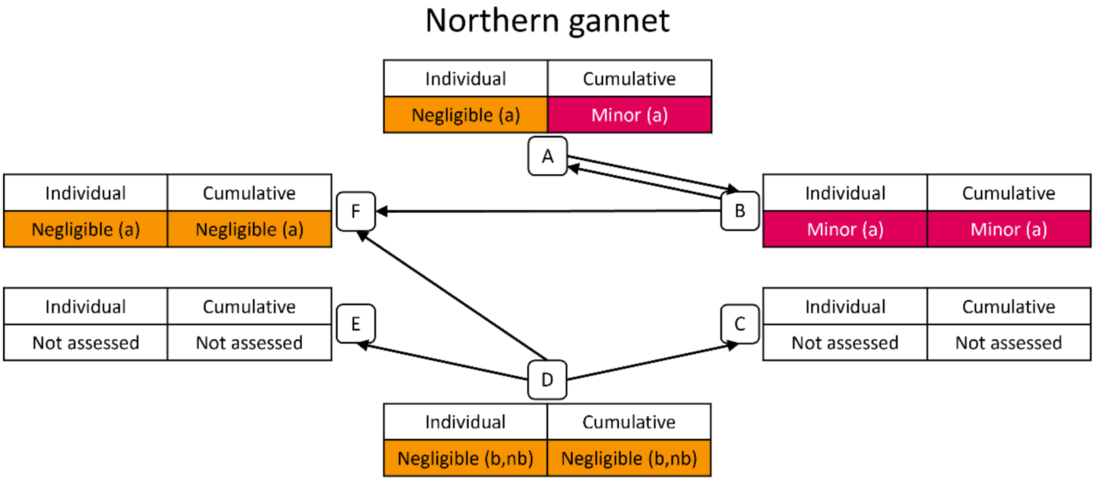

Figure 3.6. A schematic view of the result of each wind farm in the case study in terms of the individual project displacement assessment and the cumulative displacement assessment of the northern gannet.

Note: The arrow represents the wind farms included in the cumulative assessment. The origin of the arrow is the wind farm carrying out the cumulative displacement assessment. The end point of the arrow is the wind farm that was included in the origin wind farm's assessment. Where multiple results are presented in one box, this was either due to wind farms presenting two results as if unsure of the exact answer or somewhere in between the two results or as a result of the wind farm splitting impacts between the breeding season, noted by (b), and the non-breeding season, noted by (nb), or annual, noted by (a).

This can also be seen in the diagrams for great black-backed gulls (*Larus marinus*), as shown in Figure 3.7, and for lesser black-backed gulls (*Larus fuscus*), as shown in Figure 3.8. For the great black-backed gull, wind farm D assessed the cumulative effect in combination with wind farm F and wind farm E, but wind farm E did not undertake an individual assessment of the species. For lesser black-backed gulls, wind farm D assessed the cumulative effect in combination with all wind farms, yet three of the four other wind farms had not assessed the individual effect on the species.

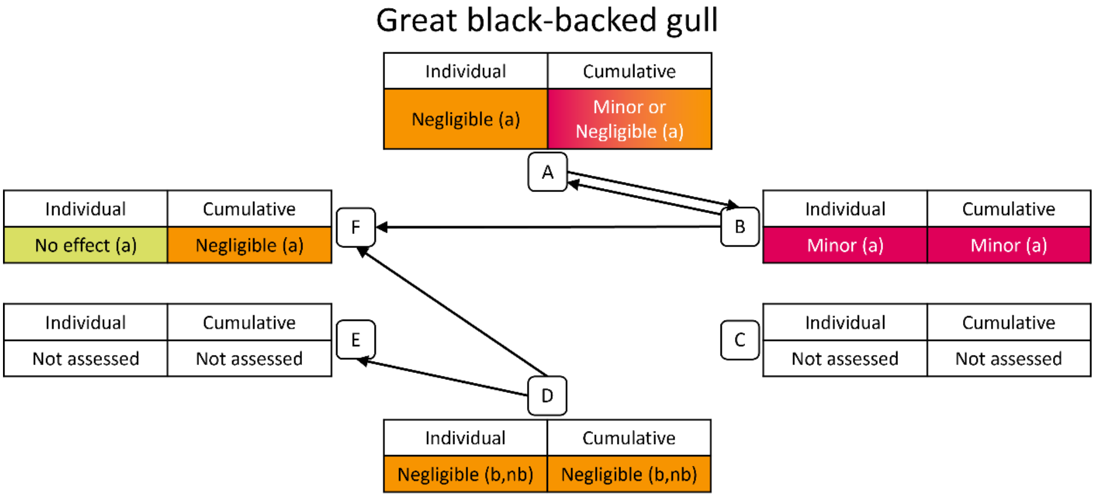

Figure 3.7. A schematic view of the result of each wind farm in the case study in terms of the individual project displacement assessment and the cumulative displacement assessment of the great black-backed gull.

Note: The arrow represents the wind farms included in the cumulative assessment. The origin of the arrow is the wind farm carrying out the cumulative displacement assessment. The end point of the arrow is the wind farm that was included in the origin wind farm's assessment. Where multiple results are presented in one box, this was either due to wind farms presenting two results as if unsure of the exact answer or somewhere in between the two results or as a result of the wind farm splitting impacts between the breeding season, noted by (b), and the non-breeding season, noted by (nb), or annual, noted by (a).

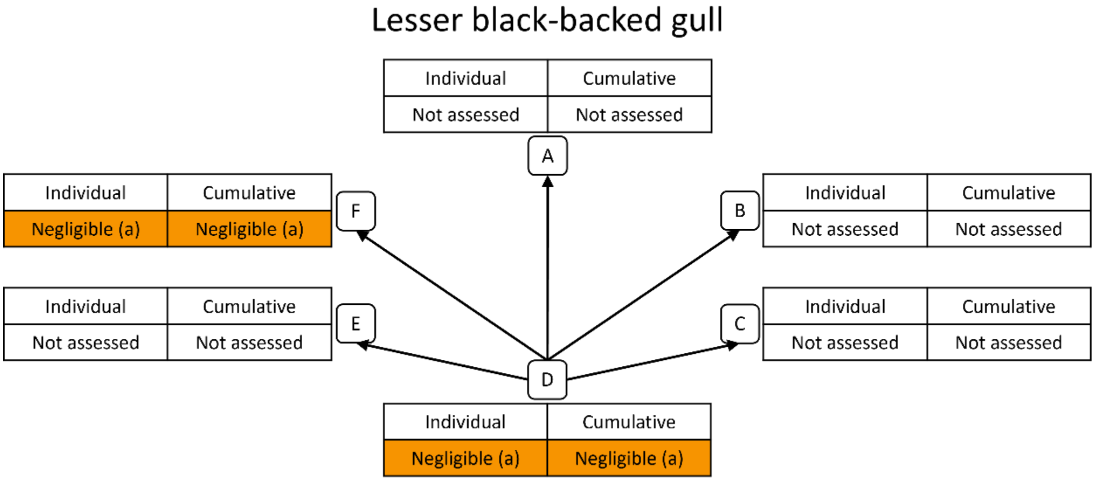

Figure 3.8. A schematic view of the result of each wind farm in the case study in terms of the individual project displacement assessment and the cumulative displacement assessment of lesser black-backed gull.

Note: The arrow represents the wind farms included in the cumulative assessment. The origin of the arrow is the wind farm carrying out the cumulative displacement assessment. The end point of the arrow is the wind farm that was included in the origin wind farm's assessment. Where multiple results are presented in one box, this was either due to wind farms presenting two results as if unsure of the exact answer or somewhere in between the two results or as a result of the wind farm splitting impacts between the breeding season, noted by (b), and the non-breeding season, noted by (nb), or annual, noted by (a).

This theme also raises issues, firstly, why a wind farm without an individual assessment of a particular species has been screened into another wind farm's cumulative assessment. Perhaps more importantly, it is uncertain how a cumulative assessment can account for the effects of wind farms which did not carry out an individual assessment of that species. If a wind farm did not assess an impact because it was certain that there would be no impact on the species (for instance, the species is not present at the wind farm), then there appears to be no reason to include said wind farm in a cumulative assessment. Without knowing what significance level was assigned to this other wind farm, there is the possibility that its impact was overestimated, thereby generating an inaccurate cumulative assessment.

3.3.2.3 Theme 3: A wind farm assessing and concluding their cumulative effect with other wind farms, whilst those other wind farms have not had a chance to carry out their own assessment as they are further behind in the consenting process

The next theme that appeared was that a wind farm could conclude a cumulative assessment result despite an assessment on the impact of the other wind farms not being made yet. This can be seen in the diagram for northern fulmar, northern gannet, great black-backed gull, and lesser black-backed gull, as shown in Figure 3.5, Figure 3.6, Figure 3.7, and Figure 3.8, respectively. It can also be seen in the diagram for black-legged kittiwake, as shown in Figure 3.9. In these figures, wind farm F came to a conclusion on the cumulative effect despite not including other wind farms in the assessment. In the Environmental Statement for this wind farm, it was stated that the cumulative effect was likely negligible but could not be fully assessed due to a lack of data from other wind farms, as they had not carried out their impact assessment yet. For northern fulmar, northern gannet, and lesser black-backed gull, the individual wind farm assessment result was negligible, and the cumulative assessment was also negligible. However, for great black-backed gulls and black-legged kittiwakes, the individual assessment result had no effect, yet the result of the cumulative assessment was negligible.

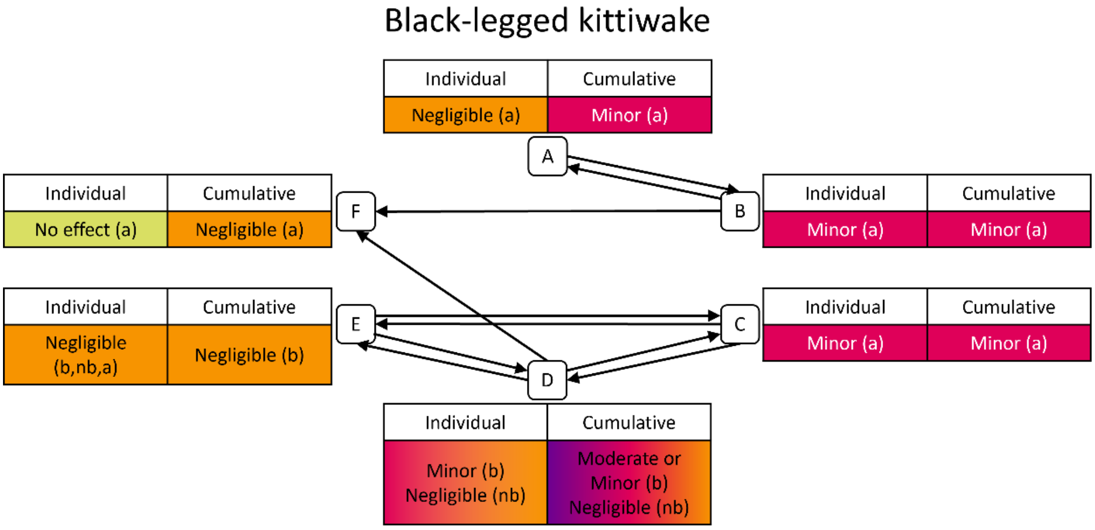

Figure 3.9. A schematic view of the result of each wind farm in the case study in terms of the individual project displacement assessment and the cumulative displacement assessment of black-legged kittiwake.

Note: The arrow represents the wind farms included in the cumulative assessment. The origin of the arrow is the wind farm carrying out the cumulative displacement assessment. The end point of the arrow is the wind farm that was included in the origin wind farm's assessment. Where multiple results are presented in one box, this was either due to wind farms presenting two results as if unsure of the exact answer or somewhere in between the two results or as a result of the wind farm splitting impacts between the breeding season, noted by (b), and the non-breeding season, noted by (nb), or annual, noted by (a).

There are further queries from this theme, beginning with the obvious uncertainties associated with estimating the impact from other wind farms which have yet to be formerly calculated. For these examples, it was not stated what the assumed impact of these other wind farms was; therefore, no judgment can be made as to whether these are under- or over-estimates. It is necessary to include future developments in a cumulative assessment. However, without transparency as to the assumed impacts of these developments, uncertainty is high and confidence in the cumulative assessment is low.

3.3.2.4 Theme 4: A wind farm assessing but not concluding their cumulative effect with other wind farms, whilst those other wind farms have not had a chance to carry out their own assessment as they are further behind in the consenting process

The fourth theme, in a way, is an inverse of the third theme. In the third theme, a wind farm made a conclusion of the cumulative effect from other wind farms that had not yet assessed their impact. However, in the fourth theme, a wind farm did not make a conclusion on the cumulative effect with other wind farms, which again had not yet assessed their impact. The other notable aspect of this theme is that the individual effect of the focal wind farm was much larger than in the third theme. This can be seen in the case of wind farm F. This wind farm had a moderate individual effect on the common guillemot (*Uria aalge*), as shown in Figure 3.10, and a minor individual effect on razorbill (*Arca torda*) and Atlantic puffin (*Fratercula arctica*), as shown in Figure 3.11 and Figure 3.12, respectively. However, the cumulative assessment for these species was inconclusive.

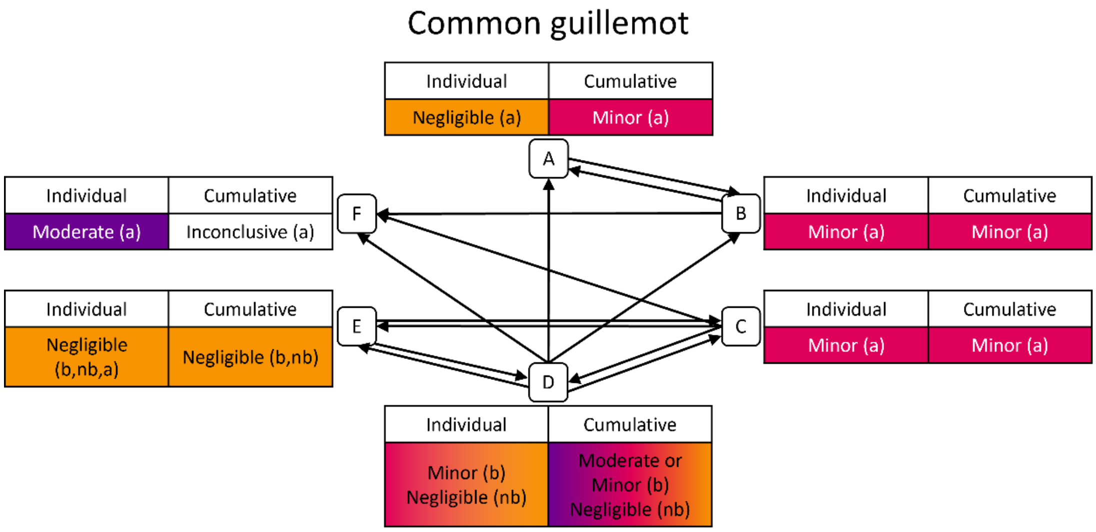

Figure 3.10. A schematic view of the result of each wind farm in the case study in terms of the individual project displacement assessment and the cumulative displacement assessment of common guillemot.

Note: The arrow represents the wind farms included in the cumulative assessment. The origin of the arrow is the wind farm carrying out the cumulative displacement assessment. The end point of the arrow is the wind farm that was included in the origin wind farm's assessment. Where multiple results are presented in one box, this was either due to wind farms presenting two results as if unsure of the exact answer or somewhere in between the two results or as a result of the wind farm splitting impacts between the breeding season, noted by (b), and the non-breeding season, noted by (nb), or annual, noted by (a).

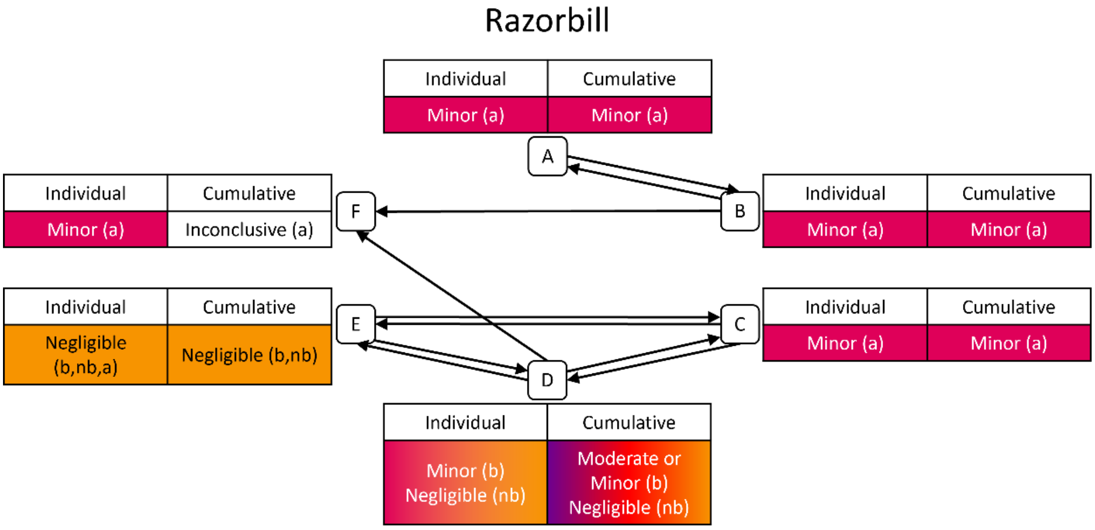

Figure 3.11. A schematic view of the result of each wind farm in the case study in terms of the individual project displacement assessment and the cumulative displacement assessment of razorbill.

Note: The arrow represents the wind farms included in the cumulative assessment. The origin of the arrow is the wind farm carrying out the cumulative displacement assessment. The end point of the arrow is the wind farm that was included in the origin wind farm's assessment. Where multiple results are presented in one box, this was either due to wind farms presenting two results as if unsure of the exact answer or somewhere in between the two results or as a result of the wind farm splitting impacts between the breeding season, noted by (b), and the non-breeding season, noted by (nb), or annual, noted by (a).

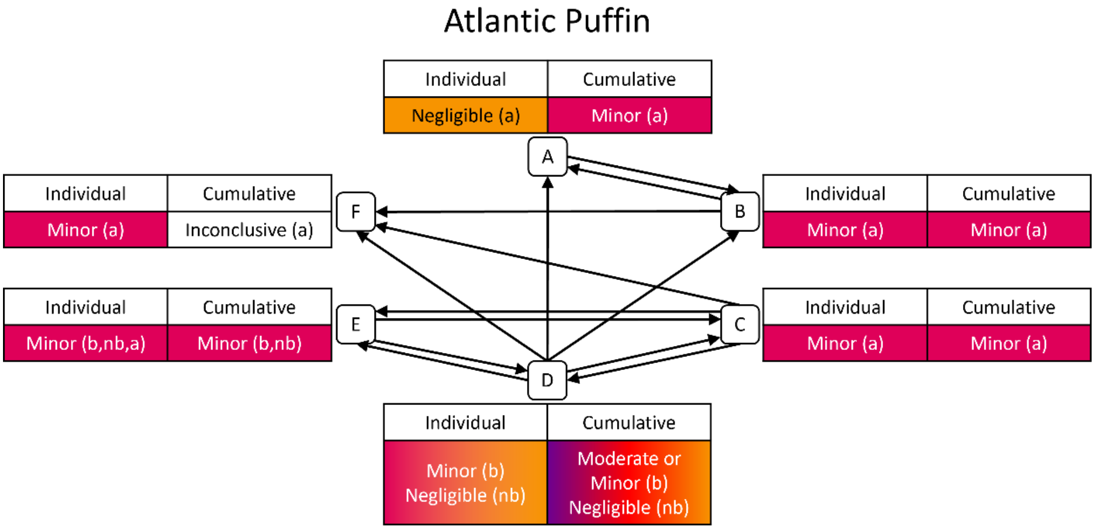

Figure 3.12. A schematic view of the result of each wind farm in the case study in terms of the individual project displacement assessment and the cumulative displacement assessment of Atlantic puffin.

Note: The arrow represents the wind farms included in the cumulative assessment. The origin of the arrow is the wind farm carrying out the cumulative displacement assessment. The end point of the arrow is the wind farm that was included in the origin wind farm's assessment. Where multiple results are presented in one box, this was either due to wind farms presenting two results as if unsure of the exact answer or somewhere in between the two results or as a result of the wind farm splitting impacts between the breeding season, noted by (b), and the non-breeding season, noted by (nb), or annual, noted by (a).

This theme poses further considerations. It would appear that wind farm F, with its larger impacts on three species, could not come to a conclusion on the cumulative effect. Again, the reasoning for this was not stated. However, it is possible that due to a non-negligible impact from the individual wind farm, there was a likelihood that there would also be non-negligible impacts from other wind farms. Including these unknown but potentially larger impacts in a cumulative assessment would, perhaps, result in a cumulative conclusion with an uncertainty higher than it is useful. Regardless of the reason, this is yet another inconsistency in approaches. Where some wind farms estimate the cumulative effect with no individual assessments to use, other wind farms make a conclusion without any information from the other developments. Again, what is unclear is whether these differences make an appreciable difference to the overall outcome of cumulative assessments.

3.3.2.5 Theme 5: Wind farms concluding larger cumulative effects than their individual assessment due to comparatively large effects from other wind farms acting in combination

Another theme arose on inspection of how cumulative assessment had been carried out. This theme centres around the level of cumulative effect compared to the level of individual effects. In the case of northern gannet, as shown in Figure 3.6, and the case of black-legged kittiwake, as shown in Figure 3.9, the individual effect of wind farm A was negligible, and the individual effect of wind farm B was minor. In its cumulative assessment, wind farm A concluded the cumulative effect of itself in combination with wind farm B to be minor. Similarly, wind farm B concluded the cumulative effect of itself in combination with wind farm A and wind farm F (with an individual effect of negligible for gannet and no effect for black-legged kittiwake) to be minor.

There are some interesting points to note from this theme. First, this suggests that one wind farm is predicted to have a larger effect compared to the other. The second point is that both wind farms recognised that one wind farm in particular had a larger effect, and this was reflected in the result of the cumulative assessment. Lastly, this raises an important note relating to themes three and four. Two wind farms may have different individual effects; therefore, it is not necessarily right to assume that other wind farms may have a similar individual effect to the focal wind farm. It is likely unfair to use this assumption when no assessment has been carried out for those other wind farms, as appears to have been done in themes three and four.

3.3.2.6 Theme 6: Wind farms assessing one another cumulatively but coming to different conclusions on the cumulative assessment

Wind farms coming to different conclusions on the level of cumulative effect is another theme coming out of this analysis of cumulative effects assessment. This can be seen in the diagrams for black-legged kittiwake, common guillemot, and razorbill, as shown in Figure 3.9, Figure 3.10, and Figure 3.11, respectively, where the results of the cumulative assessment were very different from wind farm E, wind farm C, and wind farm D. Wind farm E took its own negligible effect, the minor effect from wind farm C, the minor breeding season and negligible non-breeding season effect from wind farm D, and concluded a negligible cumulative effect. Meanwhile, wind farm C took the same three individual effects from itself, wind farm E, and wind farm D, but concluded a minor cumulative effect. Wind farm D took a similar approach to wind farm C, concluding a moderate or minor cumulative effect in the breeding season. However, the approach was more similar to wind farm E in the non-breeding season, concluding with a negligible effect.

It would appear that multiple wind farms came to different conclusions on the cumulative effect when presented with the same information. Unless there were legitimate reasons for these differences (reasons which are not mentioned), it is concerning that diverging conclusions are reached. Perhaps thresholds for determining the significance level of effect were different across assessments. This suggests that diverging approaches have resulted in a meaningful difference in the overall outcome of cumulative assessments. However, which results are the most accurate remains unknown.

3.3.2.7 Theme 7: Wind farms assessing individual and cumulative effects either annually or splitting effects per season

The penultimate theme, which is apparent with some species and wind farms, is the assessment of either annual effects or splitting effects between the breeding and the non-breeding seasons. In the latter approach, for one wind farm, a combination of seasonal results was not provided to conclude an annual effect, but another wind farm did provide annual results as well as seasonal results. In the case of all species, wind farm D split individual and cumulative effect results between the breeding and the non-breeding season. Meanwhile, wind farm E provided individual effect results for the breeding season, non-breeding season, and annually for black-legged kittiwake, common guillemot, razorbill, and Atlantic puffin (Figure 3.9, Figure 3.10, Figure 3.11, and Figure 3.12, respectively). However, wind farm E presented cumulative effect results for the breeding and non-breeding season only, and even the breeding season only for black-legged kittiwake.

From this research, it appears that cumulative assessments are somehow able to combine impacts across different temporal scales. This includes combining different seasons into an annual effect and also splitting annual effects into seasonal ones. The methodology for undertaking either a splitting or combining is not given; therefore, the validity of the approaches is unknown.

3.3.2.8 Theme 8: Wind farms providing more than one significance level for individual and cumulative assessments

The final theme from this analysis of cumulative effects assessment is that some wind farms presented more than one effect level. Unlike theme seven, where this was due to different temporal scales of effect, this was just presented as the possibility that either effect level could be the true effect, but there was uncertainty around the level. This can be seen in the cumulative assessment of the great black-backed gull and herring gull (*Larus argentatus*) from wind farm A (Figure 3.7 and Figure 3.13, respectively). It can also be seen in both the individual and cumulative assessments for black-legged kittiwake, common guillemot, razorbill, and Atlantic puffin from wind farm D (Figure 3.9, Figure 3.10, Figure 3.11, and Figure 3.12, respectively).

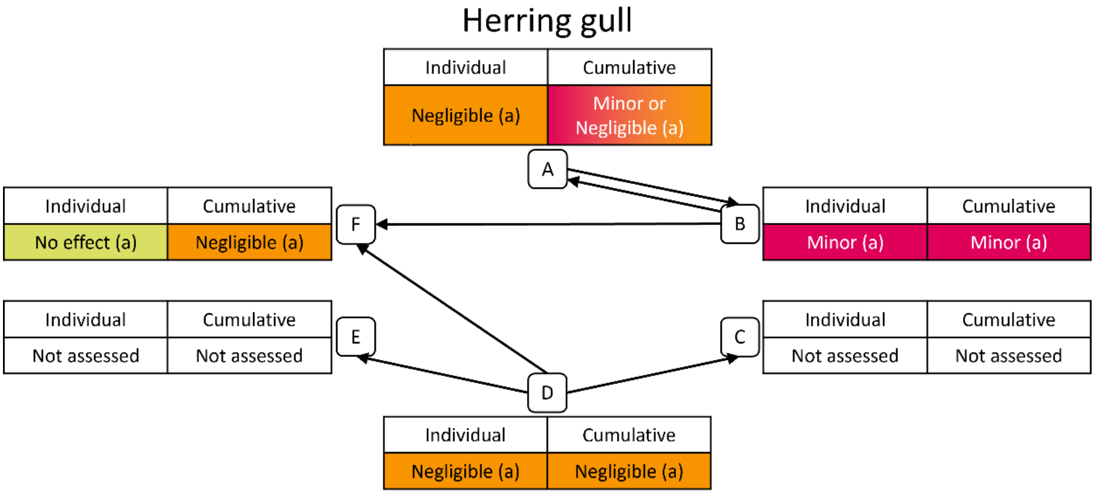

Figure 3.13. A schematic view of the result of each wind farm in the case study in terms of the individual project displacement assessment and the cumulative displacement assessment of herring gull.

Note: The arrow represents the wind farms included in the cumulative assessment. The origin of the arrow is the wind farm carrying out the cumulative displacement assessment. The end point of the arrow is the wind farm that was included in the origin wind farm's assessment. Where multiple results are presented in one box, this was either due to wind farms presenting two results as if unsure of the exact answer or somewhere in between the two results or as a result of the wind farm splitting impacts between the breeding season, noted by (b), and the non-breeding season, noted by (nb), or annual, noted by (a).

This theme raises several things of note, firstly, the cause of the uncertainty in the cumulative result. Previous themes indicate some of the differences in approaches to scoping other wind farms and utilising results from other wind farms, which may be some of the causes of uncertainty. Do uncertainties stem from individual wind farm uncertainties, the mechanism behind cumulative effects from multiple sources, or both? Some wind farms were able to generate one cumulative significance level whilst others were not; again, it is unclear why that is the case, particularly where the same species is concerned. Perhaps it is the case that a cumulative assessment with one significance level is reflective of the certainty of individual effects. Meanwhile, a range of cumulative significance levels account for uncertainty in individual wind farm effects. This could suggest that a divergent approach is favourable in order to clearly display uncertainties.

3.4 Discussion on how cumulative seabird displacement is assessed for offshore wind farms

The ways in which seabirds and impacts have been chosen for individual and cumulative assessments and which wind farms were included in cumulative assessments have varied across wind farm EIAs around the UK. As scoping is one of the first stages of an EIA, this non-standard approach is likely to mean that EIA results are inconsistent. During the assessment itself, standard methods are applied for collision and displacement, barring any major changes in techniques. The use of standard methods applied to assess individual impacts may give a false sense that EIAs are carried out in a standardised manner. In fact, the scoping of species, impacts, and wind farms can result in markedly different outcomes. With wind farms in different locations, in different years, and with different design parameters, it is obvious that there will be differences between the outcomes of wind farms. However, when the method of scoping is different across wind farms, all else being equal, there would be inconsistencies when the approach to scoping is variable.

There may, of course, be legitimate reasons for taking a specific approach to individual and cumulative assessments. One key reason, for instance, may be that prior to 2015, there was no standard quantitative approach to assessing the displacement of seabirds from offshore wind farms in UK waters. Therefore, it may be inevitable that there are differences in the approaches to which species and wind farms were assessed for this impact. In 2015, the UK Statutory Nature Conservation Bodies (SNCB) published a guidance note advising on which species may need to be assessed for displacement and a standard methodology for doing so (Statutory Nature Conservation Bodies, 2022b). Therefore, wind farms with Ess written after 2015 are more likely to have a standard approach to the species assessed for displacement.

Similarly, when scoping in wind farms to a cumulative assessment, the spatial scale over which a species may be impacted is a key consideration. To determine which wind farms a species may interact with requires knowledge of where these birds travel to and from. With increasing knowledge about seabird movements, which may be different throughout the year, this may again lead to later wind farms taking a different approach to earlier wind farms. It may also be that some wind farms are not included in a cumulative assessment if seabirds do not cover a large area, or conversely, including more wind farms should a species range over a larger area.

Another reason why wind farms differ in their approach may be that later wind farms attempt to re-calculate the impact of earlier wind farms, particularly once a standardised approach to displacement was generated. Therefore, there may be new displacement results compared to those produced by early wind farms to be included in cumulative assessments, leading to overall different cumulative outcomes. Indeed, it may be pertinent to re-analyse the impact of operational wind farms once new methodologies for doing so are generated. Under the assumption that these give more accurate impact predictions, the cumulative impact should be more accurately calculated.

The legislation surrounding the need for a cumulative assessment is ambiguous as to which projects should be included in a cumulative assessment. Both the EIA Directive and UK legislation state that the combination of effects with other existing and approved developments should be considered but offer no guidance on how to determine what these projects are. In an advice note from the Planning Inspectorate, the body through which some offshore wind farms in the UK are consented, it states that any project completed before the proposed project is consented should form part of the “dynamic baseline” (The Planning Inspectorate, 2019). What this means in practice, though, is not described. Without clear instructions on how to scope other projects into a cumulative assessment, individual projects are again left to determine this.

Similarly, how to use and interpret the results from other wind farms when calculating the cumulative impact has been done in a range of ways, and is ambiguous as to how it should be carried out. Guidance on using data from other developments does not appear to be available in the public domain, yet the variety of ways this has been done, as seen throughout this chapter, suggests that it would be warranted to generate standardised and appropriate methods. A top-down approach to generate standardisation would be applicable here, but also with input from those undertaking cumulative assessments of projects in order to understand the issues with data interpretation and use.

It would appear that for the assessment by some wind farms, the other wind farms were scoped in or out of the cumulative assessment before consideration was given to whether a species may be affected cumulatively due to those other wind farms. It is, therefore, possible that the cumulative effect of wind farms on some species was excluded before the species had even been considered. This is an important consideration, especially where species of importance are affected, and impacts are significant, whether on an individual wind farm or cumulative basis. If species are considered first when scoping a cumulative assessment, perhaps by applying a species-site-specific approach, there is the potential for important species at one site not being cumulatively assessed at another site. Instead, using a blanket approach might help encompass species and impacts over the broader spatial and temporal scale over which cumulative effects occur. This would need to be done in an efficient manner to prevent increasing the burden of carrying out assessments. It would also need to ensure that the existing uncertainties in assessment are not increased further.

A key question is whether a non-standard approach to scoping makes a difference to the overall outcome of the EIA to the point that standard approaches would be advantageous. Ideally, this question would be answered by proving that the EIA was accurate in its predictions for each wind farm. As it stands, however, a combination of factors makes this difficult to achieve. The project design envelope allows for a worst-case scenario of wind farm development to be assessed, with the likelihood that a less impactful wind farm will actually be built. Indeed, many wind farms are built to a lower capacity than is assessed (Womble Bond Dickinson, 2021). Therefore, assessing the actual impact of an operational wind farm does not provide a direct comparison to the predicted impact in the EIA. Even if the wind farm was built exactly as described in the EIA, rigorous monitoring of each seabird species would be needed after construction was complete to accurately gauge the actual impact.

Monitoring would need to cover each stage of a project, including decommissioning. In reality, only key species are chosen for monitoring, and often only displacement is monitored; collisions are rarely monitored due to the complexity of observing this impact (Collier *et al.*, 2011). Then, even if all seabirds were sufficiently monitored, there needs to be an appropriate level of certainty that the observed effects were due to the wind farm itself, as opposed to natural fluctuations in bird movements, distribution, or behaviour. It can be challenging to attribute an effect to a wind farm, in part because it relies on a good baseline characterisation of those parameters but also because a wind farm may have indirect effects on seabirds. Changes in forage fish distributions, for example, may occur due to the presence of a wind farm, which may, in turn, influence the distribution of seabirds (Raoux *et al.*, 2017; Olin *et al.*, 2020). However, monitoring of an ecosystem is not currently carried out, so indirect effects are not fully understood and cannot be attributed to the wind farm, neither individually nor cumulatively (Borja *et al.*, 2016; Declerck *et al.*, 2023).

3.5 Conclusion of how cumulative seabird displacement is assessed for offshore wind farms

In conclusion, this chapter has shown that cumulative wind farm impact assessments have each scoped in different species and impacts and have differing reasons for doing so. These various approaches and issues with data collection and assessment furthers the uncertainty already associated with largely unknown cumulative effects. The inconsistencies and problems mentioned are just a few of the queries regarding cumulative assessments; scoping projects, time frame cut-off, appropriate baselines, use of thresholds, and whether additive calculations are accurate to reality are just a few others. These all support the need for a more consistent approach, and doing so in a strategic way such that more robust assessments of cumulative effects can be made.

This chapter has evaluated the first part of the cumulative seabird displacement assessment by considering how species are scoped into a cumulative assessment. The disparity in approaches taken and the potential implications of this to the overall result of a cumulative assessment have been discussed. This is, however, only one source of uncertainty in understanding the cumulative displacement of seabirds at the point of assessing potential impacts. Other sources of uncertainty, such as in collecting empirical evidence of displacement and how cumulative displacement is calculated, are explored in subsequent chapters. The next chapter will follow this one by exploring another aspect of assessing displacement but with more direct implications for the building of wind farms. This will entail investigating how seabird displacement may be influenced by the design of a wind farm. This will focus on one of the most sensitive species to displacement, the red-throated diver.

Chapter 4 How does offshore wind farm design influence red-throated diver displacement?

Abstract

Renewable energy is being built around the world at a rapid pace and to aid this, minimising negative impacts to sensitive species is crucial. The displacement of seabirds from offshore wind farms is one such way that species can be negatively impacted. Reduction or mitigation of displacement effects is currently difficult to achieve due to the presence of structures being the cause of displacement. Therefore, there are few options besides removing turbines. Therefore, this research aimed to determine whether elements of wind farm design has an influence on the displacement of one of the most sensitive species, red-throated divers. A meta-analysis was undertaken of red-throated diver displacement evidence from post-construction monitoring, and statistically analysed correlations with parameters of wind farm design, such as the number of turbines and wind farm area. Results indicated that high densities of turbines, smaller wind farm areas, and closely sited turbines resulted in larger displacement within wind farms. Meanwhile, displacement occurred over a larger distance from the large wind farms and when more turbines were present. Therefore, when designing the area of a wind farm, both the within-wind farm displacement rate and displacement distance need to be carefully considered to take account of the whole displacement effect within and outside the wind farm. This study indicates that there may opportunities to modify wind farm design to minimise the effect of displacement on red-throated divers, but a holistic view would be needed to consider the impact to other species and other impacts so as whether collisions with turbines would increase or decrease.

4.1 Introduction to how offshore wind farm design influences red-throated diver displacement

Mitigation of the effects of displacement is hard to achieve. The mitigation hierarchy states that impacts should first be avoided, then minimised, then the environment restored, and finally, any remaining impacts compensated (Glasson and Therivel, 2019; The Biodiversity Consultancy, 2022). The behavioural response of seabirds to the presence of an offshore wind farm means that avoidance can only really be obtained by not building the wind farm in the location where an impact may occur. Where an impact cannot be avoided, minimisation can play a large part in the mitigation of a development's overall impact.

The mitigation of collisions may be obtained by increasing the turbine's hub height so that less of the rotor swept area overlaps with the flight height of seabirds. This means that wind farm power capacity can be retained but impacts reduced. However, the mere presence of the turbines is the cause of displacement. Removing a proportion of the turbines could, therefore, minimise impacts; however, this would likely come with an associated loss of wind farm capacity. There is no consensus on whether the spatial design of a wind farm has any bearing on this behavioural response, and few studies have explored this idea. Suppose it is the case that certain wind farm parameters have more of an impact on displacement than others. In that case, there may be a potential mitigation route through modifying these parameters whilst retaining wind farm capacity.

The previous chapter evaluated part of the first stage of the process in considering the cumulative displacement of seabirds by assessing how and why species are scoped into a cumulative displacement assessment. This chapter follows by evaluating how wind farm design may influence seabird displacement in order to understand how reductions to both individual and cumulative displacement impacts may be achieved. Investigations into mitigation of impacts would be carried out at an impact assessment stage but would also utilise empirical evidence of displacement at existing wind farms.

Within the overall aim of the thesis, this chapter addresses how cumulative seabird displacement from offshore wind farms is assessed and verified by reviewing the parameters which can be used to quantify displacement, determining which wind farm design parameters affect displacement, and discussing how wind farms could be designed to minimise displacement. The chapter focuses on red-throated divers as one of the most sensitive species to displacement. It begins by discussing the parameters that can describe displacement and reviewing studies that mention wind farm parameters in relation to displacement. The chapter then collates evidence of red-throated diver displacement and relevant parameters of the wind farms in question. It then performs statistical analyses to determine whether wind farm design could be a factor in diver displacement. It ends by discussing how wind farms may be designed to mitigate red-throated diver displacement.

4.2 Parameters of displacement considered in this study

Several parameters can be used to describe displacement:

- *displacement rate* — the proportion of birds that are displaced from an offshore wind farm and adjacent area
- *displacement distance* — the distance from the boundary of an offshore wind farm that birds are displaced
- *gradient of displacement* — the change in displacement rate with distance from an offshore wind farm
- *distance band* — the distance region within which a displacement rate is described

These displacement parameters are used throughout this thesis to describe displacement and are explored in more detail in Chapter 6. The parameters can be seen in Figure 4.1, with “A” representing an offshore wind farm, “B” representing the maximum displacement distance, “C” representing the distance band, the colour scale representing the displacement rate, and the displacement gradient seen as a change in displacement rate with distance from the wind farm. Figure 4.1 shows a within-wind farm displacement rate of 100%, distance bands of 1km, a declining displacement gradient of 10% every 1km distance band, and a maximum displacement distance of 5km. As displacement outside of a wind farm is described in terms of its distance from the wind farm boundary, displacement inside the wind farm boundary is referred to as within-offshore wind farm displacement, or simply “OWF” for ease in tables and figures. For example, Table 4.1 describes the displacement rates at distance bands in Figure 4.1.

Table 4.1. Example displacement rates in distance bands within and around an offshore wind farm.

Distance band	Displacement rate (%)
Within offshore wind farm (OWF)	100
0 — 1 km	85
1 — 2 km	70
2 — 3 km	55
3 — 4 km	40
4 — 5 km	25

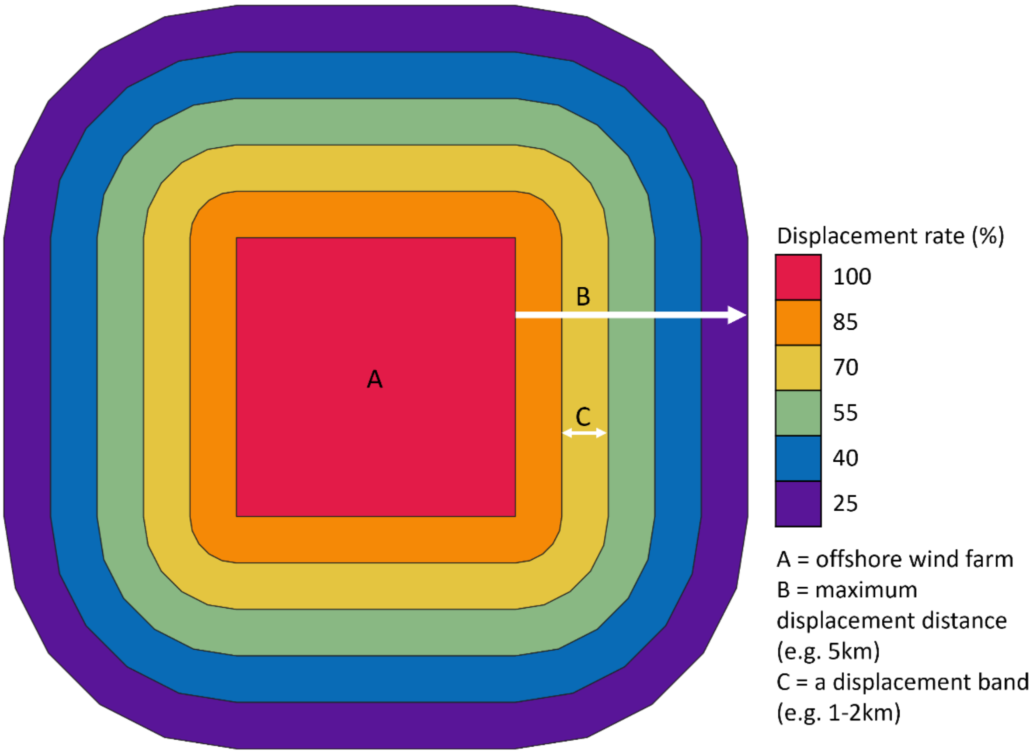

Figure 4.1. A top-down representation of a wind farm, where A is the wind farm with concentric rings around the wind farm describing displacement outside of the wind farm within each of the distance bands (in this case, distance bands are 1km wide).

These are the typical parameters which can be used to describe the number of birds displaced from the wind farm and the surrounding area. However, an additional parameter, mortality rate, is used during an impact assessment to describe the proportion of displaced birds likely to die due to being disturbed. This parameter has not been observed during post-construction monitoring of wind farms due to the difficulty in detecting mortalities at sea, as any carcasses are likely to be washed away or predated. Even if carcasses are detected, determining that the mortality was due to being displaced would be problematic as any fatality is likely to occur sometime after the disturbance and possibly some distance from the wind farm. The mortality rate is therefore not considered further within this research as there is no empirical evidence of displacement mortality to analyse against wind farm design parameters. It may be feasible that wind farm parameters may have a bearing on mortality rates; however, it cannot currently be investigated due to a lack of evidence from existing wind farms.

4.3 Displacement in relation to turbine parameters from previous studies

Reports from several wind farms have posed the idea that the parameters of wind farm design may have influenced the displacement of birds (Hötker, 2006; Krijgsveld *et al.*, 2011; Leopold *et al.*, 2011). Turbine density may affect the within-wind farm displacement rate of auks; for instance, a higher density of turbines at Princess Amalia wind farm was proposed as a reason for a higher displacement rate inside the wind farm, compared to a neighbouring wind farm with a lower density of turbines and lower associated displacement rate (Leopold *et al.*, 2011). Alternatively, the space between turbines may influence within-wind farm displacement. Krijgsveld *et al.* (2011) found that more birds flew between turbines spaced further apart, prompting the notion that wind farm displacement is lower when turbines are spaced further apart. The height of turbines potentially affects the displacement distance of lapwing from onshore wind farms, with data from 24 studies globally contributing to a significant rise in displacement distance with turbine height (Hötker, 2006). Other terrestrial species, however, showed no statistically significant trend in displacement distance with turbine height, suggesting this may just be a species-specific phenomenon.

Alternatively, rather than looking for a trend in wind farm parameters and displacement parameters, one set of studies looked to determine whether there was any significant difference in wind farm parameters at wind farms with a significant displacement effect on guillemots and razorbills (APEM, 2022b) and northern gannet (APEM, 2022a) compared to wind farms that had no displacement effect. They found that the density of the rotor-swept area (total rotor-swept area as a proportion of total wind farm area) and distance to the coast were significantly different between wind farms with a significant displacement effect on auks and those that had no displacement effect. This suggests these parameters could influence displacement (APEM, 2022b). Displacement of gannets was significantly correlated with the area of a wind farm, turbine density (number of turbines per km^2), the maximum distance between turbines, and distance to shore (APEM, 2022a). Again, there appear to be some species-specific effects of these wind farm parameters.

For guillemot, razorbill, and gannet, wind farms further from the coast showed higher displacement rates (APEM, 2022b; APEM, 2022a). It was hypothesised that this could be due to less spatial constraint on foraging activity further from the coastline, with fewer sources of anthropogenic disturbance, so locations outside of a wind farm would be more readily used for foraging (APEM, 2022b; APEM, 2022a). This may then mean that close to shore, where space is more limited and other sources of disturbance also exist, guillemot, razorbill, and gannet continue to forage within wind farms. Perhaps this is because other anthropogenic activities are a stronger source of disturbance, or they have become tolerant to some disturbance, or competition for resources is high. What is unclear is the level of impact on a population as a whole. It is also not clear whether there is a difference between locations with less wind farm-induced displacement and multiple other disturbance sources or spatial restrictions, compared to locations with more wind farm displacement but less other disturbance sources or spatial restriction. Is it the case that lower displacement close to shore results from many sources of disturbance such that the presence of a wind farm is the lesser source of disturbance? In this case, potentially detrimental levels of disturbance are present at a cumulative scale, and the fact that a wind farm close to shore has a lower displacement effect is not necessarily a good thing.

Variables outside of those directly related to wind farm parameters may also influence displacement rate or compound the effects due to certain designs. A low abundance of guillemot and razorbill was associated with larger displacement effects, possibly because competition for food is lower, so they can move to areas away from sources of disturbance. Conversely, high competition in areas of high seabird density may restrict where they forage, meaning not being displaced by a wind farm (APEM, 2022b). Larger displacement effects have been seen in the breeding season compared to the non-breeding season for gannet (APEM, 2022a), guillemot and kittiwake (Peschko *et al.*, 2020). Again, this may be due to other environmental factors across seasons and may have different population effects, for instance, if it results in reduced chick provisioning and survival during the breeding season (Peschko *et al.*, 2020).

Red-throated divers are one of the most sensitive species to disturbance, with evidence of large displacement rates with displacement occurring over vast areas (Petersen *et al.*, 2006; Percival, 2014; Mendel *et al.*, 2019; Vilela *et al.*, 2020; APEM, 2021); yet, no studies have been carried out on the impact of wind farm design on red-throated diver displacement. Mitigation of detrimental impacts to the red-throated diver is necessary as wind farms continue to be built across inshore European waters. Therefore, this work aims to investigate if and how any aspects of physical wind farm design have influenced the distance and proportion of displaced red-throated divers.

The null hypothesis was that there was no correlation between parameters of displacement and wind farm design parameters:

1. No correlation between within-wind farm displacement rate and the rotor diameter
2. No correlation between within-wind farm displacement rate and the rotor swept area
3. No correlation between within-wind farm displacement rate and the height of turbines to tip of blade
4. No correlation between within-wind farm displacement rate and the air gap
5. No correlation between within-wind farm displacement rate and the density of rotor swept area (total rotor swept area as a percentage of total wind farm area)
6. No correlation between within-wind farm displacement rate and the number of turbines
7. No correlation between within-wind farm displacement rate and the area of the wind farm
8. No correlation between within-wind farm displacement rate and the average spacing of turbines (blade tip to blade tip)
9. No correlation between within-wind farm displacement rate and the average spacing of turbines (tower to tower)
10. No correlation between within-wind farm displacement rate and the density of turbines (turbines/km^2)
11. No correlation between within-wind farm displacement rate and the wind farm capacity
12. No correlation between within-wind farm displacement rate and the distance to coast

These 12 hypotheses were then replicated by replacing within-wind farm displacement rate with the maximum distance red-throated divers are displaced from the wind farm.

4.4 Method to investigate the influence of wind farms on red-throated diver displacement

To investigate the potential influence of built wind farm parameters on the displacement of seabirds, evidence of red-throated diver displacement was collected from post-construction monitoring reports from operational wind farms, published reports and peer-reviewed articles. In addition, information regarding the as-built parameters of offshore wind farms was sourced via internet searches on the wind farm in question. Box 4.1 shows the wind farm variables that were explored within this investigation.

Box 4.1. Wind farm variables — from parameters of individual turbines to the wind farm as a whole.

Parameters of individual turbines:	*Parameters of the wind farm as a whole:*
• Rotor diameter (m) • Rotor swept area (m^2) • Height of turbines to tip of blade (m) • Air gap (m) • Density of rotor swept area (total rotor swept area as a percentage of total wind farm area)	• Number of turbines • Area of wind farm (km^2) • Average spacing of turbines (blade tip to blade tip) (m) • Average spacing of turbines (tower to tower) (m) • Density of turbines (turbines/km^2) • Wind farm capacity (MW) • Distance to coast (km)

Red-throated diver displacement was also explored through two main parameters:

- Rate of displacement within the wind farm (%)
- Maximum distance red-throated divers are displaced from the wind farm (km)

At the time of the research (June 2023), a total of 15 reports were found to quantify the displacement of red-throated divers from offshore wind farms. Eleven of these analysed the effect of individual wind farms or wind farms in very close proximity to one another. The remaining five reports considered red-throated diver displacement over a much wider area, including multiple wind farms spread apart.

The 11 individual reports quantifying red-throated diver displacement did so at offshore wind farms in four European country jurisdictions. These wind farms were Horns Rev I, Horns Rev II; Nysted; Alpha Ventus; Egmond aan Zee; Gunfleet Sands; Kentish Flats; Lincs, Lynn and Inner Dowsing; London Array; North Hoyle; and Thanet. The built parameters of these wind farms are listed in Appendix Table D1. Note that Lincs OWF and Lynn and Inner Dowsing OWF are two separate wind farms; however, they are located adjacent to one another with post-construction monitoring of red-throated diver displacement analysed for the two wind farms together. Therefore, the wind farm parameters for the Lincs OWF and the Lynn and Inner Dowsing OWF have been described separately in Table D1 in Appendix D, but parameters either averaged (e.g. rotor diameter) or summed (e.g. the number of turbines) for analysis against displacement parameters. The five reports analysing red-throated diver displacement across multiple offshore wind farms were located in German waters. However, the broader spatial scope of these analyses made it difficult to assess the impact of specific wind farm parameters; therefore, they were only selectively used throughout this research. These wind farms are listed in Table D2 in Appendix D. Details of red-throated diver displacement from the 11 individual wind farm reports are listed in Table 4.2, whilst the red-throated diver displacement from the five multiple wind farm reports is listed in Table 4.3.

Table 4.2. Red-throated diver displacement rates and displacement distances at individual offshore wind farms as reported in the literature and monitoring reports.

Offshore Wind Farm	**Distance band (km)**	**Displacement rate (%)**	**Number of turbines**	**Wind farm area (km)**	**Displacement reference**
Horns Rev I Denmark	Within OWF	100	80	20	Petersen *et al.* (2006)
	0.0 — 2.0	Not quantified			
Horns Rev II Denmark	Within OWF — 6.0	Not quantified	91	35	Petersen *et al.* (2014)
	Within OWF — 13.0	Not quantified			
Nysted Denmark	Within OWF	100	72	21	Petersen *et al.* (2006)
	0.0 — 2.0	Not quantified			
Alpha Ventus Germany	Within OWF	90	12	4	Welcker and Nehls (2016)
	0.0 — 1.5	Not quantified			
Egmond aan Zee Netherlands	Within OWF	68	36	27	Krijgsveld *et al.* (2011)
Gunfleet Sands UK	Within OWF	91.29	48	18	NIRAS (2015)
	0.0 — 1.0	65.80			
	1.0 — 2.0	20.95			
Kentish Flats UK	Within OWF	94	30	10	Percival (2014)
	0.0 — 0.5	77			
	0.5 — 1.0	69			
	1.0 — 2.0	53			
	2.0 — 3.0	56			
Lincs, Lynn & Inner Dowsing UK	Within OWF	83.3	129	55	Webb *et al.* (2017)
	0.0 — 1.0	77.4			
	1.0 — 2.0	71.4			
	2.0 — 3.0	62.5			
	3.0 — 4.0	55.2			
	4.0 — 5.0	50.8			
	5.0 — 6.0	44.8			
	6.0 — 7.0	42.3			
	7.0 — 8.0	33.6			
	Within OWF	54.68	175	100	APEM (2021)

Offshore Wind Farm	**Distance band (km)**	**Displacement rate (%)**	**Number of turbines**	**Wind farm area (km)**	**Displacement reference**
London Array UK	0.0 — 0.5	47.91			
	0.5 — 1.0	44.92			
	1.0 — 1.5	41.00			
	1.5 — 2.0	38.91			
	2.0 — 2.5	40.38			
	2.5 — 3.0	41.18			
	3.0 — 3.5	39.50			
	3.5 — 4.0	36.07			
	4.0 — 4.5	33.02			
	4.5 — 5.0	31.55			
	5.0 — 5.5	32.96			
	5.5 — 6.0	35.00			
	6.0 — 6.5	36.08			
	6.5 — 7.0	35.58			
	7.0 — 7.5	40.07			
	7.5 — 8.0	41.29			
	8.0 — 8.5	44.88			
	8.5 — 9.0	45.13			
	9.0 — 9.5	44.19			
	9.5 — 10.0	39.61			
	10.0 — 10.5	34.44			
	10.5 — 11.0	23.88			
	11.0 — 11.5	12.62			
North Hoyle UK	Within OWF — 2.5	Not quantified	30	10	May (2008)
Thanet UK	Within OWF	73	100	35	Percival (2013)

Note: Number of decimal places is the same as those reported in the relevant literature or monitoring report.

Table 4.3. Red-throated diver displacement rates and displacement distances at multiple offshore wind farms, as reported in the literature.

Offshore Wind Farm	Distance band (km)	Displacement rate (%)	Reference
Butendiek & Helgoland Cluster Germany	OWF — 3.0	70.8	Mendel *et al.* (2019)
	OWF — 10.0	44.5	
	OWF — 16.5	Not quantified	
German Bight Germany	OWF — 5.0	90	Heinänen *et al.* (2020)
	OWF — 15.0	Not quantified	
German North Sea I Germany	OWF — 10.2	Not quantified	Vilela *et al.* (2020)
German North Sea II Germany	OWF — 1.0	94	Garthe *et al.* (2023)
	OWF — 10.0	52	
Liverpool Bay UK	OWF — 3.8	Not quantified	Burt *et al.* (2017)

Note: Number of decimal places is the same as those reported in the relevant literature or monitoring report.

The methods used to determine displacement parameters across the 15 reports differ due to the type of survey and method of data analysis. For instance, studies used boat-based, visual aerial, digital aerial, radar, and telemetry methods to survey red-throated divers, with the method sometimes differing across the study period. These survey methods can result in different abundance estimates (Henkel *et al.*, 2007). Boat-based surveys, in particular, can be less accurate due to a combination of real-time identification with no opportunity for review and behavioural response to the presence of vessels which can either attract or displace different species (Briggs *et al.*, 1985; Henkel *et al.*, 2007).

Data also needs to be adjusted because birds' detection likely decreases further from the survey transect (Thomas *et al.*, 2010). This is also required for visual aerial surveys; however, flights are less likely to prompt a behavioural response from individuals, thereby providing a more accurate abundance estimate (Buckland *et al.*, 2012). In addition, some studies used a Before-After-Control-Impact approach (BACI), which compares abundance and distribution estimates after wind farm construction to estimates prior to wind farm construction. Other studies used solely post-construction data to look at the spatial patterns in abundance (see Appendix Table D3 for a full list of the survey, modelling, and displacement calculation methods of the red-throated diver displacement studies). Therefore, these differences must be considered when comparing displacement parameters across studies using different survey and data analysis methods.

The wind farms ranged from 12 small turbine sites covering 4km^2 to 175 large turbine sites covering 100km^2, from close to shore (closest to shore = 5.2km) to further offshore (furthest from shore = 45.0km). Some small wind farms were located close to shore whilst others were sited far from shore, and likewise, large wind farms were sited both close to and further from land.

The first null hypothesis was that displacement rate did not correlate with any wind farm parameter. The second null hypothesis was that maximum displacement distance did not correlate with any wind farm parameter. Therefore, correlation test were chosen to test these null hypotheses. The Shapiro test for normal distribution showed that the majority of displacement and wind farm parameters had non-normal distributions. In addition, there were several outliers in the wind farm and displacement parameters. Therefore, Kendall tau tests were chosen as the statistical test to investigate relationships between displacement and wind farm parameters. The analysis was carried out in R (R Core Team, 2022). The R markdown code is available in Appendix E.

An alternative method to investigating trends in wind farm design against displacement parameters is to determine whether there is a significant difference in wind farm parameters between those sites for which there is evidence of displacement versus sites for which there is evidence of no displacement. This type of analysis has been carried out for the displacement of auks (APEM, 2022b) and gannets (APEM, 2022a). However, for red-throated divers, very few reports show offshore wind farms had little to no displacement effects. For example, Barrow Offshore Wind Farm found no significant changes in the density or distribution of red-throated divers after three years of post-construction monitoring surveys (Barrow Offshore Wind, 2010). Other wind farms had too few red-throated diver densities to detect any density changes post-construction, such as at Robin Rigg offshore wind farm (E.ON Climate & Renewables, 2015). Therefore, comparing wind farms with little or no displacement against those with substantial displacement is not feasible statistically.

4.5 Results for the wind farms that quantified displacement of red-throated divers

For the 11 individual offshore wind farms that quantified displacement of red-throated divers, initial statistical tests for normal distribution show non-normal data distributions for both displacement parameters and wind farm parameters. In addition, small sample sizes mean that Kendall correlation tests are the best choice for the data. Kendall tests were performed on each wind farm parameter against both within-wind farm displacement rates and maximum displacement distance values.

Results in this section are split by displacement parameter: displacement rate within the wind farm (%), the maximum distance that red-throated divers are displaced from the wind farm (km), and displacement rate at the maximum distance red-throated divers are displaced from the wind farm (%).

4.5.1 Displacement rate within the wind farm

Of the 11 individual wind farms that indicated red-throated diver displacement, nine reported the displacement rate within the wind farm (Table 4.2). This displacement rate ranged from 54.68% to 100%, with a mean of 83.81% and a median of 90.00%.

There are some differences in the within-wind farm displacement rate when considering the survey platform or the method of calculating displacement, with boat-based surveys reporting similar within-wind farm displacement rates and the two visual aerial surveys reporting the same within-wind farm displacement rate (Figure 4.2). These two survey methods result in higher within-wind farm displacement rates than the other survey methods. However, there are few data points for these other methods. Therefore, it is hard to come to a conclusion as to whether the survey method makes a meaningful difference to the displacement rates reported. The BACI data analysis method appears to generate a range of displacement rates, suggesting the survey method may be a larger factor in determining what those rates are. There are two studies which report within-wind farm displacement rates using other analytical methods. One of these compares the assumed distribution, had the wind farm not been built, to the actual distribution of birds after wind farm construction. The other method compares distribution within the wind farm to that outside the wind farm. Each study, regardless of survey type, generated a displacement rate which is a relative metric, be it a comparison before and after wind farm construction or inside and outside an operational wind farm. Therefore, displacement rates from all studies were treated in the correlation analysis.

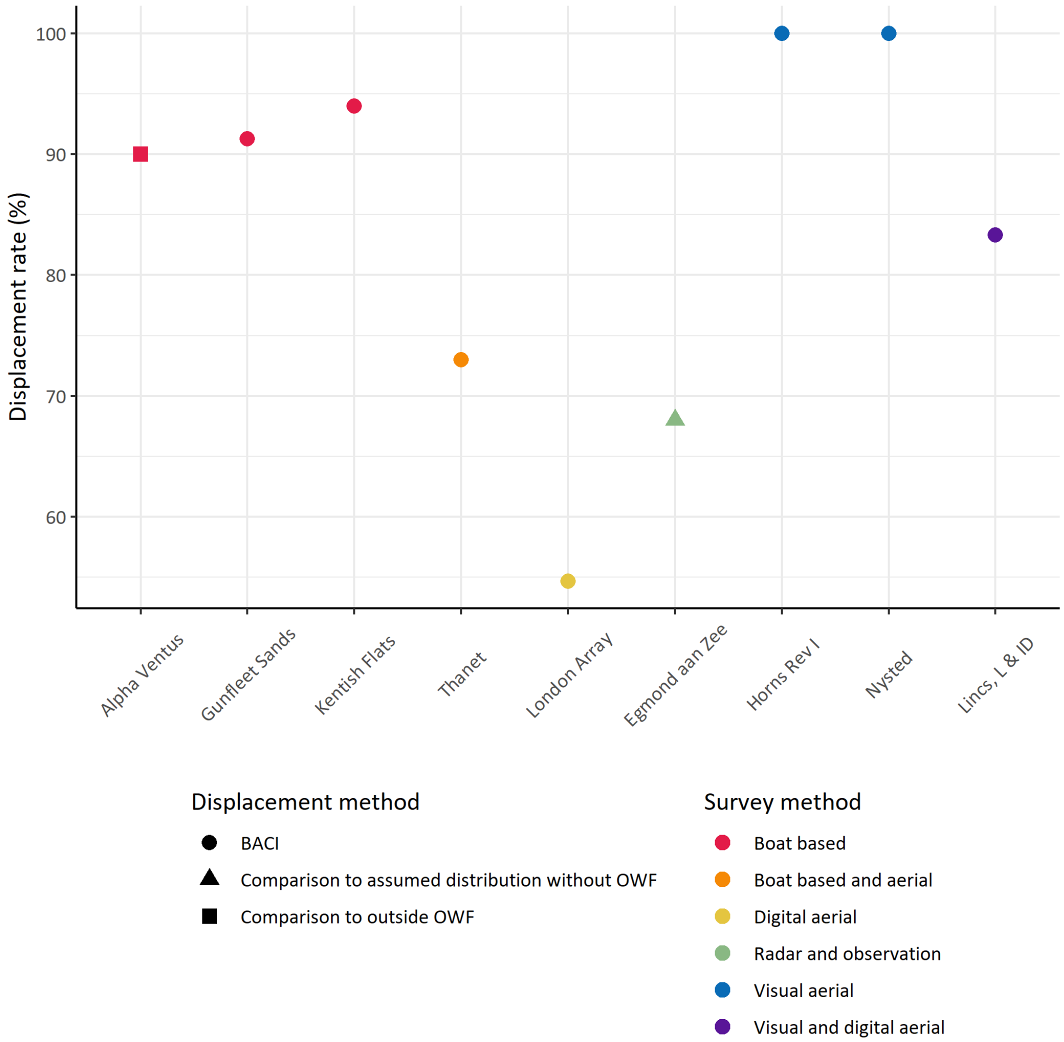

Figure 4.2. Red-throated diver displacement rates within offshore wind farms across European wind farms, and the survey and displacement methods used to calculate them, as stated in the literature and monitoring reports (nine studies spanning 2006 to 2021).

When considering whether there are any relationships between the displacement rate within the wind farm and wind farm parameters, several significant correlations are seen. A significant positive correlation exists between the turbine density and the within-wind farm displacement rate ($R_\tau = 0.74$, $n = 9$, $p < 0.01$). Wind farms with higher-density turbines show higher displacement rates within the wind farm and vice versa, from a density of 1.8 turbines/km^2 and 54.68% displacement up to 4.0 turbines/km^2 and 100% displacement (Figure 4.3). Displacement within the wind farm is also correlated, although not as significantly, with diameter ($R_\tau = -0.48$, $n = 9$, $p = 0.09$). Smaller diameter turbines show higher displacement rates within the wind farm and vice versa, from 100% displacement at 80m diameter turbines to 54.68% displacement at 120m diameter turbines (Figure 4.4).

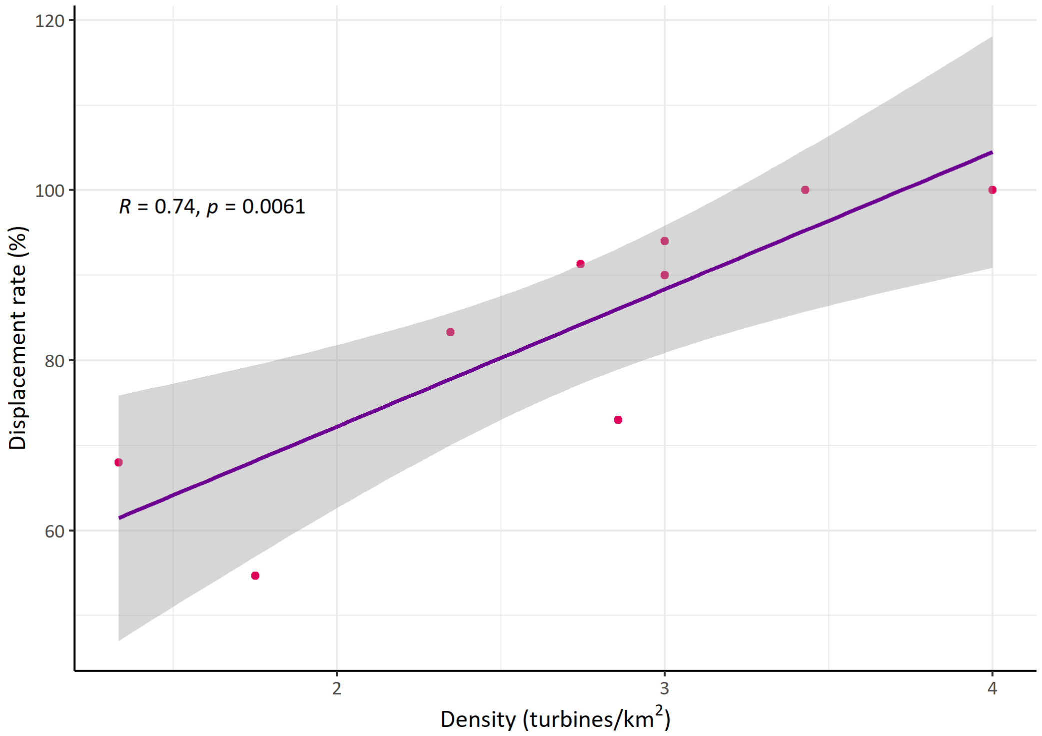

Figure 4.3. A significant relationship ($p < 0.01$) showing a higher density of turbines within a wind farm correlates with higher red-throated diver displacement rates within wind farms.

Note: Shaded area = 95% confidence intervals.

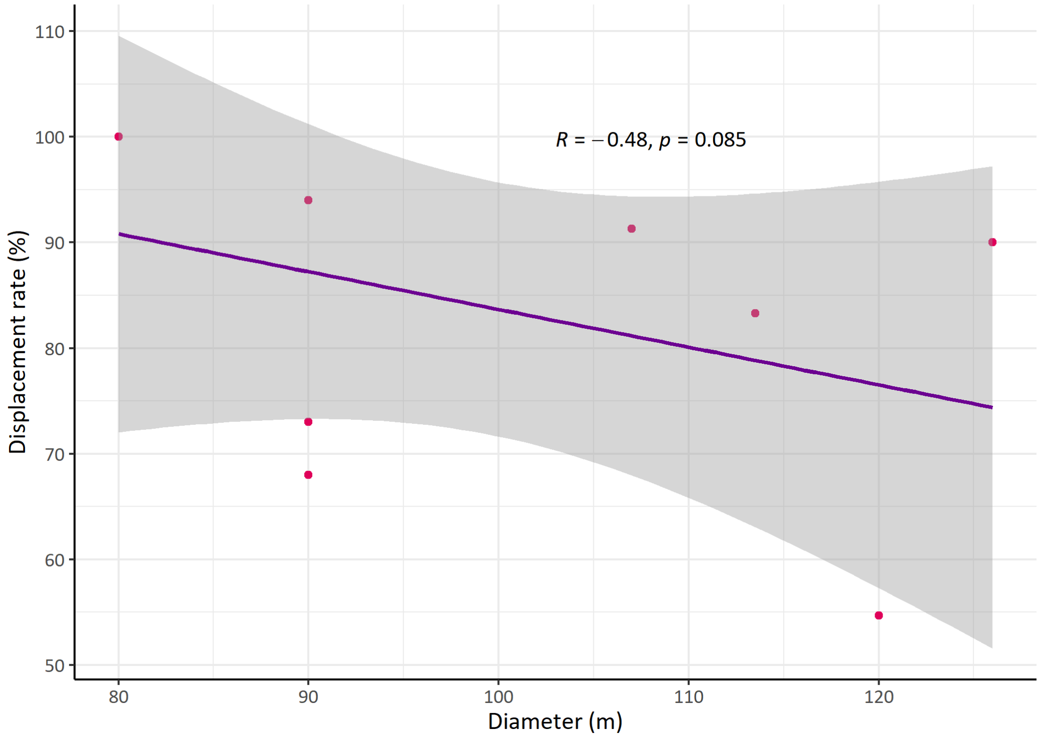

Figure 4.4. A somewhat significant relationship ($p < 0.10$) showing larger turbine diameter correlates with lower red-throated diver displacement rates within wind farms.

Note: Shaded area = 95% confidence intervals.

The displacement rate is higher at wind farms with smaller rotor diameter turbines and higher in wind farms with high turbine densities. Whilst it makes sense intuitively that higher-density turbines result in higher displacement rates as birds may perceive less space uninterrupted by anthropogenic structures, it is less obvious why smaller turbines result in higher displacement rates. However, it may be that either turbine density or rotor diameter is the actual cause of displacement, whilst the other factor is linked to the first, but itself is not a cause of displacement.

The small rotor diameter and high turbine density suggest that turbines with smaller diameters are placed close to one another in a given area, resulting in a high density of turbines. Indeed, there is a negative correlation between rotor diameter and turbine density (R_τ = -0.45, n = 9, p = 0.11). This makes sense from a wind farm power perspective, with turbines increasing in size and needing to be spaced further apart to reduce wake interactions, resulting in lower turbine density (Stevens *et al.*, 2016). This interaction between rotor diameter and turbine density was subsequently investigated through a partial correlation between turbine density and within-wind farm displacement rate, controlling for rotor diameter. A significant positive correlation is apparent between the turbine density and the within-wind farm displacement rate when controlling for turbine diameter (R_τ = 0.67, n = 9, p = 0.02). This suggests that turbine density correlates with within-wind farm displacement rate, regardless of whether or not rotor diameter is controlled for.

Similarly, there is a correlation between the height (to blade tip) of turbines and displacement rate within the wind farm, whereby there is a higher displacement rate when smaller turbines are present (R_τ = -0.45, n = 9, p = 0.11). Again, this is likely due to more dense wind farms consisting of smaller (in height) turbines. Indeed, a partial correlation between turbine density and within-wind farm displacement whilst controlling for height (R_τ = 0.69, n = 9, p = 0.02) shows that density can explain the correlation regardless of height. Furthermore, a turbine's total height is linked to the rotor diameter as a gap needs to be maintained between the bottom of the rotor and the sea surface. Therefore, as turbine diameter increases, so does turbine height (R_τ = 0.93, n = 11, p = <0.01); hence it makes sense that height is also a covariate.

It, therefore, seems plausible that the cause of the high displacement rate is the density of turbines, which occurs where there are turbines with small rotor diameters (and turbines of lower height). However, it may be that the distance between towers, rather than the size of the rotors, is more important. This would make sense as red-throated divers spend much of their time sitting on and diving through the water, potentially perceiving things lower to the water surface more than higher in the air. When in flight, red-throated divers spend 98% of the time below 30m above the sea surface and given that the average air gap between the sea surface and the bottom of the rotor swept area is 27.4m (min = 22.0m, max = 33.5m), even in flight red-throated divers often do not enter the rotor swept area (Johnston *et al.*, 2014). The same correlation is seen for displacement rate and average turbine spacing when considering the spacing between towers and for displacement rate and average turbine spacing when considering the spacing between tips of blades (R_τ = -0.42, n = 9, p = 0.12 and R_τ = -0.42, n = 9, p = 0.12, respectively). Again, this suggests that perhaps the rotor diameter does not directly influence displacement rate (Figure 4.5 and Figure 4.6).

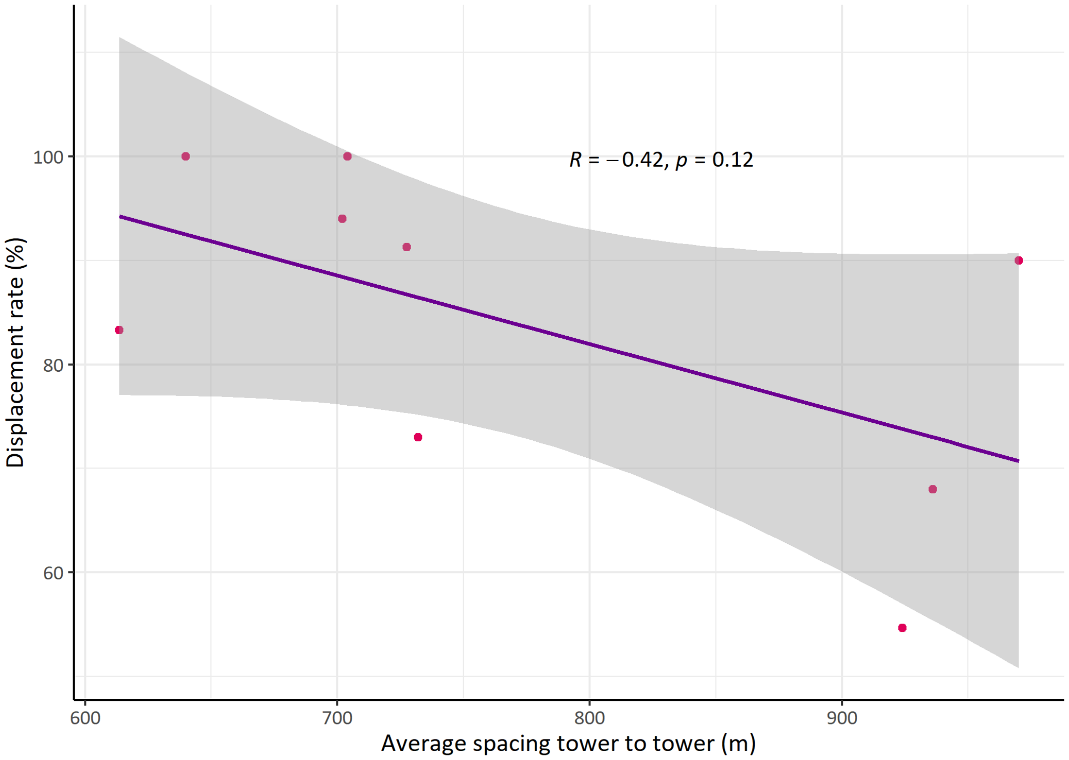

Figure 4.5. A relationship showing larger spaces between turbine towers correlates with higher red-throated diver displacement rates within the wind farm.

Note: Shaded area = 95% confidence intervals.

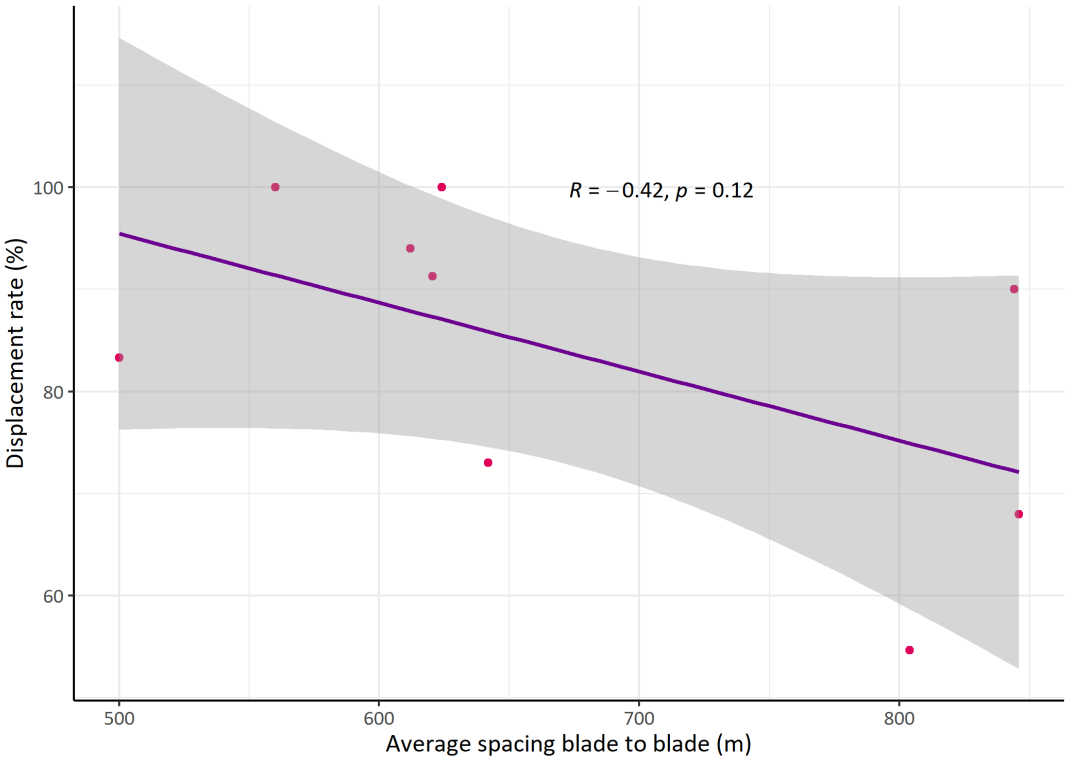

Figure 4.6. A relationship showing larger spaces between turbine blade tips correlates with higher red-throated diver displacement rates within the wind farm.

Note: Shaded area = 95% confidence intervals.

The other wind farm parameters investigated do not significantly correlate with within-wind farm displacement rates. The density of the rotor swept area, meaning the total rotor swept area as a proportion of the wind farm area, is not significantly correlated with displacement rate, further suggesting that the size of the rotor is not a significant factor influencing displacement rate. It may be that over time, as technology improves, turbines get larger and more spaced apart, but also further from the coast. However, there is no significant correlation between displacement rate and distance to the coast. There is no significant correlation between the displacement rate within the wind farm and all other wind farm parameters (number of turbines, turbine height, wind farm area, rotor swept area, wind farm capacity, and turbine air gap).

4.5.2 Displacement distance from the wind farm

Of the 15 reports that investigated the displacement of red-throated divers with sufficient data to analyse, two present displacement rates within only the wind farm, with the remaining 13 indicating a range of maximum displacement distances from 1.5km to 16.5km (Figure 4.7). The average maximum displacement distance is 6km (median = 3km, range =

within OWF to 16.5km). Not all of these reports present displacement rates within the maximum displacement distances, making it difficult to know whether the actual maximum displacement distance has been found. For instance, if a wind farm reported that displacement was seen up to 7km from the wind farm boundary but did not state the displacement rate in the outermost distance band, it is not known whether there was potential for displacement to have also occurred further than 7km. It is often also unknown whether surveys would have even been able to detect small displacement rates that might have occurred either at 7km or further than 7km.

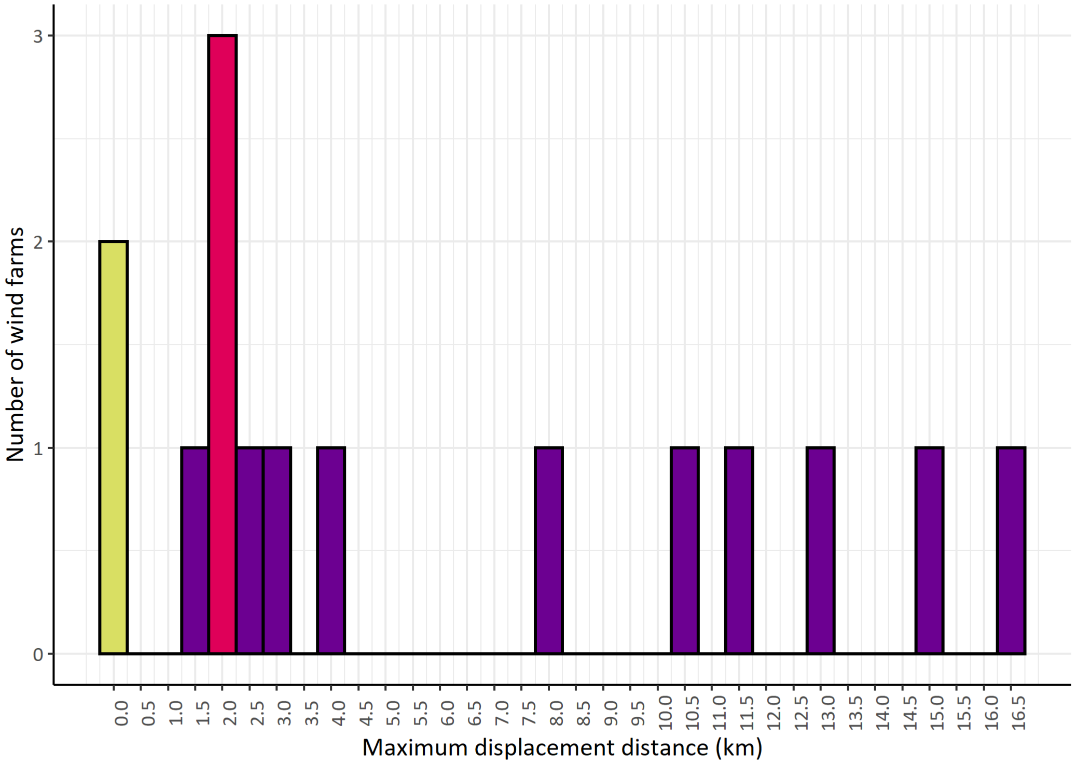

Figure 4.7. A histogram of the maximum red-throated diver displacement distances reported by the literature and monitoring reports from offshore wind farms.

Tests were carried out to determine whether any wind farm design parameters had a bearing on the maximum distance from the wind farm over which displacement was seen. However, there is no significant correlation between the maximum distance from the wind farm that displacement is observed and any of the wind farm parameters.

There may be a range of other factors that might influence the displacement rates and distances: environmental, ecological, and anthropogenic. Some of these may be known or measurable factors, whilst others are harder to determine. These may be factors such as the relative quality or importance of a habitat where a wind farm is built; the survey platform, survey design, distribution modelling method, and statistical analysis of data; variability in densities and distributions of species across months, seasons, and years; and existing levels of disturbance and habituation to anthropogenic activity.

4.6 Discussion of how offshore wind farm design influences red-throated diver displacement

This is the first investigation of how wind farm design parameters may have influenced the displacement of red-throated divers. The study found that turbine diameter, distance between turbines, and density of turbines all correlated with the within-wind farm displacement rate. Larger turbines spaced further apart over an area resulted in lower displacement within the wind farm boundary. Furthermore, the number of turbines correlated with the area over which displacement was observed to take place, with more turbines resulting in a larger overall area affected by displacement. All other parameters of wind farm design that were assessed did not appear to have had a bearing on metrics of displacement.

Currently, wind farm design parameters are not accounted for when assessing the impact of seabird displacement, with the exception of wind farm areas. This is used to determine the number of birds present in the wind farm and appropriate distance band, and subsequently, the number of birds which are predicted to be displaced. Therefore, it is assumed that wind farm area is the sole factor influencing the number of birds displaced; however, these results suggest that this is not necessarily the case. Instead, turbine diameter, the distance between turbines, and the density of turbines are all parameters which appear to have the potential to affect red-throated diver displacement rate. There may be a case to include some design parameters within an impact assessment, much like how a collision risk model uses aspects such as the number of turbines and rotor swept area to determine the number of birds at collision risk. However, whilst wind farm area is something not likely to change between impact assessment and the final wind farm design and subsequent construction, turbine diameter, distance between turbines, and density of turbines are all parameters which have the potential to change between the impact assessment, the consent conditions, and final wind farm design and construction. Therefore, although the worst-case scenario is assessed, this is not necessarily what occurs post-construction. However, an assessment accounting for differences in design may help indicate the least impactful design.

Designing to minimise displacement and designing to minimise collision may not also be compatible, as the worst-case scenario for collision estimates may not be the same as the worst-case scenario for displacement. For example, larger-diameter turbines appear to be advantageous in terms of reducing displacement; however, they would likely be worst in terms of collision mortalities. However, when considering that larger diameter turbines are spaced further apart and higher above the sea surface, this may potentially be advantageous in terms of collision mortalities. Whether or not this would negate the effects of larger diameter turbines would require further calculation. If this is the case, then larger turbines spaced further apart could, in fact, be better in terms of both displacement effects and collision mortalities. This is merely a hypothesis at this stage, as there is no way to know what the effect would be of changing wind farm parameters without a direct comparison with an unchanged wind farm. The variable nature of behavioural responses to wind farms means direct comparison would not be possible. However, repeating the study described in this chapter, utilising more displacement data as it becomes available, may shed more light on any differences that wind farm design parameters may make.

In order to shed more light on the effect of displacement and how to mitigate it, several improvements to data collection are required. As seen throughout this thesis, displacement has been described in a range of different ways (see Chapter 6 for further investigation). This includes both quantitative and qualitative metrics, different methods of analysis, and calculations within different size distance bands. This all makes comparisons across wind farms challenging, particularly on top of differences in survey methods and natural variation in species abundances, distributions, and behavioural responses.

Therefore, a standardised methodology for describing displacement is urgently needed to enable a better understanding of the effect of displacement and how it may be reduced going forward. Based on the findings of this chapter and subsequent chapters, an opinion on what standardised displacement studies could look like is provided in the conclusion. Undertaking surveys at a sufficient spatial scale to capture all displacement is also required to fully understand the extent of effects. In addition, consideration is also needed as to how displacement should be described over a large area, as displacement rates may be different on opposite sides of a wind farm.

Data on red-throated diver displacement, in a comparative format, is reasonably scarce. Therefore, this investigation is limited in the number of data sources that could be used to explore the influence of wind farm design on the displacement of this species. Therefore, more studies using consistent approaches are needed to quantify the evidence of displacement. This will allow more robust research into the influence of wind farm design such that more confidence can be given to any suggested mitigation. Furthermore, this chapter has specifically focussed on red-throated divers; therefore, further work is needed to consider how other species interact with different wind farm designs, and a holistic view will be needed to minimise impacts to all species collectively.

4.7 Conclusion of how offshore wind farm design influences red-throated diver displacement

In conclusion this first investigation into the influence of wind farm design parameters on the displacement of red-throated diver has found that turbine diameter, distance between turbines, and density of turbines all correlated with within-wind farm displacement rate. In addition, the number of turbines correlated with the area over which displacement was occurred. No other parameter appeared to influence red-throated diver displacement. This study has demonstrated the vast differences in displacement effects, ways that displacement is described, and indicated that some aspects wind farm design may be having more of an influence of the effect of displacement. This opens the door for further studies to investigate displacement mitigation options for other species and subsequently test and validate alternative wind farm designs.

This chapter has reviewed the influence of offshore wind farm design on red-throated diver displacement. This has used and reviewed empirical evidence of displacement. Comparisons between approaches to calculating displacement from evidence are explored further in Chapter 6. However, before looking into evidence of displacement, it is important to understand whether surveys are, in fact, sufficient to detect displacement in the first instance. This is also a crucial step linking predictions made in the impact assessment with the impacts that happen in reality. Therefore, the next chapter will explore the design of pre-construction and post-construction surveys to detect displacement.

Chapter 5 How much monitoring is sufficient to detect red-throated diver displacement from offshore wind farms?

Abstract

Offshore renewable energy developments have grown substantially over the last 20 years, yet there remains a large knowledge gap in the effect they have on the movement of seabirds. Being able to detect seabird movements and changes in abundance is a crucial step in understanding the impact to populations of sensitive and vulnerable species. Careful survey design is one way of enhancing the detectability of seabird displacement. This study used red-throated diver (Gavia stellata) survey data from the Outer Thames Estuary Special Protection Area to investigate how the statistical power of a survey to detect a given displacement rate was influenced by spacing between transects, the density of red-throated diver and the number of survey days. This was done through the use of a Before-After study design, comparing mean densities of red-throated diver before (pre-impact) and after (post-impact) the construction of a wind farm. The results indicated that transect spacing minorly affects the statistical power of being able to detect a given displacement rate. The number of survey days can have an impact on the power to detect displacement, however the variable able to make the largest improvement to the survey power was the displacement rate to be detected. A sufficiently powerful survey can require an impractically large number of post-impact survey days, particularly where low displacement rates are to be detected, which would be unreasonably costly. Naturally, higher displacement rates, a large number of survey days, higher densities of red-throated diver,

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With the exception of the introduction and conclusion, the content of this chapter is published as Hall, R. and Black, J. (2024) What level of monitoring is enough to detect displacement effects of offshore wind farms? *Environmental Impact Assessment Review*, 105 107449 and combinations of these factors were all more likely to result in higher statistical power of a survey. However, some of these variables are not alterable, such as the density of red-throated diver, and others have vast cost implications, such as increasing the number of survey days. Therefore, careful consideration of these variables at an early stage of designing a survey can help ensure desired displacement can be detected.

5.1 Introduction to how much monitoring is sufficient to detect red-throated diver displacement

Survey design is important within EIA at several stages, from collecting adequate baseline information about the development site to monitoring surveys to satisfy consent conditions. In terms of baseline data, current advice in the UK is to assess displacement impact within the wind farm plus a buffer of 2km for all species except divers and seaducks; a 4km buffer is recommended for these species (Statutory Nature Conservation Bodies, 2022b). There is a further exception for red-throated divers, where 10km is suggested (Statutory Nature Conservation Bodies, 2022a). There do not appear to be any standard survey designs to undertake post-consent studies (including pre-construction and post-construction) in order to validate displacement effects, though this is important to be able to detect displacement (Marques *et al.*, 2021). No other survey design attributes are recommended, and the detectability of displacement effects based on survey design remains largely unknown.

It is essential that post-consent monitoring of offshore wind farms is effective and improves understanding of impacts on marine wildlife, including displacement of sensitive species. This is especially critical given the potential for uncertainty in the significance of the environmental impacts of proposed offshore wind farm developments, particularly at the cumulative scale (Masden *et al.*, 2010b).

The previous chapter reviewed how offshore wind farm design influences red-throated diver displacement. Once a wind farm has been designed and its impacts assessed and then mitigated, confirmation is needed as to whether these predicted impacts are accurate. The need for verification of impacts is twofold. First, knowing whether an impact has been underestimated is needed, as it may be that further mitigation is required to reduce the impact. Second, it provides a feedback loop between impact assessments and the reality of impacts, such that impact assessment methods can be improved to provide more accurate predictions.

The first stage in the process of verifying impacts is to understand whether the surveys carried out pre-construction and post-construction of a wind farm are sufficient to detect the impact. This chapter explores this by modelling different scenarios of red-throated diver displacement and running a power analysis on survey designs to check if they are sufficient to detect such displacement. The chapter begins by describing the method used to analyse how much monitoring is sufficient to detect red-throated diver displacement. It then describes the results of running a power analysis on different survey designs to check if they are sufficient to detect such displacement. This is done by modifying the transect spacing (or number of transects), the mean density of red-throated divers, the standard deviation in density of red-throated divers, and the number of survey days. Finally, the results are discussed within the context of the Outer Thames Estuary Special Protection Area (SPA) study area.

5.2 Method of analysing how much monitoring is sufficient to detect red-throated diver displacement

This section first defines the study area and then describes the data used before describing the scenarios used to analyse what level of monitoring is sufficient to detect red-throated diver displacement. Finally, this section evaluates how power analyses were used to determine sufficient levels of monitoring.

5.2.1 Study area – the Outer Thames Estuary Special Protection Area

There are 286 Special Protection Areas (SPA) across the UK, covering 54,688km^2 of land and sea (JNCC, 2023). 125 of these have a marine component, protecting bird species that are dependent on the marine environment for all or part of their lifecycle (JNCC, 2020d). The study area of interest is the Outer Thames Estuary SPA in the southern North Sea and the surrounding offshore wind farm developments that potentially impact this SPA. This area was chosen as it is one of the busiest marine areas around the UK, with shipping lanes, offshore wind farms, aggregate extraction areas, and recreational water sports among the numerous anthropogenic activities occurring in the region. The Outer Thames Estuary SPA for the largest wintering aggregation of red-throated divers in the UK, which is estimated to be 6,466 individuals (JNCC, 2020e). The SPA extends from the Thames Estuary in the south to Great Yarmouth in the north, from the coastline to beyond 12 nautical miles offshore. The location of the Outer Thames Estuary SPA relative to the UK is shown in Figure 5.1.

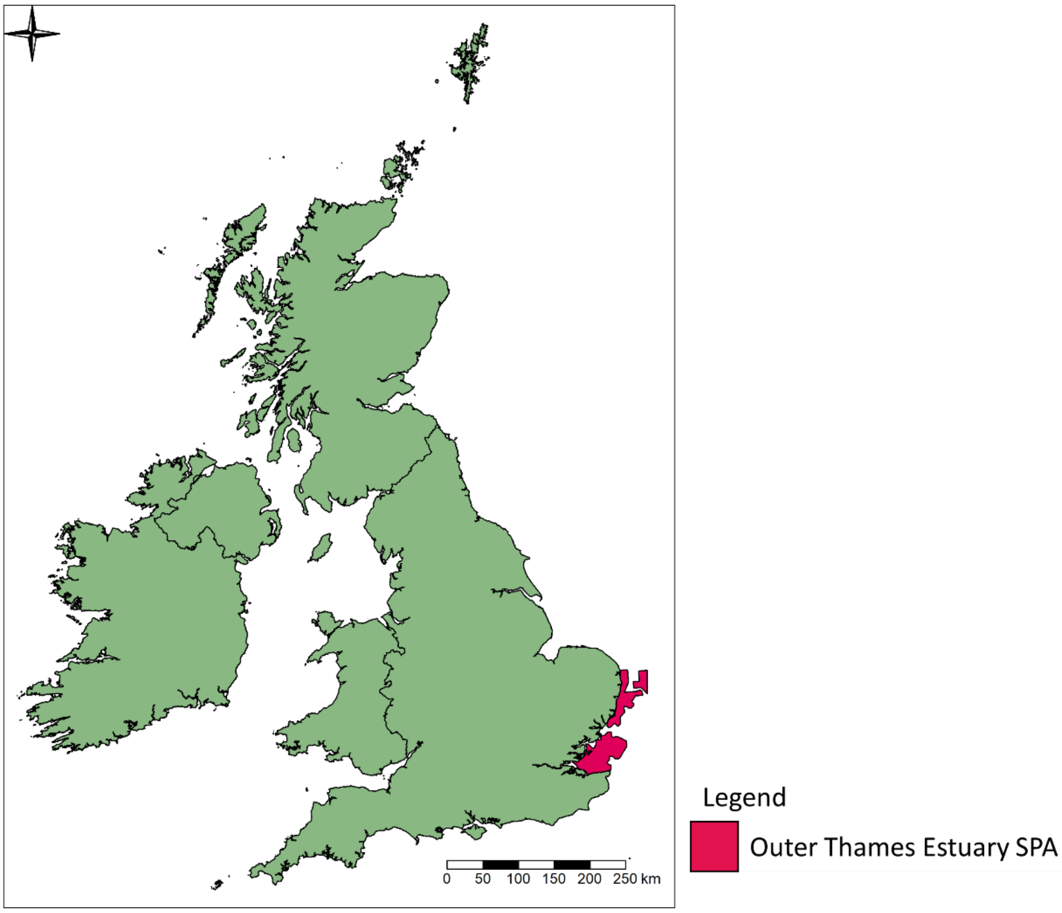

Figure 5.1. The location of the Outer Thames Estuary Special Protection Area (SPA) in relation to the UK.

The area of the Outer Thames Estuary SPA is 3,924km^2, making it the second largest SPA with a marine component by area in the UK. The cited population of red-throated divers in the SPA is 6,466 individuals, meaning the site hosts the largest aggregation of wintering red-throated divers in the UK. This value was based on visual aerial surveys undertaken between 1989 and 2007 (JNCC, 2020e), but digital aerial survey data from 2012 to 2013 suggests that the peak population of red-throated divers within the SPA is 14,161 individuals (APEM, 2013). The most recent surveys from 2018 suggest 21,997 individuals (Irwin *et al.*, 2019); therefore, Natural England uses a mean population of 18,079 individuals as the current estimate of the wintering population (Natural England, 2013).

There are multiple operational wind farms within and in close proximity to the Outer Thames Estuary SPA. In addition, there are several wind farms that have development consent allowing them to be built in the future and proposed wind farms which have not yet submitted a development consent application but have seabed leases giving them right to a particular area of seabed for wind farm development (Figure 5.2).

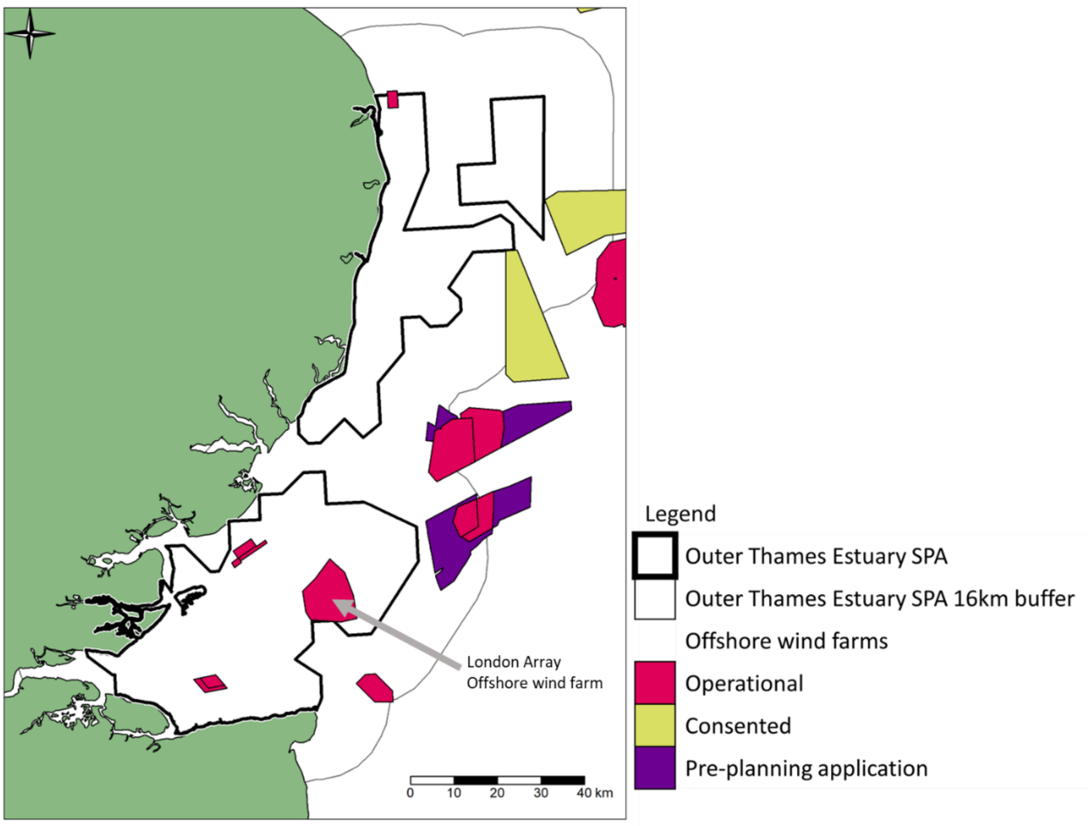

Figure 5.2. The location of the Outer Thames Estuary Special Protection Area (SPA) and nearby offshore wind farms at various stages of development (as of July 2023).

The footprint of the London Array offshore wind farm (as seen in Figure 5.2) was used to represent a typical wind farm footprint. It should be noted that this chapter makes no assessment of the impacts of any individual wind farm on red-throated divers, and the London Array footprint was simply used to conveniently represent a realistic scenario for the purposes of this analysis. The maximum extent of red-throated diver displacement from a wind farm in the literature was 16km (Mendel *et al.*, 2019). Therefore, this analysis considered the detectability of displacement within an example wind farm plus 16km outside the wind farm.

As red-throated divers are one of the most sensitive species to anthropogenic disturbance, the largest aggregation of red-throated divers is present during the wintering period, and there are multiple pressures here; this region of UK waters is prime for investigating the cumulative displacement from offshore wind developments, current and future.

5.2.2 Datasets used in analysing how much monitoring is sufficient to detect red-throated diver displacement

Several publicly available datasets were used in this study and are described in Table 5.1:

- The Crown Estate's Offshore Wind Site Agreements (England, Wales & NI) shapefile dataset, providing spatial offshore wind farm lease agreement information
- Natural England's Outer Thames Estuary Special Protection Area (SPA) survey data

Table 5.1. Datasets used to analyse how much monitoring is sufficient to detect red-throated diver displacement.

Dataset	**Crown Estate's Offshore Wind Site Agreements (England, Wales & NI) shapefile**	**Natural England's Outer Thames Estuary Special Protection Area (SPA) survey data shapefiles**
Overview	Spatial offshore wind farm lease agreement information	Spatial information on seabirds within the Outer Thames Estuary SPA
Spatial scale	England, Wales & Northern Ireland	The Outer Thames Estuary SPA
Temporal scale	Data as of July 2023. Covers all former, current, and proposed wind farms since 2000	Surveys carried out in February 2018
Detailed information	Contains boundaries of lease agreements for offshore wind farms. This is not necessarily the boundary of built wind farms but rather the boundary of the area that can be built upon.	Digital aerial surveys were flown with transects spaced 3.3km apart across the Outer Thames Estuary SPA. Raw observations of seabirds were recorded and formatted as shapefiles.

The footprint of the London Array offshore wind farm was obtained from The Crown Estate's Offshore Wind Site Agreements shapefile. Information on red-throated diver distribution in and around the wind farm was obtained from Natural England's survey of the Outer Thames Estuary SPA. The SPA was surveyed in February 2018 by digital aerial surveys, with transects flown 3.3km apart (Irwin *et al.*, 2019). Raw data of bird sightings from this survey was provided by Natural England for use within this chapter. Only data on red-throated divers were used, and only those sitting on the water were included in the data analysis. Individuals flying were removed from data analysis as although they were passing through, it was unknown as to whether they were using the area for resting or foraging on the sea surface and hence susceptible to displacement. Individuals taking off were also excluded due to the uncertainty surrounding their use of the area prior to the surveyor observing the bird.

5.2.3 Modelling undertaken to analyse how much monitoring is sufficient to detect red-throated diver displacement

The MRSea package (Scott-Hayward *et al.*, 2017) was used in R to convert raw observations into a density distribution map. This package was specifically designed by the creators to analyse changes in the abundance and distribution of species before and after offshore renewables construction. The package takes digital aerial survey data and any user-defined covariates along with a Spatially Adaptive Local Smoothing Algorithm (SALSA) to generate a density distribution map. The operational offshore wind farms within and in close proximity to the study region may have had an influence on the distribution of red-throated divers at the time of the survey. However, the aim was to obtain a representative distribution of red-throated divers; therefore, the location of the wind farms was not considered a covariate in the model. Similarly, shipping was not included as a covariate for the same reason. Bathymetry was included as a covariate, as it has consistently been found as a predictive covariate in describing red-throated diver distributions (Maclean *et al.*, 2006; APEM, 2016). A density surface map was created on a 250m^2 grid. This map was used as the baseline distribution to represent red-throated divers in the area.

5.2.4 Creation of scenarios used to analyse how much monitoring is sufficient to detect red-throated diver displacement

A 16km buffer around the London Array wind farm footprint was generated, and the red-throated diver density distribution map was clipped to the wind farm, plus a 16km buffer. Hypothetical transects were laid over the density surface map to simulate survey transects. Transects with a width of 500m were generated and spaced apart by 0.5km, 1km, 1.5km, 2km, 2.5km, and 3km from the transect centre. The transects were oriented in the same direction as used in the original aerial survey, approximately perpendicular to water depth contours (Irwin *et al.*, 2019). The 0.5km-spaced transect covered 100% of the study area without any overlaps or gaps and, therefore, represented the baseline to assess all other transect spacings against. The other transect spacing scenarios, therefore, covered smaller proportions of the survey area, as outlined in Table 5.2. Results are presented in terms of changes to transect spacing; however, this term could easily be replaced with the number of transects, the area covered by transects, or the proportion of survey area covered by transects.

Table 5.2. Parameters of hypothetical transects laid over the Outer Thames Estuary Special Protection Area in the study of simulating levels of monitoring to detect red-throated diver displacement from offshore wind farms.

Transect spacing (km)	**Number of transects**	**Area covered by transects (km^2)**	**Proportion of survey area covered by transects**
0.5	87	1174	1.00
1.0	43	585	0.50
1.5	29	391	0.33
2.0	21	293	0.25
2.5	18	234	0.20
3.0	15	193	0.16

The density of red-throated divers within each transect spacing scenario was sampled from the baseline distribution map, and the mean density and standard deviation of red-throated divers across the entire study area were calculated for each transect spacing. Compared to the 0.5km transect spacing scenario, the mean density of red-throated divers detected was higher in each of the other transect spacing scenarios, ranging from 0.18% (1.5km transect spacing) to 2.2% (2.5km transect spacing) larger (Figure 5.3). The standard deviation of red-throated diver density also differed between transect spacings; however, it was both higher (up to 2.0%) and lower (up to 1.9%) than the 0.5km transect spacing scenario (Figure 5.4).

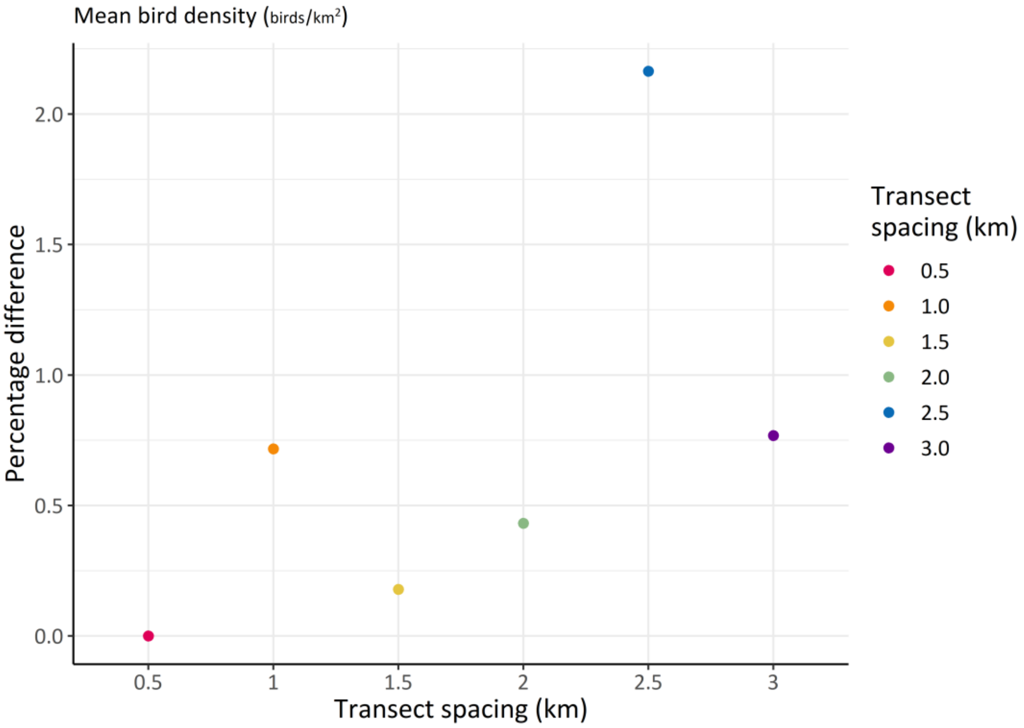

Figure 5.3. Percentage difference in mean red-throated diver density in each transect spacing scenario compared to the 0.5km transect spacing scenario in a study of simulating levels of monitoring to detect red-throated diver displacement from offshore wind farms.

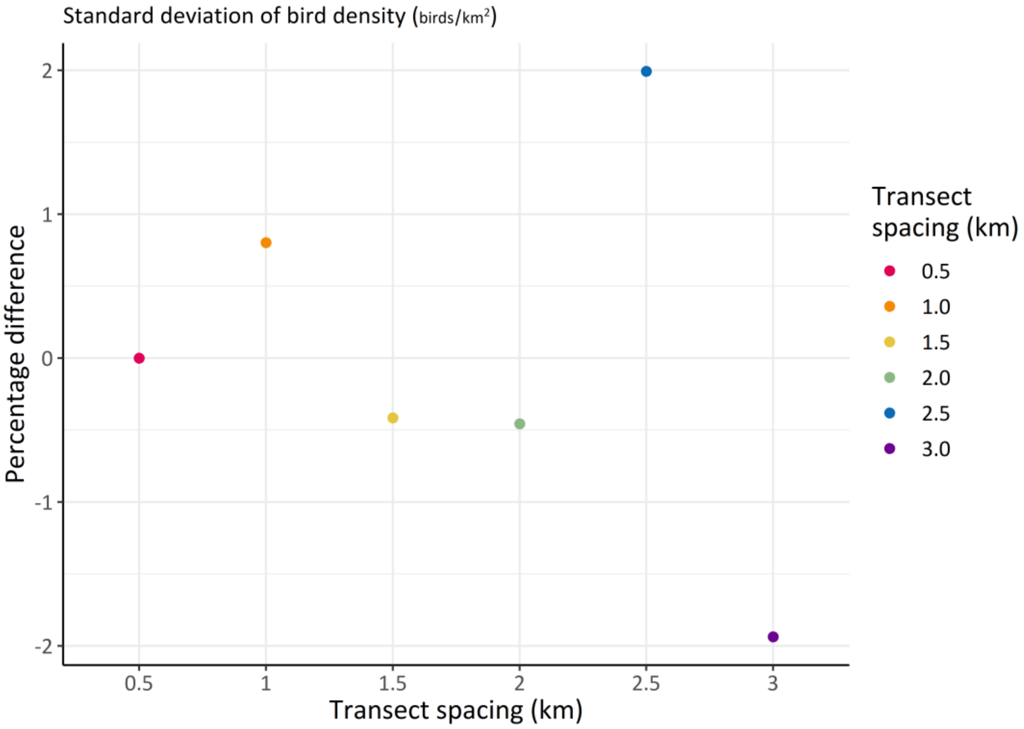

Figure 5.4. Percentage difference in the standard deviation of red-throated diver density in each transect spacing scenario compared to the 0.5km transect spacing scenario in a study of simulating levels of monitoring to detect red-throated diver displacement from offshore wind farms.

In this simulation, 100% of the red-throated divers within each transect were counted. In practice, digital surveys can have a reasonably high detectability of seabirds due to the ability to review collected footage post-survey in the case of video surveys (Žydelis *et al.*, 2019). There is also less disturbance and attraction of species than can occur with boat-based surveys (Fliessbach *et al.*, 2019). However, red-throated divers spend much of their daylight hours foraging, with hundreds of dives per day (Duckworth *et al.*, 2020). Therefore, the detectability of red-throated divers when they are diving is very low. This can be accounted for by applying an availability bias, which describes the ratio of time spent underwater to above water (Webb and Nehls, 2019). There is no standard availability bias value for red-throated divers; therefore, one could not be applied in this study. However, in all likelihood this has resulted in a lower density of red-throated divers being detected across the study site, therefore only the density of red-throated divers is affected. This study was designed to investigate changes in survey design using a representative distribution of red-throated divers, as opposed to investigating a specific circumstance therefore the results are not expected to have been impacted significantly.

5.2.5 Setup of the power analyses to explore how much monitoring is sufficient to detect red-throated diver displacement

Power analysis is a statistical tool used to determine the sample size required in order to detect an effect with a certain level of likelihood (McDonald, 2018). Power analyses were run on a set of input variables in order to analyse the effect of different survey designs on both the power to detect displacement and the number of survey days needed to achieve a minimum statistical power (Table 5.3).

Table 5.3. Variables within the power analysis used in a study of simulating levels of monitoring to detect red-throated diver displacement from offshore wind farms.

Input	**Variable**	**Variable value**
Number of pre-impact survey days	Number of pre-impact survey days	12, 24
Effect size	Pre-impact red-throated diver density (birds/km^2)	5, 10 (adjusted for the proportional difference compared to the 0.5km transect spacing scenario)
	Displacement rate (%)	5, 10, 15…95
	Pooled standard deviation (birds/km^2)	2, 4 (adjusted for the proportional difference compared to the 0.5km transect spacing scenario)
Significance level	Type I error probability	0.05
Power	1 minus Type II error probability	0.8

Note: Power analyses were run to either determine power or the number of survey days. In the case of determining power, the power variable was null. In the case of determining the number of survey days, the number of survey days variable was null.

The statistical power was determined using the "pwr.t.test" function in *R* (R Core Team, 2022) by inputting the number of surveys, the effect size (Cohen's d effect size as calculated using Equation 5.1, and the significance level, and outputting the power.

$$Effect\ size = \frac{\bar{x}_1 - \bar{x}_2}{s}$$

Equation 5.1. Effect size parameter within statistical power test.

where

$\bar{x}_1$ is the mean of population 1 (the pre-impact density of red-throated divers)

$\bar{x}_2$ is the mean of population 2 (the post-impact density of red-throated divers)

s is the pooled standard deviation (as calculated in Equation 5.2)

$$s = \sqrt{\frac{{s_1}^2 + {s_2}^2}{2}}$$

Equation 5.2. Pooled standard deviation parameter within statistical power test.

where

s_1 is the standard deviation of population 1 (the pre-impact density of red-throated divers)

s_2 is the standard deviation of population 2 (the post-impact density of red-throated divers)

Displacement was defined in this study as the movement of birds away from a wind farm or the surrounding area. The reduction in the density of red-throated divers was calculated and quantified as a displacement rate, meaning the difference in the density of red-throated divers pre-impact to post-impact as a percentage of the density of red-throated divers pre-impact. Therefore, the post-impact density of red-throated divers was calculated based on the displacement rate in question. For instance, if the pre-impact density of red-throated divers was 5 birds/km^2 and the displacement rate in question was 40%, the post-impact density of red-throated divers was 3 birds/km^2 (40% of pre-impact red-throated divers were displaced; therefore 60% of pre-impact red-throated divers remain). For simplicity, displacement was assumed to occur evenly across the study area. The same principle was applied to calculate the standard deviation post-impact: the displacement rate in question was applied to the pre-impact standard deviation. The pre-impact and post-impact densities, as well as pre-impact and post-impact standard deviation, were then adjusted to account for transect spacing using the proportional difference in density and standard deviation compared to the 0.5km transect spacing scenario.

The first set of power analyses assumed the same number of survey days were taken pre- and post-impact. This was done using 12 and 24 survey days in the power analysis, meaning 12 pre-impact and 12 post-impact survey days (24 total) and 24 pre-impact and 24 post-impact survey days (48 total), respectively. However, in reality, it may not always be the case that there are the same number of survey days pre-impact and post-impact. Pre-impact surveys may be designed to describe the baseline environment and provide a base on which to predict potential impacts. The design of post-impact surveys may come later once a baseline has been established, impacts have been predicted, and the wind farm has been built (having previously been a range of potential designs under the project design envelope, as described in Section 2.9 (Caine, 2018)). Therefore, a second set of power analyses was carried out, which allowed for different numbers of survey days to be assessed. This used a similar function in *R*, which allows for different numbers of survey days pre-impact and post-impact, the “pwr.t2n.test”. The pre-impact number of survey days was pre-determined, and a range of post-impact numbers of survey days was assessed to determine the power of the survey. The pre-impact number of survey days was again set as 12 and 24 in the two scenarios.

The same survey area was sampled pre-impact and post-impact; therefore, it was likely that the pre-impact and post-impact samples were dependent as red-throated divers are known to return to the same area year on year, be it breeding sites or wintering grounds (Black *et al.*, 2015; Duckworth *et al.*, 2022). It follows that paired power *t*-tests were carried out in the power analysis when the number of pre-impact and post-impact survey days were the same. However, the nature of having a different number of surveys pre-impact and post-impact meant that paired *t*-tests could not be used when assessing the effect of differing number of survey days pre-impact and post-impact. Consequently, for these scenarios, unpaired *t*-tests were used.

Finally, variables for the Outer Thames Estuary Special Protection Area (SPA) case study were applied to power analyses in order to get site-specific results using mean red-throated diver density and standard deviation from this SPA. The same displacement rates were applied as previously (5%, 10%, 15%…95%). This was initially done using the same number of survey days pre-impact and post-impact, then a different number of survey days pre- and post-impact was also allowed. The number of survey days required to detect various displacement rates was calculated and compared to a baseline of 24 survey days, which accounted for one survey per month for two years. The power analysis was carried out using 4.5 birds/km^2, the average density of red-throated divers from the population estimate of the SPA (Irwin *et al.*, 2019). It should be noted that although a range in the number of survey days was examined and often compared to a baseline of one survey per month for two years, this study considered non-breeding red-throated divers, which are typically only present in the Outer Thames Estuary SPA between October and May. Therefore, in reality, perhaps only eight surveys per year would actually detect the species, so the amount of time a species is present needs to be accounted for when designing surveys. The analysis was carried out in R (R Core Team, 2022). The R markdown code is available in Appendix F.

5.3 Results of analysing how much monitoring is sufficient to detect red-throated diver displacement

This section first discusses the results of using the same number of survey days pre-impact and post-impact on being able to detect red-throated diver displacement from offshore wind farms. The influence of using a different number of pre-impact and post-impact survey days is then described. The case study of red-throated divers in the Outer Thames

Estuary SPA is then discussed, first using the same, then a different number of survey days pre-impact and post-impact. Finally, a comparison is made between varying the displacement rate and the number of survey days in terms of the detectability of red-throated diver displacement.

5.3.1 Using the same number of survey days pre- and post-impact to detect red-throated diver displacement

The impact of transect spacing on the power to detect displacement rates was investigated for a given number of survey days and red-throated diver density, and how this changed with changing the density of red-throated divers, number of survey days, and standard deviation. For example, if 5 birds/km^2 are present pre-impact with a standard deviation of 2 birds/km^2, with 12 pre-impact survey days, and the same number post-impact, the surveys are powerful enough to detect ≥35% displacement using all transect spacings (Figure 5.5). If the number of survey days is increased to 24 pre-impact and 24 post-impact, and 5 birds/km^2 are still present pre-impact, the surveys are powerful enough to detect ≥25% displacement with all transect spacings (Figure 5.5). Note that this doubling of number of survey days is assumed to occur over the same time period.

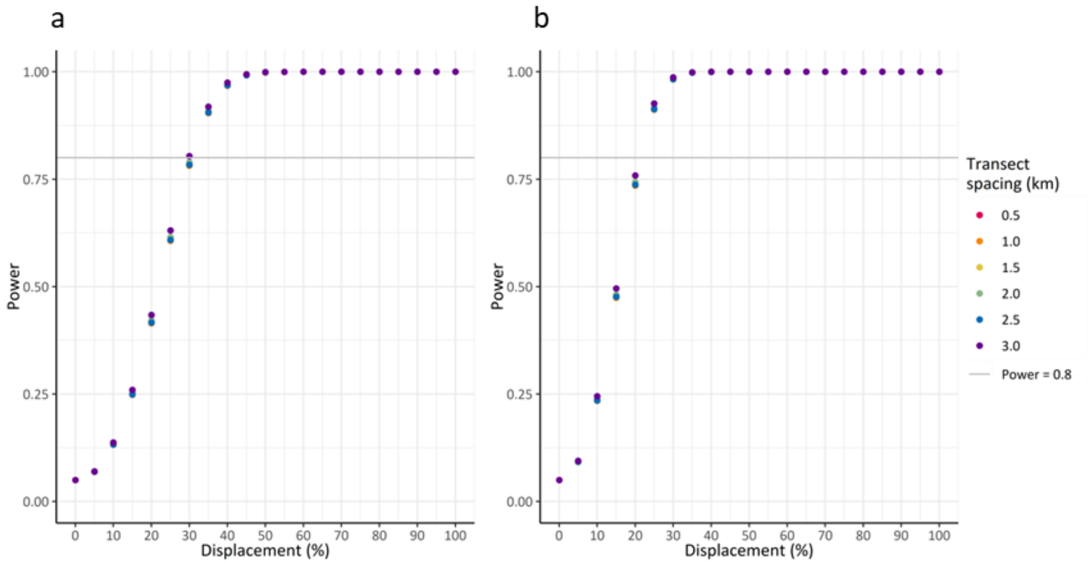

Figure 5.5. The trend in the statistical power of a survey with the density of red-throated divers and the number of pre-impact survey days with comparison across transect spacings. The mean red-throated diver density was set at 5 birds/km^2 with a standard deviation of 2 birds/km^2.

Note:

- Figure 5.5.a shows 12 survey days, and Figure 5.5.b shows 24 survey days.

- Figures show that more surveys result in higher statistical power and allow a lower displacement rate to be detected.

If there is a higher density of pre-impact red-throated divers at 10 birds/km^2, again with 12 survey days pre-impact and the same number post-impact, the survey is powerful enough to detect ≥20% displacement with all transect spacings (Figure 5.6). If both the number of survey days and density of red-throated divers are larger at 24 pre- and 24 post-impact survey days and 10 birds/km^2, the surveys are powerful enough to detect ≥15% displacement with most transect spacings (Figure 5.6).

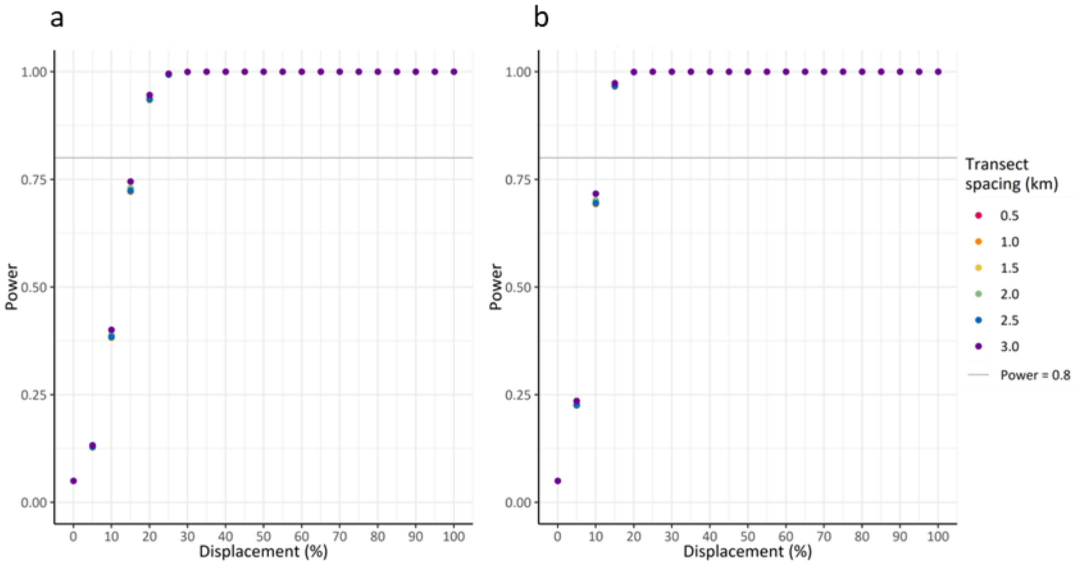

Figure 5.6. The trend in the statistical power of a survey with the density of red-throated divers and the number of pre-impact survey days with comparison across transect spacings. The mean red-throated diver density was set at 10 birds/km^2 with a standard deviation of 2 birds/km^2.

Notes:

- Figure 5.6.a shows 12 survey days, and Figure 5.6.b shows 24 survey days.
- Figures show that more survey days resulted in higher statistical power and allowed a lower displacement rate to be detected.

The standard deviation of red-throated diver density was also taken into account in the power analysis. A lower standard deviation results in lower displacement rate detectability. For instance, setting the density at 5 birds/km^2 and the number of survey days at 24, a standard deviation of 2 birds/km^2 allows 25% displacement to be detected by transects of all spacings. A standard deviation of 4 birds/km^2 allows 40% displacement to be detected by transects of all spacings (Figure 5.7).

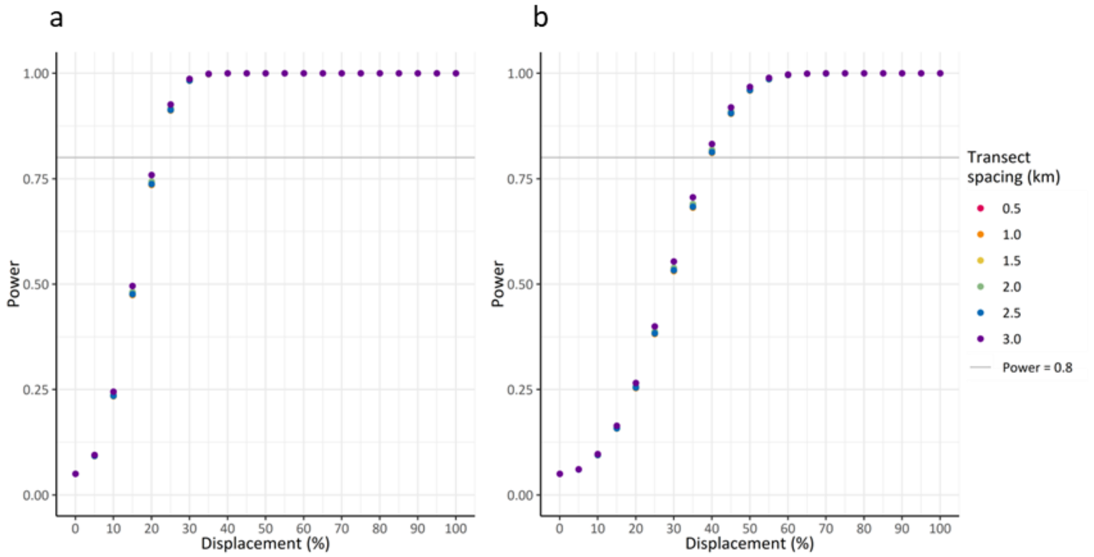

Figure 5.7. The trend in statistical power of a survey with the standard deviation of the density of red-throated divers with comparison across transect spacings. The mean red-throated diver density was set at 5 birds/km^2, and the number of survey days was 24.

Note:

- Figure 5.7.a shows a standard deviation of 2 birds/km^2, and Figure 5.7.b shows a standard deviation of 4 birds/km^2.
- Figures show that less variation in red-throated diver density results in higher statistical power and allowed a lower displacement rate to be detected.

The differences in mean red-throated diver density and standard deviation across transect spacing scenarios influence the statistical power. The 3km transect spacing results in a reasonably high mean density relative to the 0.5km scenario (0.77% higher) and a much lower standard deviation relative to the 0.5km scenario (1.94% lower). This combination of high density and low standard deviation is conducive to a higher power. The 1km transect spacing results in a similarly high mean density relative to the 0.5km scenario (0.72% higher); however, there is a much higher standard deviation relative to the 0.5km scenario (0.80% higher). This combination of high density and high standard deviation is conducive to a lower power. This can be seen by looking at individual displacement rate results, such as for the 5 birds/km^2 pre-impact and 12 pre-impact survey days scenario. Here, the 3km transect spacing results in the highest power and the 1km transect spacing results in the lowest power of all the transect spacing scenarios (Figure 5.8).

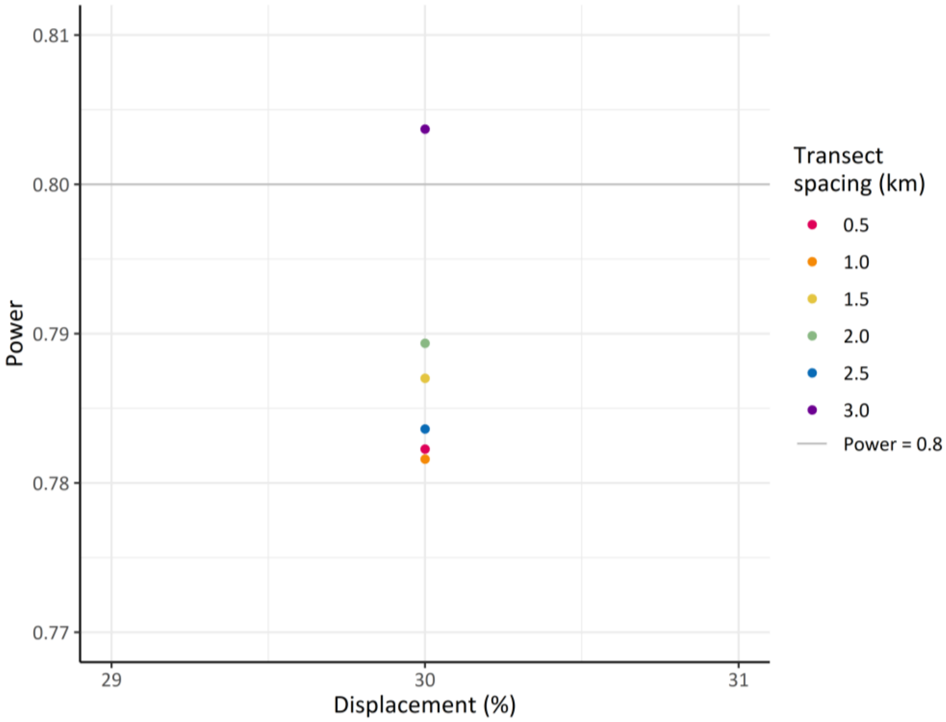

Figure 5.8. The influence of transect spacing on power showing the 3km transect spacing resulting in the highest power and the 1km transect spacing resulting in the lowest power (in this case, with 12 survey days and 30% displacement).

This same trend is seen throughout the remaining analysis. This phenomenon could be due to the exact placement of the transects, and placing them in slightly different, but still parallel to the original, locations could result in different means and standard deviations in red-throated diver density.

This section discussed the results of assuming the same number of surveys are undertaken before and after wind farm construction. The next section will go on to explore how these results change when a different number of surveys are undertaken before and after wind farm construction.

5.3.2 Using a different number of survey days pre- and post-impact to detect red-throated diver displacement

Results in this section are analysed where the number of survey days pre- and post-impact are different. The post-impact number of survey days required to detect displacement by different transect spacings is investigated, and again, the influence of the number of pre-impact survey days and the density of red-throated divers is examined. The mean red-throated diver density was set at 10 birds/km^2 with a standard deviation of 2 birds/km^2.

For a given displacement rate and a set number of pre-impact survey days, different transect spacings require a different number of post-impact survey days. For instance, to detect 15% displacement with 12 pre-impact survey days, an impractical number of post-impact survey days is required: between 256 and 7,325 post-impact survey days, depending on transect spacing (Table 5.4). Naturally, larger displacement rates result in more practical numbers of post-impact survey days. However, sometimes, only small modifications to the displacement rate are needed. For instance, to detect 20% displacement, a more manageable 15 to 17 survey days is required (depending on transect spacing), and only seven survey days (for all transect spacings) are required to detect 25% displacement.

Table 5.4. Influence of displacement rate and number of pre-set pre-impact survey days on number of post-impact survey days with comparison across transect spacings. Mean red-throated diver density = 10 birds/km^2 and standard deviation = 2 birds/km^2.

Scenario		**Number of post-impact survey days required**				
Displacement rate (%)	**Number of pre-impact survey days**	**1km transect**	**1.5km transect**	**2km transect**	**2.5km transect**	**3km transect**
15	24	26	26	25	26	24
20	24	10	9	9	10	9
25	24	5	5	5	5	5
30	24	3	3	3	3	3
15	12	N/A*	1327	846	7325	256
20	12	17	16	16	16	15
25	12	7	7	7	7	7
30	12	4	4	4	4	4
15	6	N/A*	N/A*	N/A*	N/A*	N/A*
20	6	N/A*	N/A*	N/A*	N/A*	N/A*
25	6	16	15	15	16	14
30	6	7	7	7	7	6

Notes:

- (*) a calculation was not possible using pwr.t2n.test (maybe because the value was larger than the bounds of the searchable number of survey days).
- Table shows that both a lower number of pre-impact survey days and lower levels of displacement forced an increase in the number of post-impact survey days.

At a lower number of pre-impact survey days, the same displacement rates require a larger number of post-impact survey days, often too high to be able to calculate (Table 5.4). However, by halving the number of pre-impact survey days to six, 25% displacement can be detected using between 14 and 16 post-impact survey days (depending on transect spacing). This is compared to a similar number of post-impact survey days being able to detect 20% displacement with 12 pre-impact survey days (Table 5.4). Therefore, to detect a very similar displacement rate and use a similar number of post-impact survey days, the number of pre-survey days could be substantially reduced.

Of course, the opposite is also true, whereby the more pre-impact surveys are carried out, the fewer post-impact surveys are required. If 24 pre-impact survey days are used, nine or ten post-impact survey days would be required to detect 20% displacement, or 24 to 26 survey days to detect 15% displacement. However, caution is advised in reducing the number of surveys too far, either pre-impact or post-impact, as this may result in obtaining insufficient information to characterise monthly, seasonal, and annual variations in abundance and distribution.

These last two sections have discussed the results of assuming either the same number or a different number of surveys undertaken before and after wind farm construction. The following two sections will repeat this process but within the context of a case study of the Outer Thames Estuary SPA population of red-throated divers. This is first done assuming the same number of surveys are undertaken before and after wind farm construction.

5.3.3 Results of the case study of the Outer Thames Estuary Special Protection Area using the same number of survey days pre- and post-impact to detect red-throated diver displacement

The power analysis was then applied to the case study site of the Outer Thames Estuary Special Protection Area, first assuming the same number of survey days pre- and post-impact. To detect displacement in the study site example, the density of red-throated divers within the SPA was used: a population of 18,079 individuals making an average density of 4.6 birds/km^2 and maintaining a standard deviation of 2 birds/km^2.

A displacement rate of 35% is detectable with a similar number of surveys as a typical survey regime (12 surveys pre-impact and the same number post-impact). However, any smaller displacement rates require more survey days, with an almost exponential growth in the number of surveys once very low displacement rates are considered, e.g. over 500 pre-impact and over 500 post-impact surveys to detect 5% displacement (Table 5.5).

Table 5.5. Influence of displacement rate and number of variable pre-impact survey days on number of post-impact survey days with comparison across transect spacings. Mean red-throated diver density = 4.6 birds/km^2 and standard deviation = 2 birds/km^2.

Scenario	**Number of survey days required**				
Displacement rate (%)	**1km transect**	**1.5km transect**	**2km transect**	**2.5km transect**	**3km transect**
5	567	560	556	565	537
10	136	135	134	136	129
15	59	58	58	59	56
20	32	32	32	32	31
25	21	20	20	20	20
30	14	14	14	14	14
35	11	11	10	11	10
40	8	8	8	8	8
45	7	7	7	7	7
50	6	6	6	6	6

Note: Table shows that both a lower number of pre-impact survey days and lower levels of displacement forced an increase in the number of post-impact survey days.

A pragmatic view is therefore needed with regard to the number of surveys it would be feasible to carry out and the displacement rate the surveys would be aiming to detect. Note should also be given to how a small change in the number of survey days can achieve quite a different displacement rate at higher displacement rates. For example, there are only two days of difference (both pre-impact and post-impact) in the number of survey days to detect a 40% displacement rate and a 50% displacement rate.

The case study of the Outer Thames Estuary SPA is now used to contextualise the results of assuming a different number of surveys are undertaken before and after wind farm construction.

5.3.4 Results of the case study of the Outer Thames Estuary Special Protection Area using a different number of survey days pre- and post-impact to detect red-throated diver displacement

The power analysis was applied to the case study site of the Outer Thames Estuary Special Protection Area, assuming a different number of survey days pre- and post-impact. The mean red-throated diver density was set at 4.6 birds/km^2 with a standard deviation of 2 birds/km^2.

A low number of pre-impact survey days prompts the need for a large number of post-impact survey days, often too high to be able to calculate (Table 5.6) unless a sufficiently large displacement rate is considered. As this is a site-specific case, it gives an indication as to the number of survey days which would be required to detect various levels of displacement and highlights the need to consider both pre-impact and post-impact surveys early when designing monitoring. For instance, if six pre-impact surveys are undertaken and the aim is to detect 45% displacement, between 25 and 32 post-impact survey days (depending on transect spacing) are required. However, if 12 pre-impact surveys are undertaken to detect the same 45% displacement, only nine or ten post-impact survey days would be required (Table 5.6).

Table 5.6. Influence of displacement rate and number of pre-set pre-impact survey days on number of post-impact survey days with comparison across transect spacings. Mean red-throated diver density = 4.6 birds/km^2 and standard deviation = 2 birds/km^2.

Scenario		**Number of post-impact survey days required**				
Displacement rate (%)	**Number of pre-impact survey days**	**1km transect**	**1.5km transect**	**2km transect**	**2.5km transect**	**3km transect**
30	12	N/A*	N/A*	N/A*	N/A*	439
35	12	36	34	34	35	30
40	12	16	15	15	16	14
45	12	10	9	9	9	9
50	12	7	6	6	6	6
30	6	N/A*	N/A*	N/A*	N/A*	N/A*
35	6	N/A*	N/A*	N/A*	N/A*	N/A*
40	6	N/A*	N/A*	N/A*	N/A*	1671
45	6	32	30	29	31	25
50	6	16	13	13	16	12

Notes:

- (*) a calculation was not possible using pwr.t2n.test (maybe because the value was larger than the bounds of the searchable number of survey days).
- Table shows that both a lower number of pre-impact survey days and lower levels of displacement forced an increase in the number of post-impact survey days.

In comparing whether or not the same number of pre-impact and post-impact surveys should be sought, consideration should be given to the displacement rate required to be detected. For instance, if 12 pre-impact survey days are chosen and fixed, and 30% displacement is to be detected, at least 439 post-impact survey days would be required (under the 3km transect spacing scenario), amounting to 451 survey days in total (Figure 5.9). However, if 30% displacement detection is the aim and the number of pre-impact and post-impact surveys are calculated at the beginning of the survey design, only 24 pre-impact samples and 24 post-impact samples would be required (under the 3km transect spacing scenario), amounting to only 48 survey days altogether.

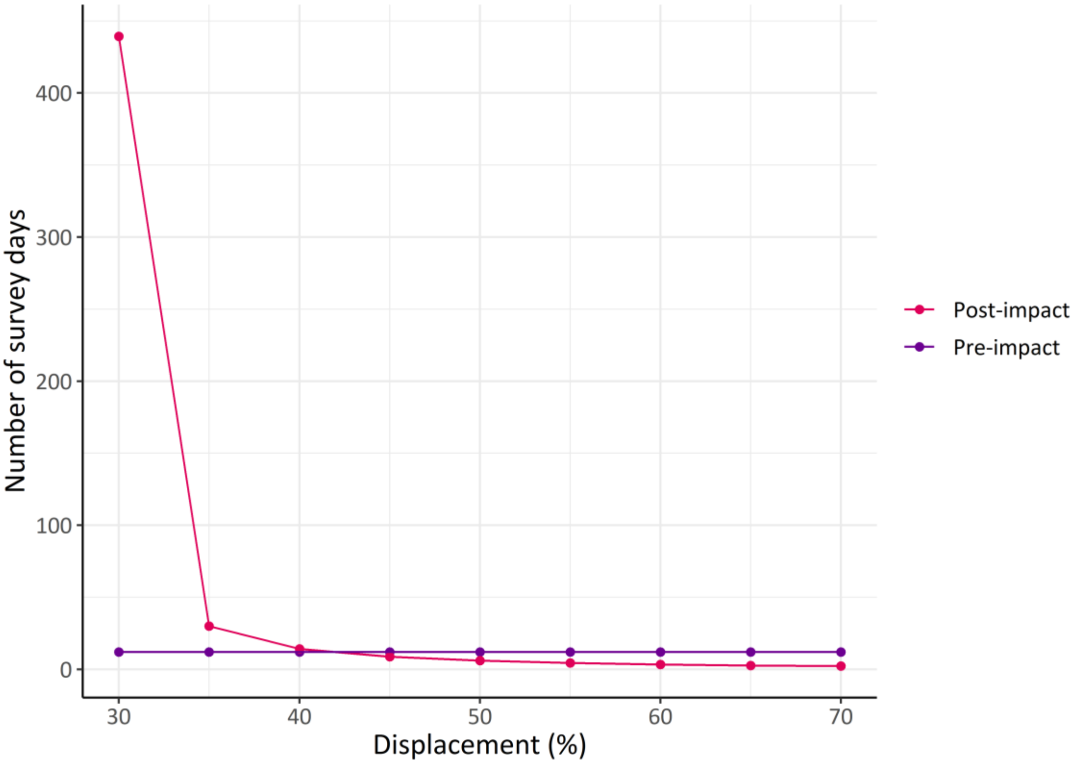

Figure 5.9. Comparison of the number of post-impact survey days required with a fixed number of pre-impact survey days (12) when different displacement rates are required to be detected shows that detecting very small displacement rates would require very large numbers of post-impact survey days.

A sensible option would be to run through a range of pre-impact and post-impact surveys in order to determine the least total number of survey days (pre-impact plus post-impact) that would be required. A thought may also be given to the limitations of undertaking surveys pre-impact when time is limited before wind farm construction begins, but time is less constrained after the wind farm becomes operational. Therefore, it may be inevitable that there will be an unequal number of survey days pre-impact and post-impact. Yet, thought still needs to be given to the number of pre-impact surveys, particularly when aiming to detect low displacement rates. As seen in Table 5.6, too few pre-impact surveys can still lead to a disproportionately large number of post-impact surveys.

5.3.5 Comparison of varying the displacement rate versus varying the number of survey days on the detection of red-throated diver displacement

It is clear that a number of variables influence the power of survey design; therefore, their modification can increase or decrease power. However, some of these variables are unalterable within the survey design, such as the number and variability in the density of red-throated divers present in the study area. Nevertheless, the number of survey days may be adapted, and the detectable displacement rate may be an adjustable aim of the survey design. As has been investigated in previous sections, the number of survey days and displacement rate can have a large impact on the statistical power. The obvious next question is, therefore, which makes the most difference to statistical power, and how should this be taken into account when designing a survey?

To investigate this, the mean red-throated diver density was set at 4.6 birds/km^2 with a standard deviation of 2 birds/km^2 as per the case study. To detect 15% displacement with 12 survey days results in a survey power of 0.22. Doubling the number of survey days to 24 (and keeping the 15% displacement rate) results in a survey power of 0.44. Conversely, doubling the displacement rate to 30% (and keeping the 12 survey days) results in a power of 0.71 (Table 5.7). This suggests that the power changes more quickly with displacement rate than the number of survey days. This trend generally holds at a range of displacement rates and number of survey days, but there is a larger increase in power when increasing the number of survey days when the displacement rate is high.

Obviously, increasing the number of survey days in conjunction with increasing the displacement rate results in the best improvement in power, but this is a small improvement over increasing the displacement rate alone (Table 5.7). However, as noted above, some variables which go into the power analysis are adjustable through survey design. The displacement rate will be determined by the effect of an offshore wind farm; therefore, having an indication of the displacement rate that might be expected or the displacement rate that would ideally be detectable will guide the survey design.

Table 5.7. Changes in survey power with displacement rate and the number of survey days show the interplay between the number of survey days at different displacement rates on statistical power, in this case, using 1km transect spacing.

Statistical power		**Number of survey days**						
		12	**14**	**16**	**18**	**20**	**22**	**24**
Displacement rate (%)	**15**	0.22	0.25	0.29	0.32	0.35	0.38	0.44
	20	0.36	0.42	0.48	0.53	0.58	0.62	0.66
	25	0.54	0.61	0.68	0.74	0.79	0.83	0.86
	30	0.71	0.79	0.85	0.89	0.92	0.95	0.96
	35	0.85	0.91	0.95	0.97	0.98	0.99	0.99
	40	0.94	0.97	0.99	0.99	0.99	0.99	0.99

Note: Mean red-throated diver density = 4.6 birds/km^2 and standard deviation = 2 birds/km^2.

Consideration should be given to whether the addition of a small number of surveys would be beneficial in the wider objective of the survey. For instance, multiple 12 surveys are typically carried out in order to understand the baseline environment of an offshore wind farm site, as this ensures a full year, including a month in each season, is surveyed. Therefore, increasing the number of survey days may, in fact, mean increasing by 12 such that a whole additional year is surveyed, and the data can be used in seasonal summary statistics. Increasing the number of survey days might provide an increase in statistical power when the detection of a specific displacement rate is required. However, a balance must be struck between the costs associated with adding in additional surveys and the power gained.

5.4 Discussion on how much monitoring is sufficient to detect red-throated diver displacement

Given the need for an improved understanding of the potential impacts of offshore wind development on marine wildlife, this study examined the power of post-consent (pre-impact and post-impact) monitoring. This will aid in the collection of data that will reduce uncertainty in estimating the scale of displacement of a sensitive marine bird species to future developments. The aim of such post-consent monitoring surveys can be varied, and objectives might include the detection of displacement at different scales, e.g. site-wide or within a specific region or buffer. Monitoring aims and objectives should dictate appropriate survey design (Gregory *et al.*, 2004), but in reality, factors such as resources, logistics, time and weather constraints, etc., can have a considerable influence on survey design.

Biological aspects of survey design also need to be accounted for. For instance, the detectability of distributed or clustered species and the potential for autocorrelation with transects close together (Maclean *et al.*, 2006; Petersen *et al.*, 2011). Species that tend to collect in flocks may be missed where wider transects are used, leading to an under-representation of the population or an over-estimate if they are seen in transects (Thaxter and Burton, 2009; Buckland *et al.*, 2012). Consideration must also be given to spatial autocorrelation such that close transects together do not erroneously double-count individuals (Lichstein *et al.*, 2002). A grid-based sampling design, as opposed to line transects, may be one method to overcome problems with biases associated with clustered species and autocorrelation (Buckland *et al.*, 2012).

The broad aim of post-consent wind farm monitoring is usually to validate predictions made in an EIA or Habitats Regulations Assessment (or Habitats Regulations Appraisal in Scotland) (HRA) (Marine Management Organisation, 2014). Objectives usually relate to detecting displacement, although they are not always clear nor precise in terms of displacement rates, distances or spatial patterns being tested.

Survey design needs depend on specific objectives: for example, if an objective is to detect a certain displacement rate, then the required combination of number of survey days and transect spacing, both pre-impact and post-impact, can be calculated in order to achieve a high power to detect that displacement rate. Alternatively, if an objective is to detect displacement for a certain density of pre-impact birds for a given number of survey days or a range of survey days, the detectable displacement rate can be calculated. This density of pre-impact birds could be an estimated average for the site or an estimate within a particular region of interest. It may also be an estimate of an acceptable maximum effect size in terms of the density of birds potentially affected. How such an acceptable threshold is determined may vary according to the relevant legislation but could be based on societal values or on population viability analyses, for example (Green *et al.*, 2016).

Designing the study in order to detect displacement if it were occurring in the region with the lowest density of birds (the hardest to detect displacement where it occurs) would ensure that displacement in all other regions would be detectable. However, for a cost-effective survey, this should be based on the level of change that needs to be detected. It should also consider whether the change needs to be detected across the whole site or only where higher bird densities are present. The level of change to be detected could be that which would cause a change in the population trend. For instance, the level of mortality of birds would cause a change in the population status from increasing to flatlining or causing a certain percentage increase in the baseline mortality rate.

The variation in abundance is also a key consideration in determining survey design. A wide spread of data may lead to insignificant results even when the density of birds, displacement rate, and number of surveys are large. The variability of birds per month, per season, or per year may be very different, so consideration also needs to be given to the temporal scale of the pre- and post-impact phases of a displacement study and the variability that may be present in these phases.

Consideration of post-impact survey needs as part of pre-impact survey design would maximise the overall efficiency of pre- and post-impact surveys, especially where there is some knowledge of bird densities expected in the study region. This may be the case for protected areas or for species that have been extensively surveyed or modelled (Wakefield *et al.*, 2017; Waggitt *et al.*, 2019). However, in order to make the most of surveys, a clear aim and objective are required. This may, in part, be dictated by licence conditions, but regulators and statutory nature conservation bodies can play a part in deciding what the aims and objectives should be.

A strategic and objectives-driven approach to monitoring and survey design could lead to improvements in the ability of post-consent monitoring to inform the overall understanding of displacement effects of offshore wind farms on red-throated divers and other sensitive species of marine birds. This, in turn, can give a more accurate evidence base for other tools and assessment techniques, such as relative seabird sensitivity assessments (Furness *et al.*, 2013; Bradbury *et al.*, 2014) and estimates of energetic costs caused by displacement leading to changes in adult survival and productivity (Searle *et al.*, 2021). This could ultimately reduce uncertainty in the impact assessment process and facilitate marine renewable energy goals and climate emission reduction targets.

Post-consent monitoring reports from offshore wind farms are intended to detect impacts and confirm whether those predicted in the EIA actually occur and at the levels expected. However, they need to be designed to meet this aim sufficiently. The design and spatial coverage of surveys can have a large effect on whether or not displacement can be detected, especially where displacement occurs over a large area outside of the wind farm, but surveying does not cover the same area. The limited spatial coverage of several early offshore wind farms is thought to have contributed to the survey design having a lower power to detect changes in species distributions (Marine Management Organisation, 2014).

The considerations listed here are, of course, based on the intention to obtain the best evidence. However, the cost implications of survey design must also be examined in order to make cost-effective decisions. A balance must, therefore, be sought between expenditure and the quality of data obtained.

In broad terms, the spacing of transects influenced the statistical power or number of surveys required based on a combination of the mean density of red-throated divers the transects could detect and the standard deviation. If the same spacing transects had been positioned across the survey area slightly differently, it could be that the densities and standard deviations for each transect spacing were different. The non-uniform distribution of red-throated divers has likely led to some transect spacings detecting hotspots of high-density red-throated divers and other transect spacings detecting lower densities of red-throated divers, hence the differences in mean density and standard deviation. Compared to the number of survey days and displacement rate, the transect spacing in this study only made a small difference to the power of survey design.

Naturally, the number of survey days affected the power to detect displacement, but in a different manner to how transect spacing did. Whilst the transect spacing related to the precision of data collected within individual surveys, a larger source of variability was likely due to variability between surveys. Careful planning of the number of survey days is required, particularly with regard to the displacement rate to be detected and the relative number of samples pre-impact and post-impact.

The variable making the largest difference to the power was the displacement rate. This variable is a factor to be detected by the surveys and, therefore, is not necessarily adjustable; however, surveys can be designed with the aim of being able to detect a minimum displacement rate thus can be a very useful aspect of designing a survey. Where red-throated divers are considered, studies have typically shown a very high displacement rate, often above 70%; therefore, this chapter has shown that most scenarios of survey design would be able to detect such a change in red-throated diver density (Dierschke *et al.*, 2016; Mendel *et al.*, 2019; Heinänen *et al.*, 2020; Marques *et al.*, 2021). However, for other species less susceptible to displacement from offshore wind farms, different survey designs may be required to detect smaller displacement effects.

A higher density of red-throated divers in the study region with a low standard deviation (outside of how this is affected by transect spacing) also increases the statistical power. The impact of variation in red-throated diver density was only briefly assessed here, as it was not the focus of the study; however, this is likely to also have a large impact on the detectability of changes in the density of red-throated divers (Maclean *et al.*, 2013), and can for some species and regions be roughly anticipated based on available information.

Monitoring the impact of offshore wind farm displacement has been investigated in this chapter. However, the principles of designing surveys and carrying out power analyses are widely applicable to other industries and other impacts. Seabird collisions with wind turbines are monitored less frequently than distributional changes, in part because of the technical difficulties in doing so (Collier *et al.*, 2011). Regardless, monitoring carried out in a standardised manner, or at least with comparable methods or presentation of results, makes for better utilisation of data (see Ozsanlav-Harris *et al.* (2023) for an example of comparability and utilisation of empirical seabird collision data).

The data collected from pre-construction and post-construction surveys is critical to understanding the true impact of offshore wind farm development. The quality of such data may make the difference between proving the predicted level of impact and not knowing the level of impact. This is also true with regard to mitigation; the ability to demonstrate that mitigation has succeeded or not is determined by the quality of the data collected. Data quality also plays a role in enhancing scientific knowledge.

5.5 Conclusion of how much monitoring is sufficient to detect red-throated diver displacement

This chapter has demonstrated how aspects of survey design interact with baseline red-throated diver densities and levels of impact to influence the statistical power to detect changes in red-throated diver densities as a result of anthropogenic impacts. It also shows the importance of considering such factors early in order to obtain sufficiently powerful surveys prior to carrying them out. This is particularly pertinent at the pre-construction phase of development, but also during Environmental Impact Assessments such that impacts can be verified post-construction. The highly dependent nature of survey attributes on the detectability of change within one species shows how case-specific this issue is. The research has been illustrated using a specific species, yet the method is replicable for others, as well as different locations and causes of change. This work has shown how power analysis can be used to tailor surveys such that the goal of the survey can be achieved, and contingencies accounted for.

The adequacy of data collection has been explored in this chapter by examining the power of detecting red-throated diver displacement through the design of pre-construction and post-construction surveys. The presentation and analysis of data are other aspects that influence the quality and usefulness of data. The next chapter, therefore, explores the results of monitoring surveys and methods of calculating red-throated diver displacement.

Chapter 6 How does red-throated diver displacement change with distance from offshore wind farms?

Abstract

Offshore wind developments are becoming more prevalent across the globe, and our understanding of interactions with a multitude of environmental receptors grows with it. Certain species, such as red-throated diver, are known to have strong behavioural responses to operational wind farms. Evidence suggests that the response is strong within the wind farm, but also occurs outside the wind farm, but to a lesser degree. This research collated and evaluated existing evidence of red-throated diver displacement rates within and outside of offshore wind farms. It then suggests and reviews methods of generating a representative gradient of displacement rates for application in displacement assessments. This study found that displacement rates do decline with distance from wind farms, at some wind farm in a linear manner, and less so at other sites. It also indicates that lower rates of displacement within wind farms may be associated with displacement affects over a large region outside the wind farm. A range of methods to generate a representative gradient have been analysed, each with their own benefits, drawbacks, and potential for different applications. The analysis within this chapter may aid offshore wind farm impact assessments by providing representative gradients of red-throated diver displacement for use within displacement assessments. It also provides information on the interaction between the largest displacement rates and the greatest spatial extent of displacement. This indicates further research is needed into individual responses to wind farms, the implications of this to populations, and how these effects can be reduced or mitigated.

6.1 Introduction to changes in red-throated diver displacement at distances from offshore wind farms

Spatial planning of offshore wind farms is crucial to avoid environmental impacts on a range of receptors, particularly as they may be located in areas overlapping with the foraging ranges of numerous seabird species. One method of assessing the potential scale of displacement of a particular species is to assume a certain percentage of birds (displacement rate) move away from a wind farm and some area around the wind farm. For instance, in the UK, this has lately been done using a 100% displacement rate within the wind farm and within 4km from the wind farm boundary. However, as there is evidence that red-throated diver displacement can occur much further than 4km from a wind farm, the assessment process was updated in 2020 to analyse displacement within a 10km region around a wind farm (Statutory Nature Conservation Bodies, 2022a). A displacement rate to use within the 10km region is therefore required to complete the assessment. It is unlikely that even the most sensitive species are completely displaced from this wider area, and it is hypothesised that a lower proportion of birds are displaced further from a wind farm.

Therefore, a gradient of displacement rates is likely to occur with distance. There have not been many wind farms whereby a gradient of displacement with distance from the wind farm has been required to be assessed. Natural England advised that for the East Anglia One North and East Anglia Two wind farms, an assessment should include the declining displacement rate of red-throated diver as 100% within the wind farm and the surrounding 1km distance band, then a linearly declining gradient to 0% at 12km from the wind farm (MacArthur Green and Royal HaskoningDHV, 2021). Both evidence of such a gradient and generalisation of a gradient are required in order to assess the full extent of red-throated diver displacement. This is crucial for marine spatial planning of future wind farm development locations and assessment of effects in combination with multiple other anthropogenic and natural pressures.

This chapter aims to analyse how displacement changes with distance from wind farms. It also aims to explore different options for generating a representative displacement gradient. This was done in order to consider the potential application of each method, for example within impact assessments.

The last chapter evaluated the design of surveys to determine the power to detect red-throated diver displacement. Following pre-construction and post-construction surveys, the full extent of displacement can then be assessed, which is done in this chapter. Within the overall aim of the thesis, this chapter addresses how cumulative seabird displacement from offshore wind farms is verified. This chapter begins by evaluating evidence of red-throated diver displacement rates both within and outside of offshore wind farms. It then suggests and reviews methods of generating a representative gradient of displacement rates for application in displacement assessments. Finally, the results are discussed in the context of red-throated divers within the Outer Thames Estuary Special Protection Area (SPA).

6.2 Method of investigating changes in red-throated diver displacement at distances from offshore wind farms

The method is split into several stages. First, the datasets used in this analysis are described. Then, the spatial extent of red-throated diver displacement from offshore wind farms is explored through the use of distance bands, displacement rates in these distance bands, and maximum displacement distances. Next, displacement rates and the spatial extent of displacement are converted into relative metrics to standardise parameters of displacement from different wind farms. Then, different ways of generating a representative displacement gradient from the data are explored. Finally, a representative displacement gradient was used to calculate the total displacement impact across a range of scenarios and then applied to a case study of the Outer Thames Estuary SPA.

6.2.1 Datasets used to investigate changes in red-throated diver displacement at distances from offshore wind farms

In order to investigate gradients of red-throated diver displacement, the evidence of displacement collected in chapter 4 and presented in table 4.2 was used. These 11 reports analysed the displacement effect of individual wind farms or wind farms in very close proximity to one another.

6.2.2 Method of exploring displacement rates in terms of the spatial extent of displacement

First, red-throated diver displacement was investigated with regard to how displacement was described across different spatial areas in and around the wind farms and compared across wind farms. This included considering the size of the distance bands, the maximum displacement distance recorded, and whether the wind farm and the adjacent area were described together or separately. This was carried out to gain an understanding of the manner in which displacement has been quantified and to determine whether the data could subsequently be analysed together. Displacement parameters were described through scatter plots, histograms, and top-down maps to better illustrate the spatial nature of displacement.

6.2.3 Method of exploring relative displacement rates with relative distances from wind farms

Red-throated diver displacement data was transformed by converting it to proportional values. This was done by calculating the displacement rate within each distance band as a proportion of the within-wind farm displacement rate. Similarly, each distance band was described as a proportion of the maximum displacement distance. This gave a holistic view as to how quickly the displacement rate declined with distance from each wind farm. These proportion calculations were done to generate non-dimensional data, which allowed subsequent direct comparisons between wind farms.

6.2.4 Methods of generating a representative displacement gradient

Representative displacement gradients were generated, which could be used to assess future wind farm displacement where displacement happens at a range of distances from a wind farm. Data was used from wind farms with displacement rates in distance bands outside of the wind farms. Different methods of summarising displacement data to generate representative displacement gradients were explored, which may each have different applications.

a) “All data” method – The first method was to plot all the available data on displacement rate against the distance band and generate a linear regression line through the data. The equation of the line was then used to generate a value for each 1km distance band. This method was named “All data” due to its use of all available displacement data points. This gradient could be used should it be intended to have a representative gradient where all data points are incorporated.
b) “Average 1km” method – A second method was to average data before generating a trend line. The displacement rate within each 1.0km distance band was averaged,

and then a linear regression was performed on this averaged data as with the first method. Again, the equation of the line was used to generate a value for each 1km distance band. This method was named “Average 1km” due to the averaging in each 1km distance band. This gradient could be used where all data are used, but extremes data points have less of an influence through averaging in each 1km distance band.

c) “Maximum 1km” method – The third method was to retain only the maximum value within each distance band and once again generate a linear regression to obtain a value for each 1km distance band. This method was named “Maximum 1km” because it took the maximum value in each 1km distance band. This gradient represents arguably the most precautionary gradient in terms of its use within a displacement impact assessment, as the highest displacement rates within each 1km distance band are used. Given the uncertainty around red-throated diver displacement at different wind farms, this gradient may characterise the worst-case scenario.

d) “Relative” method – The final method was to calculate displacement rates within distance bands as a percentage of the displacement rate within the wind farm. It also calculated each distance band as a percentage of the maximum displacement distance. This generated relative values of both displacement rate and displacement distance. These values were plotted with a linear regression, and values within each 1km distance band were obtained from the equation of the regression line. This method was named “Relative” due to the use of relative displacement rates and displacement distances. This method is the most easily transferrable in terms of generating gradients with different within-wind farm displacement rates and maximum displacement distances. It also accounts for differences in maximum displacement distance and within-wind farm displacement rate by generating non-dimensional values, therefore best describes the variety of gradients from wind farms.

6.2.5 Methods of extrapolating displacement beyond the bounds of the survey

However, before these gradients could be calculated, it was imperative to understand whether the full extent of displacement had been captured by the existing studies. For the studies where displacement was only recorded within the wind farm, it was assumed that this was the full extent of displacement. This may not actually be the case, but without another displacement rate, e.g. at some distance outside the wind farm, it cannot be established if there was a declining gradient with distance or if displacement may have actually occurred outside the wind farm as well as within it. The red-throated diver displacement gradients reported from the Gunfleet Sands, Kentish Flats, and Lincs, Lynn and Inner Dowsing offshore wind farms extend to a limited area around the wind farms due to the area over which surveys were carried out. In the furthermost distance bands from these wind farms, the displacement rate is not very low, indicating that displacement could have occurred outside of these furthermost regions. This is further evidenced by the decline in displacement rate with distance from the wind farm, which indicates that displacement could continue to zero percent (Table 6.1).

Table 6.1. Red-throated diver displacement rates with distance from Gunfleet Sands, Kentish Flats, and Lincs, Lynn and Inner Dowsing offshore wind farms as reported in the literature and monitoring reports.

Offshore wind farm	**Distance band (km)**	**Displacement rate (%)**
Gunfleet Sands (NIRAS, 2015)	Within OWF	91.29
	0-1	65.80
	1-2	20.95
Kentish Flats (Percival, 2014)	Within OWF	97
	0-0.5	77
	0.5-1	69
	1-2	53
	2-3	56
Lincs, Lynn and Inner Dowsing (Webb *et al.*, 2017)	Within OWF	83.3
	0-1	77.4
	1-2	71.4
	2-3	62.5
	3-4	55.2
	4-5	50.8
	5-6	44.8
	6-7	42.3
	7-8	33.6

Note: Number of decimal places is the same as those reported in the relevant literature or monitoring report.

Table 6.2 shows that the London Array wind farm was surveyed beyond the point of displacement rates declining beyond zero, which provides more certainty that the full spatial extend was surveyed, and what the maximum displacement distance was. In the 11.0km to 11.5km distance band, the displacement rate was 12.62%, and in the 11.5km to 12.0km distance band the displacement rate was -7.2%. A negative displacement rate indicates that the density of birds after wind farm construction was higher than before wind farm construction. The remaining area outside of this distance band all reported negative displacement rates, indicating an increase in red-throated diver density before and after construction of the wind farm (Table 6.2).

Table 6.2. Red-throated diver displacement rates with distance from the London Array offshore wind farm over the entire survey area showing loss of birds up to 11.5km, and increase in birds beyond 11.5km from the wind farm boundary (APEM, 2021).

Distance band (km)	**Displacement rate (%)**
Within OWF	54.68
0.0-0.5	47.91
0.5-1.0	44.92
1.0-1.5	41.00
1.5-2.0	38.91
2.0-2.5	40.38
2.5-3.0	41.18
3.0-3.5	39.50
3.5-4.0	36.07
4.0-4.5	33.02
4.5-5.0	31.55
5.0-5.5	32.96
5.5-6.0	35.00
6.0-6.5	36.08
6.5-7.0	35.58
7.0-7.5	40.07
7.5-8.0	41.29
8.0-8.5	44.88
8.5-9.0	45.13
9.0-9.5	44.19
9.5-10.0	39.61
10.0-10.5	34.44
10.5-11.0	23.88
11.0-11.5	12.62
11.5-12.0	-7.20
12.0-12.5	-20.00
12.5-13.0	-33.43
13.0-13.5	-47.95
13.5-14.0	-46.05
14.0-14.5	-59.02
14.5-15.0	-77.48

Note: Number of decimal places is the same as those reported in the relevant literature or monitoring report.

In order to generate displacement rates out to the full spatial extent of displacement, the following method was applied to the existing displacement gradient from Gunfleet Sands, Kentish Flats, and Lincs, Lynn and Inner Dowsing offshore wind farms.

A linear regression was put through the existing displacement gradient for each wind farm. This generated an equation of the linear regression. This equation was used to generate displacement rates for displacement distances beyond those which already existed. For example, a linear regression through the Lincs, Lynn and Inner Dowsing offshore wind farm data (Figure 6.1) resulted in the trend shown in Equation 6.1.

$$y = -6.15x + 82.52$$

Equation 6.1 Linear regression through the Lincs, Lynn and Inner Dowsing offshore wind farm red-throated diver displacement data.

where

y = displacement rate in distance band x

x = distance band

Equation 6.1 was then used to generate displacement rates beyond the 7-8km distance band (the maximum distance band surveyed at this wind farm), in 1km distance bands, until a negative displacement rate was found. In the 12km-13km distance band, there was a displacement rate of 2.57%, and in the 13km-14km distance band, there was a displacement rate of -3.58% (Figure 6.2Figure 6.2. Extrapolated red-throated diver displacement gradient at the Lincs, Lynn and Inner Dowsing offshore wind farm, out to the maximum spatial extent of displacement using a linear regression through the original data.). Therefore, it could be suggested that displacement actually occurred out to 13km from this wind farm.

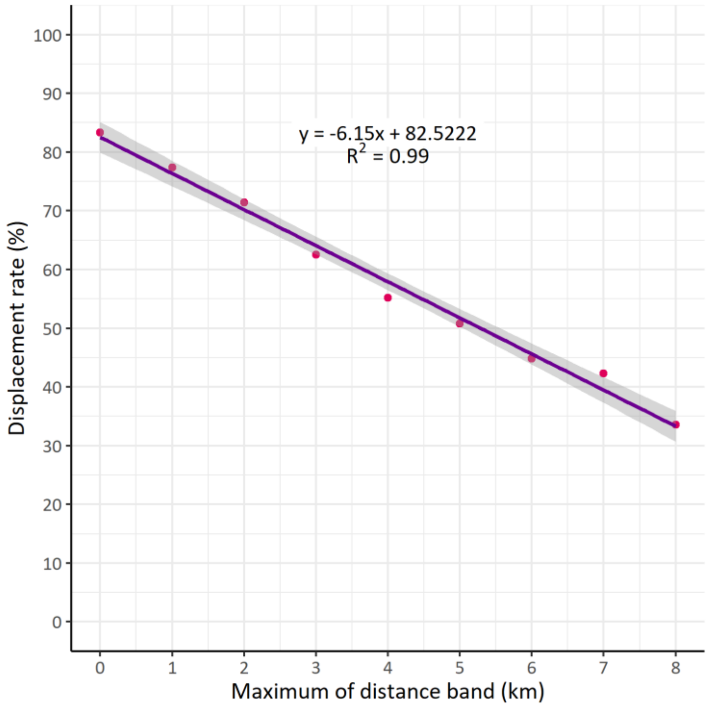

Figure 6.1. Linear regression trend line through red-throated diver displacement gradient at the Lincs, Lynn and Inner Dowsing offshore wind farm using original wind farm data.

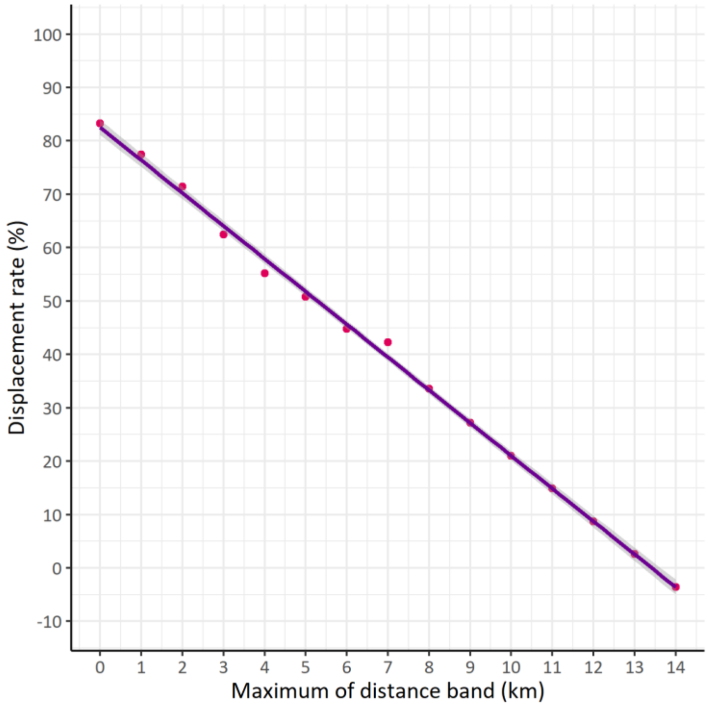

Figure 6.2. Extrapolated red-throated diver displacement gradient at the Lincs, Lynn and Inner Dowsing offshore wind farm, out to the maximum spatial extent of displacement using a linear regression through the original data.

For the Kentish Flats wind farm, a linear regression through the data resulted in the trend shown in Equation 6.2 and Figure 6.3.

$$y = -12.45x + 85.98$$

Equation 6.2. Linear regression through the Kentish Flats offshore wind farm red-throated diver displacement data.

Extrapolation of the existing data via linear regression generated displacement rates out to a spatial extent of 6km from the wind farm. In the 5km-6km distance band, there was a displacement rate of 11.29%, and in the 6km-7km distance band, there was a displacement rate of -1.16% (Figure 6.4). A negative values means an increase in bird density after wind farm construction, therefore displacement only occurs in regions of a positive displacement rate value.

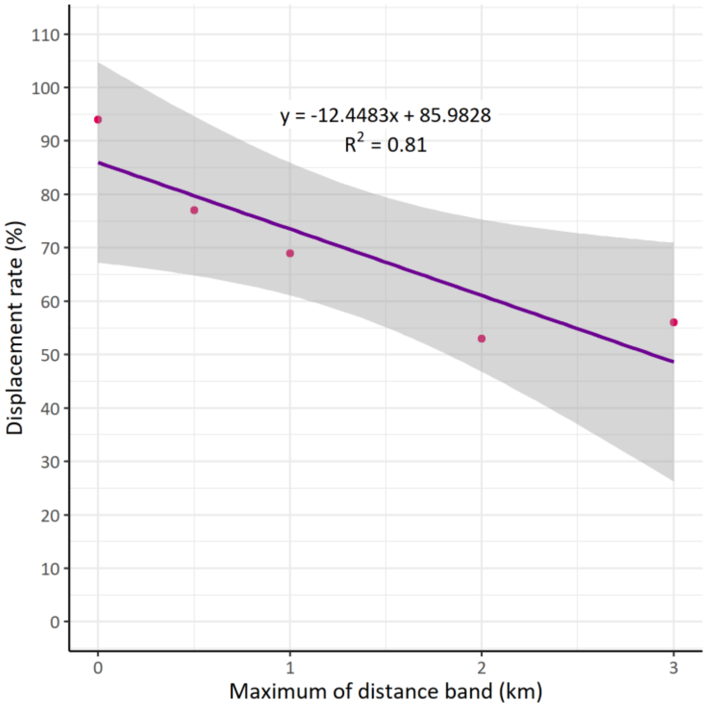

Figure 6.3. Linear regression trend line through red-throated diver displacement gradient at the Kentish Flats offshore wind farm using original wind farm data.

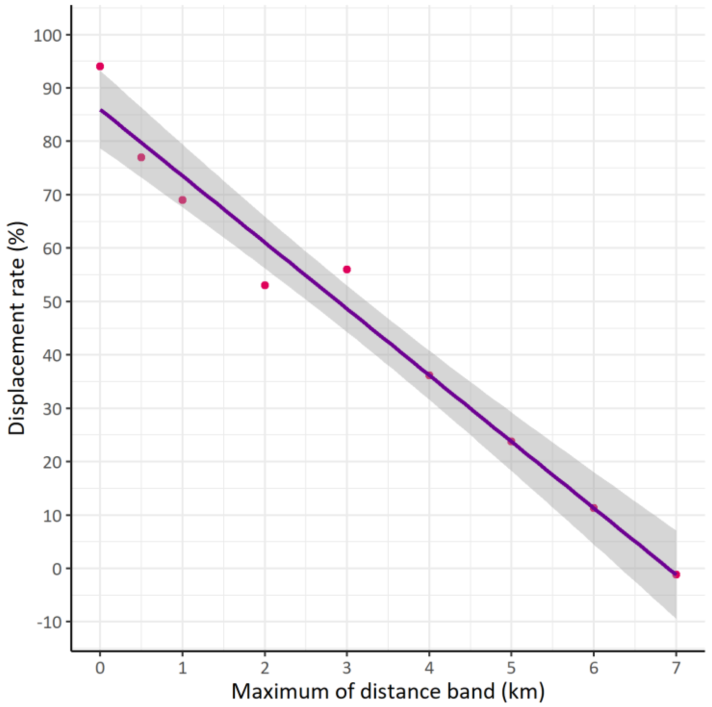

Figure 6.4. Extrapolated red-throated diver displacement gradient at the Kentish Flats offshore wind farm, out to the maximum spatial extent of displacement using a linear regression through the original data.

For the Gunfleet Sands wind farm, a linear regression through the data resulted in the trend shown in Equation 6.3 and Figure 6.5.

$$y = -35.17x + 94.52$$

Equation 6.3. Linear regression through the Gunfleet Sands offshore wind farm red-throated diver displacement data.

Extrapolation via linear regression showed that in the 2km-3km distance band there would be a negative value, where a higher density of birds would be present (Figure 6.6). Therefore the existing data, showing displacement out to 2km from the wind farm, fully described the extent of displacement and hence there was no need for extrapolation.

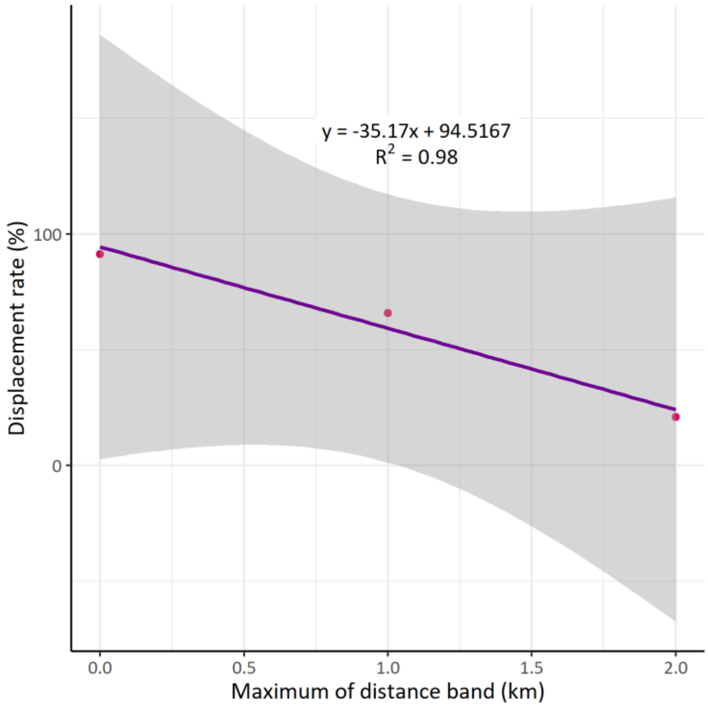

Figure 6.5. Linear regression trend line through red-throated diver displacement gradient at the Gunfleet Sands offshore wind farm using original wind farm data.

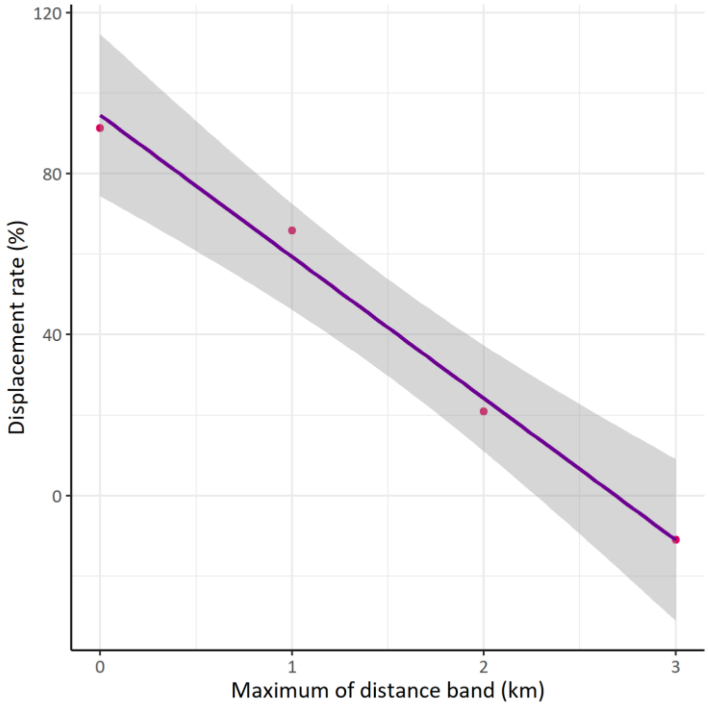

Figure 6.6. Extrapolated red-throated diver displacement gradient at the Gunfleet Sands offshore wind farm, out to the maximum spatial extent of displacement using a linear regression through the original data.

In summary, Figure 6.2 and Figure 6.4 show that the original surveys did not cover the full spatial extent of displacement, and extrapolation of wind farm data beyond the extent of surveys was required for Kentish Flats and Lincs, Lynn and Inner Dowsing wind farms. In comparison, in the case of Gunfleet Sands and London Array wind farms, the surveys had covered the full spatial extent of displacement, therefore extrapolation was not required. The final displacement gradients for each wind farm are shown in Table 6.3.

Table 6.3. Red-throated diver displacement rates with distance from offshore wind farms for the full spatial extent of displacement. Extrapolated values in the yellow shaded cells.

Offshore wind farm	**Distance band (km)**	**Displacement rate (%)**
Horns Rev I	Within OWF	100
Nysted	Within OWF	100
Alpha Ventus	Within OWF	90
Thanet	Within OWF	73
Egmond aan Zee	Within OWF	68
Gunfleet Sands	Within OWF	91.29
	0-1	65.80
	1-2	20.95
Kentish Flats	Within OWF	94
	0-0.5	77
	0.5-1	69
	1-2	53
	2-3	56
	3-4	36
	4-5	24
	5-6	11
Lincs, Lynn and Inner Dowsing	Within OWF	83.3
	0-1	77.4
	1-2	71.4
	2-3	62.5
	3-4	55.2
	4-5	50.8
	5-6	44.8
	6-7	42.3
	7-8	33.6
	8-9	27.2
	9-10	21.0
	10-11	14.9
	11-12	8.7
	12-13	2.6
London Array	Within OWF	54.68
	0.0-0.5	47.91
	0.5-1.0	44.92
	1.0-1.5	41.00
	1.5-2.0	38.91
	2.0-2.5	40.38

Offshore wind farm	Distance band (km)	Displacement rate (%)
	2.5-3.0	41.18
	3.0-3.5	39.50
	3.5-4.0	36.07
	4.0-4.5	33.02
	4.5-5.0	31.55
	5.0-5.5	32.96
	5.5-6.0	35.00
	6.0-6.5	36.08
	6.5-7.0	35.58
	7.0-7.5	40.07
	7.5-8.0	41.29
	8.0-8.5	44.88
	8.5-9.0	45.13
	9.0-9.5	44.19
	9.5-10.0	39.61
	10.0-10.5	34.44
	10.5-11.0	23.88
	11.0-11.5	12.62

6.2.6 Method of using a representative displacement gradient to calculate total displacement impact

The “Relative” displacement gradient can be used to generate displacement gradients for a range of maximum displacement distances. Therefore, this gradient was taken forward to investigate how the total displacement effect may differ when there are different displacement rates and maximum displacement distances within the wind farm. In this chapter, so far it has been seen that when displacement occurs over a large distance, the displacement rate within the wind farm is smaller. Therefore, there is a critical question that a representative displacement gradient may be able to answer: How different is the displacement across the entire displacement-affected area when displacement occurs over a small distance but with a high displacement rate (within the wind farm) compared to displacement over a large distance but with a low displacement rate? There are multiple factors at play here, in part due to the displacement rate within the wind farm and the maximum displacement distance but also due to the size of the wind farm itself. In this investigation, the distance bands are set at 1km for a consistent application across wind farms. However, the size of a wind farm will differ, as may the displacement rate, and hence influence the number of birds displaced. It also influences the area of the 1km distance bands, again influencing the number of birds displaced within each distance band.

The trend previously generated (see section 6.2.3) of within wind farm displacement rate with maximum displacement distance was used to generate a series of displacement rates. These were done for a set of maximum displacement distances, from a minimum of within-wind farm only up to 13km from the wind farm boundary. These generated displacement rates for within the wind farm only. The "Relative" representative displacement gradient was then used to generate displacement rates within each distance band between the wind farm and the maximum displacement distances. The "Relative" displacement gradient was used as this was the sole displacement gradient which could be applied to other scenarios of maximum displacement distance and displacement rates within a wind farm.

6.2.7 Method of applying a representative displacement gradient to calculate the total displacement impact of wind farms in the Outer Thames Estuary Special Protection Area

The Outer Thames Estuary SPA was used as an example of red-throated diver density, as the SPA hosts the largest UK population of non-breeding divers, as described in section 5.2.1. The latest population estimate for the SPA is 18,079 individuals, which covers 3,924km^2, therefore giving a red-throated diver density of 4.61 birds/km^2. One wind farm was assumed to be present, with an area equal to the average wind farm area (28km^2) from the 11 wind farms from which displacement data is available (see section 4.4 and Appendix Table D1). The displacement rates (calculated in section 6.2.6) were applied to each distance band in each maximum displacement distance scenario. For simplicity and to maintain comparative scenarios, the red-throated diver density of 4.61 birds/km^2 was applied evenly to the wind farm and surrounding area. The total displacement-affected area was calculated using Equation 6.4.

$$i = \left(\sqrt{j/\pi} + k\right)^2 \times \pi$$

Equation 6.4. Total displacement affected area

where

i = total displacement affected area (km^2)
j = OWF area (km^2)
k = maximum displacement distance (km)

To calculate the area of each distance band, the above calculation was used, with *k* representing the distance band in question, minus the same calculation but with k representing the next-smaller distance band (Equation 6.5).

$$m = \left(\left(\sqrt{j/\pi} + n\right)^2 \times \pi\right) - \left(\left(\sqrt{j/\pi} + p\right)^2 \times \pi\right)$$

Equation 6.5. Distance band area

where

m = distance band area (km^2)
n = distance band (km)
p = next-smallest distance band (km)

The reduction in red-throated divers within each distance band was calculated, and thus the total displacement rate over the entire displacement-affected was calculated in each scenario. The same principle of investigating relative overall displacement rates across the displacement-affected areas was then applied to the four wind farms with displacement gradient information. This was done using the displacement gradients as stated in the literature and monitoring reports from these wind farms to analyse the real displacement observed at these wind farms. However, to make the results more comparable across wind farms, a flat distribution of red-throated divers based on the average density in the Outer Thames Estuary SPA was used. In reality, three of these four wind farms are located in different areas of the Outer Thames Estuary SPA, and one is outside of the SPA; therefore, densities at those wind farms are highly likely to be different to each other and different to the average for the Outer Thames Estuary SPA, but this fact makes them less directly comparable.

The analysis was carried out in R (R Core Team, 2022). The R markdown code is available in Appendix G.

6.3 Results of investigating changes in red-throated diver displacement at distances from offshore wind farms

This section first discusses the results of exploring the spatial extent of red-throated diver displacement from offshore wind farms. This is done in terms of the distance bands used to describe displacement, the displacement rates observed in these distance bands, and over differing maximum displacement distances. Next, the results of converting these displacement rates and spatial extent of displacement into relative metrics are described to standardise parameters of displacement from different wind farms. Then, the results of using different ways of generating a representative displacement gradient, which may be used to assess future wind farm displacement, are described. The results of using a representative displacement gradient to calculate the total displacement impact are presented. Finally, the application of a representative displacement gradient to calculate the total displacement impact of wind farms in the Outer Thames Estuary SPA is presented.

6.3.1 Results of exploring displacement rates in terms of the spatial extent of displacement

The wind farms range from having displacement only within the wind farm to up to 16.5km from the wind farm boundary. The average maximum distance at which displacement is detected is 3.6km, with a median of 0.0km. Where displacement was recorded outside the wind farm, average maximum distance at which displacement is detected is 8.1km, with a median of 8.8km. Displacement rates within the wind farm range from 54.68% to 100%, with an average of 83.81% and a median of 90%. A displacement rate is not always provided for all distance bands outside the wind farm, and some studies report displacement across very wide distance bands, which sometimes includes the wind farm. These wider distance bands with a single displacement rate value do not provide data on a gradient of displacement over distance. Therefore, in this thesis any displacement rates given within distance bands larger than 2km were removed from further analysis of displacement gradients.

Displacement rate and maximum displacement distance are often recorded in reports. However, what is less often recorded is the displacement rate at those maximum distances or within distance bands. For instance, the largest reported displacement distance of 16.5km does not record the displacement rate at that distance. In addition, there are differences in the size of the distance bands. For example, one wind farm recorded the displacement rate in each 0.5km distance band from the wind farm boundary, whilst others did so in each 1.0km distance band. Another report analysing the effect of multiple wind farms recorded the displacement rate over a 3.0km radius around the wind farms and also over a 10km radius of the wind farms, which incorporates the 3.0km radius. Therefore, not only does the distance band over which displacement rate is calculated differ between reports, but also whether discrete distance bands or cumulative distance bands are used.

The displacement rate across distance bands is quite different across the wind farms, as well as the distance over which displacement is seen. The gradient of displacement with distance therefore very different, but all wind farms with displacement beyond the wind farm boundary (and with discrete distance bands) show a declining displacement rate with distance (Figure 6.7).

The displacement rate detected at the maximum distance is also different across the wind farms. For instance, the Gunfleet Sands wind farm recorded a 20.95% displacement rate at the maximum distance from the wind farm (2km), whilst the London Array wind farm detected a 12.62% displacement rate at the maximum distance (11.5km). It may be that aspects of survey design do not allow for lower displacement rates to be detected. The displacement rate is usually calculated as the difference in seabird density pre-construction to post-construction of the wind farm. The design of pre-construction and post-construction surveys may not be sufficiently statistically powerful enough to detect lower displacement rates, which are likely to occur at larger distances from a wind farm (see Chapter 5).

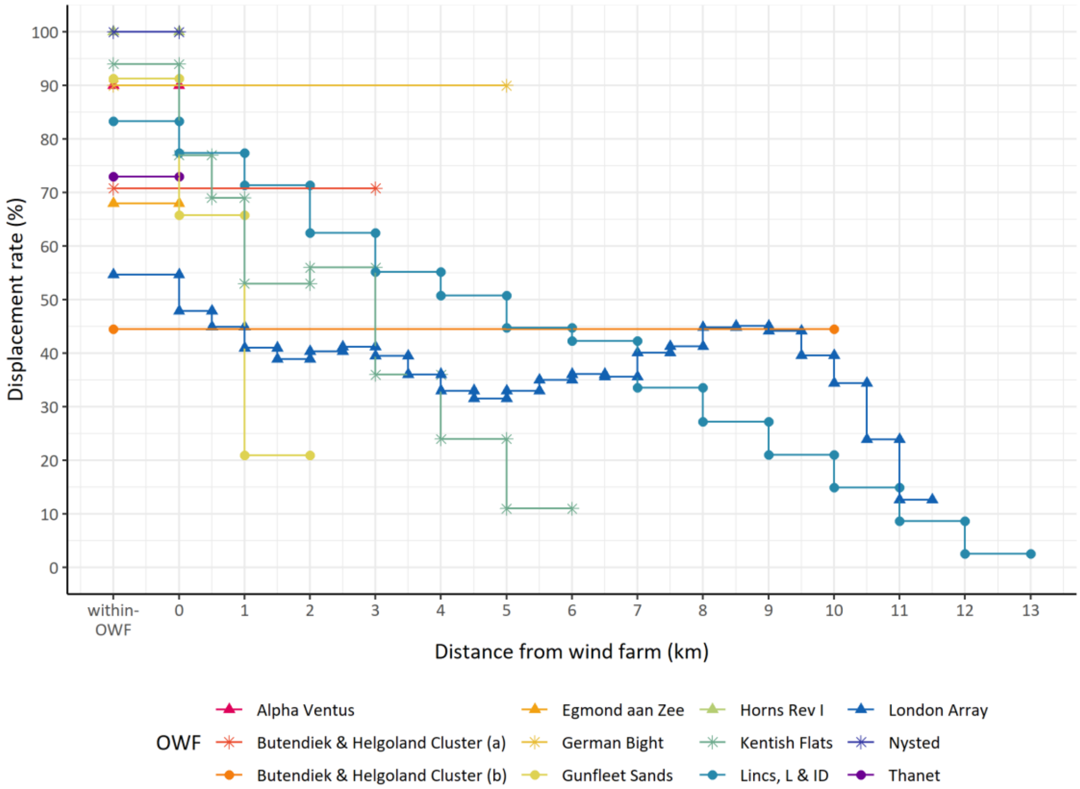

Figure 6.7. Displacement rates of red-throated divers at distances from 11 offshore wind farms, taking account of the different distance bands over which displacement has been measured, as reported in the literature and monitoring reports (with extrapolation).

Note: See Table 4.2 for study references.

As previously mentioned, different offshore wind farms reported displacement rates in a range of different size distance bands. These distance bands range from 0.5km to 10km, with one wind farm even reporting in both 0.5km increments for the distance band closest to the wind farm and 1km increments in distance bands further from the wind farm (Figure 6.7). Particularly striking are the very large distance bands of the Butendiek and Helgoland Cluster, and the German Bight study. Both these studies reported displacement rates for areas that included wind farms plus distance bands. The Butendiek and Helgoland Cluster study also presented two displacement rates, one covering the wind farm plus a 3km distance band (Butendiek and Helgoland Cluster (a) in Figure 6.7), and another covering the wind farm plus a 10km distance band (Butendiek and Helgoland Cluster (b) in Figure 6.7). For these studies, there are few data points and the displacement rate is only described over one very large area, giving no indication as to whether displacement rates vary across the survey area. Meanwhile, for other studies, such as at London Array and Lincs, Lynn and

Inner Dowsing, there are many data points providing a detailed view of how displacement changes with distance.

Table 6.4 displays these different size distance bands and whether or not the wind farm is included within a distance band. The German Bight study reported a displacement rate within an area covering the wind farm and 5km outside the boundary. Due to these studies including both the distance band and inside the wind farm in one value of displacement and the much larger distance bands, these were excluded from further analysis in this chapter as they were less comparable with the other studies.

There are several wind farms reporting displacement at a range of distances from the wind farm, meaning at each distance band, there is often more than one wind farm reporting a displacement rate. However, as also mentioned, the distance bands used to calculate the displacement rate themselves are also different across the studies. For instance, in a 1km-wide distance band, some wind farms just calculate one value for the whole width of the distance band, whilst other wind farms present two values, each half of the width of the distance band.

Table 6.4. Displacement distance band sizes used in the literature to quantify red-throated diver displacement at offshore wind farms.

Wind farm	**Distance band**			**Distance band size beyond OWF boundary**
	Wind farm only	**Wind farm and distance bands separate**	**Wind farm and distance band together**	
Alpha Ventus	✓			N/A
Butendiek & Helgoland Cluster (a)			✓	3.0km
Butendiek & Helgoland Cluster (b)			✓	10.0km
Egmond aan Zee	✓			N/A
German Bight			✓	5.0km
Gunfleet Sands		✓		1.0km
Horns Rev I	✓			N/A
Kentish Flats		✓		0.5km, 1.0km
Lincs, Lynn & Inner Dowsing		✓		1.0km
London Array		✓		0.5km
Nysted	✓			N/A
Thanet	✓			N/A

Note: See Table 4.2 for study references.

Within-wind farm displacement rates, maximum displacement distances, and the size of distance bands appear quite different when viewed as top-down diagrams of the wind farms themselves. Figure 6.8 shows how the displacement rates in the distance bands actually appear around wind farms (which themselves are also different sizes). The wind farms in the figure are depicted as simple circles but with the same area as the built wind farms for comparison. The much larger within-wind farm displacement rate at the smaller wind farms can clearly be seen. This is compared to the larger wind farms displaying smaller within-wind farm displacement rates. Similarly, the larger decline in displacement rate in each distance band is seen at the small wind farms, with a much shallower change in displacement rate in distance bands around the larger wind farms.

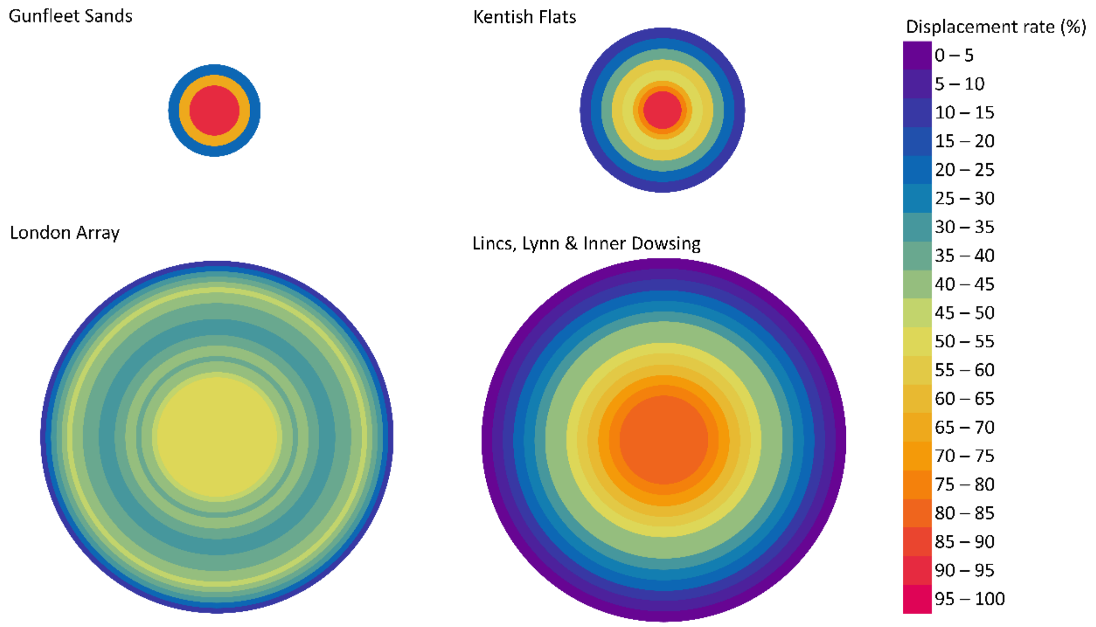

Figure 6.8. Red-throated diver displacement rates at offshore wind farms, with each circle size proportional to the areal extent of each wind farm (including extrapolation, top left Gunfleet Sands; top right Kentish Flats; bottom left London Array; bottom right Lincs, Lynn & Inner Dowsing).

Note: Wind farm areas are equivalent to those built but shown schematically as circles.

The displacement rate in the distance bands is shown in Figure 6.8 as the same throughout each individual distance band, i.e. at a particular distance from the wind farm, the same value is seen in every direction from the wind farm. The values reported for these distance bands are typically averages for the distance band, however, the likelihood that the same displacement rate actually occurs in every direction seems low. Some asymmetries in displacement rate might be expected due to the variability in environmental factors and red-throated diver distribution across the Outer Thames Estuary SPA and surrounding region. This directional difference in effect is seen in several studies investigating species distributions in response to other anthropogenic pressures (Benítez-López *et al.*, 2010). This effect is also seen in two of the case studies: the German North Sea study and the Horns Rev I. These both found that larger displacement rates were seen in some directions from the wind farms compared to other directions (Petersen *et al.*, 2014; Vilela *et al.*, 2020).

The same may well be true for the four wind farms in Figure 6.8. Gunfleet Sands, Kentish Flats, Lincs, Lynn and Inner Dowsing are all positioned relatively close to the coast, with variations in water depth surrounding the wind farms and a range of other anthropogenic activity around them. A busy shipping lane runs between Gunfleet Sands and London Array and north of Kentish Flats, further adding to potential sources of disturbance in particular directions from the wind farms. In addition, the London Array sits at the boundary of the Outer Thames Estuary SPA, suggesting that larger densities of red-throated divers are to be expected on the side of the wind farm within the SPA compared to the side of the wind farm outside of the SPA. This potential for differing displacement rates on opposite sides of a wind farm is problematic when generalising the displacement rate within a distance band, particularly if that distance band is several kilometres from the wind farm boundary. For instance, the outer distance band showing a displacement effect at the London Array was 11.5km from the wind farm boundary. Therefore, there could be up to 34km between the northern extent and the southern extent of the displacement-affected area, assuming the wind farm is circular. In reality, this wind farm is not circular, so at its widest extent, the 11.5km distance band is almost 37km from one side to the other. Thus, summarising the displacement rate within a distance band spanning several tens of kilometres without considering the directional differences may result in the loss of localised displacement information as well as the potential directional differences.

6.3.2 Results of exploring relative displacement rates with relative distances from wind farms

To understand the gradient of displacement rate with distance, it is helpful to generate relative displacement rates and displacement distances so that wind farms can be directly compared. This is done by calculating, for each distance band, the percentage of the distance from the maximum displacement distance. Similarly, the displacement rate within each distance band is calculated as a percentage of the within-wind farm displacement rate. Figure 6.9 shows that Gunfleet Sands, Kentish Flats, and Lincs, Lynn and Inner Dowsing wind farms all have a similar gradient of relative displacement rate with relative displacement distance, at least out to 50% of the maximum displacement distance. This shows that, even though the wind farms have different within-wind farm displacement rates and different maximum displacement distances, the gradient of displacement rate with distance is very similar. For example, at 50% of the maximum displacement distance, the wind farms all have a displacement rate of around 60% of the within-wind farm displacement rate. The data from the London Array wind farm is a little different as the displacement rate does not continually decline over all of the distance bands but instead declines, then increases, and finally declines again. As the maximum displacement distance for this wind farm is so large (11.5km), it is possible that other environmental or anthropogenic factors also play a part in red-throated diver distribution at those outer distance bands.

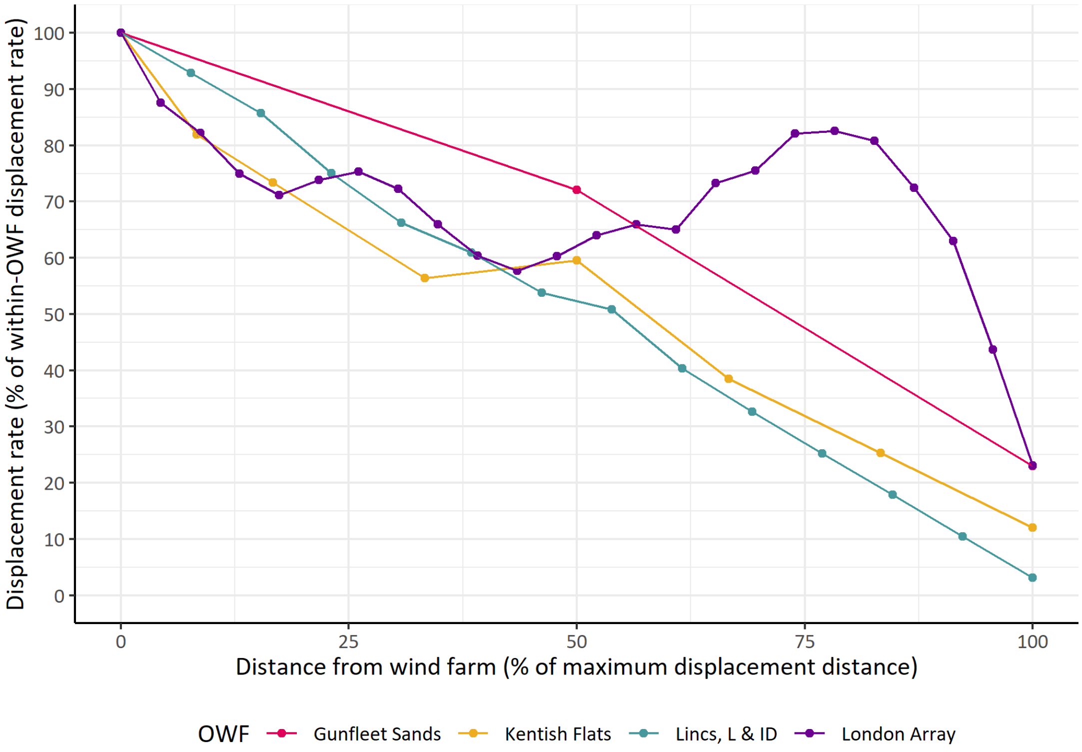

Figure 6.9. Relative red-throated diver displacement rates (displacement rate within a distance band as a percentage of the within-wind farm displacement rate) at relative distances from an example wind farm (distance band as a percentage of the maximum displacement distance).

Although not statistically significant, for these four wind farms shown in Figure 6.9, there is a general trend in the maximum displacement distance with displacement rate within the wind farm. The larger the distance over which displacement occurs, the lower the within-wind farm displacement (R_τ = -0.38, n = 4, p = 0.39, Figure 6.10). This relationship can be described by Equation 6.6.

$$y = -2.18x + 98.53$$

Equation 6.6. Linear regression of within-wind farm displacement rate with maximum displacement distance.

Gunfleet Sands and Kentish Flats show much higher within-wind farm displacement rates (91% and 94%, respectively) and lower displacement distances (2km and 6km, respectively). This is compared to the lower within-wind farm displacement rate (83%) and larger maximum distance (13.0km) at Lincs, Lynn and Inner Dowsing, and even lower displacement rate (55%) and large distance (11.5km) at London Array.

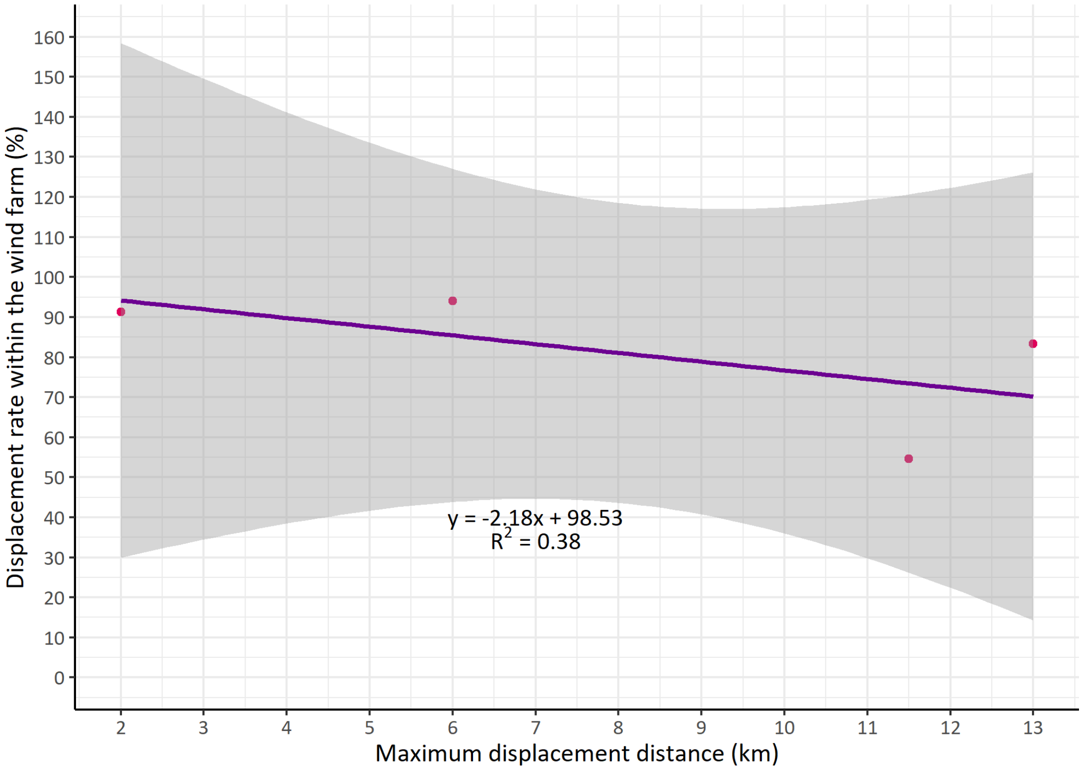

Figure 6.10. A non-significant but negative trend shows a lower red-throated diver displacement rate within wind farms with a larger maximum displacement distance.

Note: shaded area = 95% confidence intervals.

The data in Figure 6.10 may suggest that the lower within-wind farm displacement rates occur when displacement affects a much larger area than the wind farm alone. Therefore, basing mitigation measures on how wind farm parameters influence within-wind farm displacement only may not be the most appropriate option. This would not consider the possibility that reducing within-wind farm displacement may cause displacement to instead occur at greater spatial scales, albeit at a lower displacement rate. The issue in investigating how the spatial scale of displacement outside the wind farm may be interacting with wind farm design parameters is that few studies quantify this information, making it difficult to analyse statistically.

6.3.3 Results of generating a representative displacement gradient

Four representative displacement gradients are generated from available red-throated diver displacement data using different methods to summarise the data. These methods include using all the data (“All data”), taking an average displacement rate within each 1km distance band (“Average 1km”), taking the maximum displacement rate within each 1km distance band (“Maximum 1km”), and taking relative displacement rates and distances (“Relative”).

The first method, “All data”, plots the displacement rate against the distance band and generates a linear regression line through the data. This method has the advantage of directly using each data point and accounting for different numbers of data points at different distance bands. However, due to the large spread of data, the linear regression line is not very representative of the raw data ($R^2 = 0.58$) (Figure 6.11). The relationship can be described by Equation 6.7.

$$y = -4.63x + 68.75$$

Equation 6.7. “All data” displacement gradient.

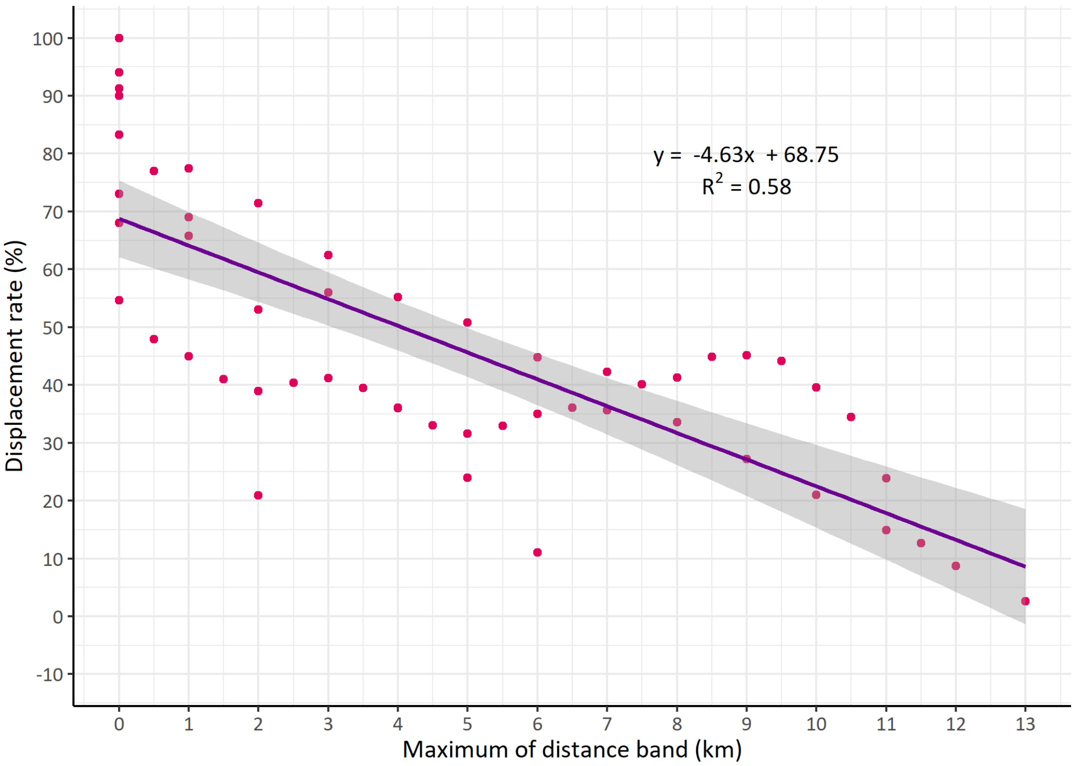

Figure 6.11. Linear regression using the "All data" method of all red-throated diver displacement rates available with displacement distance from offshore wind farms.

Note: Shaded area = 95% confidence intervals.

A different approach to take is to average data before generating a trend line. Within each 1.0km distance band, the displacement rate is averaged, and then a linear regression is performed on this averaged data. Unlike the previous method, the trend line better represents the averaged data as there is only one data point per distance band ($R^2 = 0.81$). However, the very notion of averaging first loses some detail within the data. Furthermore, any outliers in the averaged data could have a large influence on the slope of the linear regression (Figure 6.12). The relationship can be described by Equation 6.8.

$$y = -4.23x + 64.59$$

Equation 6.8. "Average 1km" displacement gradient.

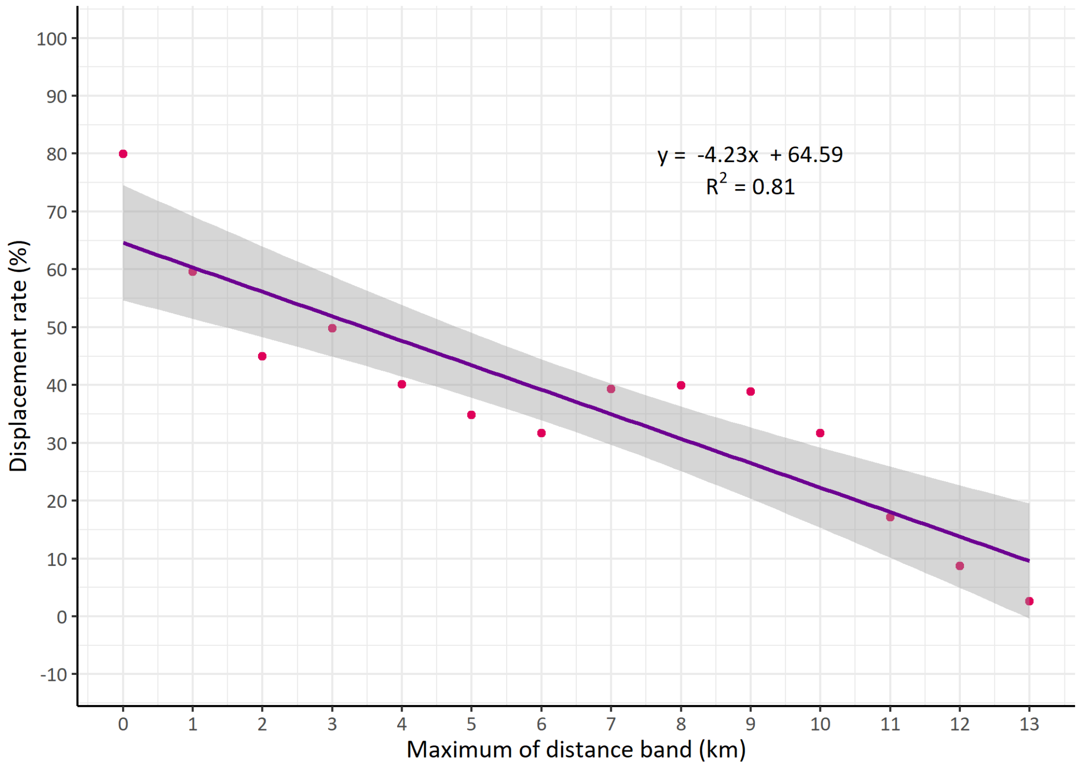

Figure 6.12. Linear regression using the "Average 1km" method of the average red-throated diver displacement rate within 1km distance bands with displacement distance from offshore wind farms.

Note: Shaded area = 95% confidence intervals.

Similar to the prior method, the third option is to take the maximum displacement rate within each distance band and generate a linear regression from these values. The same issues exist with this method as the last, but it has the advantage of being a more precautionary approach. Larger displacement rates could be lost through averaging, but by taking only the highest rate, the worst-case scenario is accounted for. This may be an approach preferred by nature conservation bodies due to its precautionary nature. The reverse could also be done by taking the lowest displacement rate in each distance band in order to obtain the best-case scenario. This method generates the highest R^2 value of 0.91, suggesting the trend most closely follows the data. However, caution is advised with this method, as there is generally a lower statistical power to detect lower displacement rates, so uncertainty in these rates can be high (Figure 6.13). The relationship can be described by Equation 6.9.

$$y = -5.89x + 86.19$$

Equation 6.9. "Maximum 1km" displacement gradient.

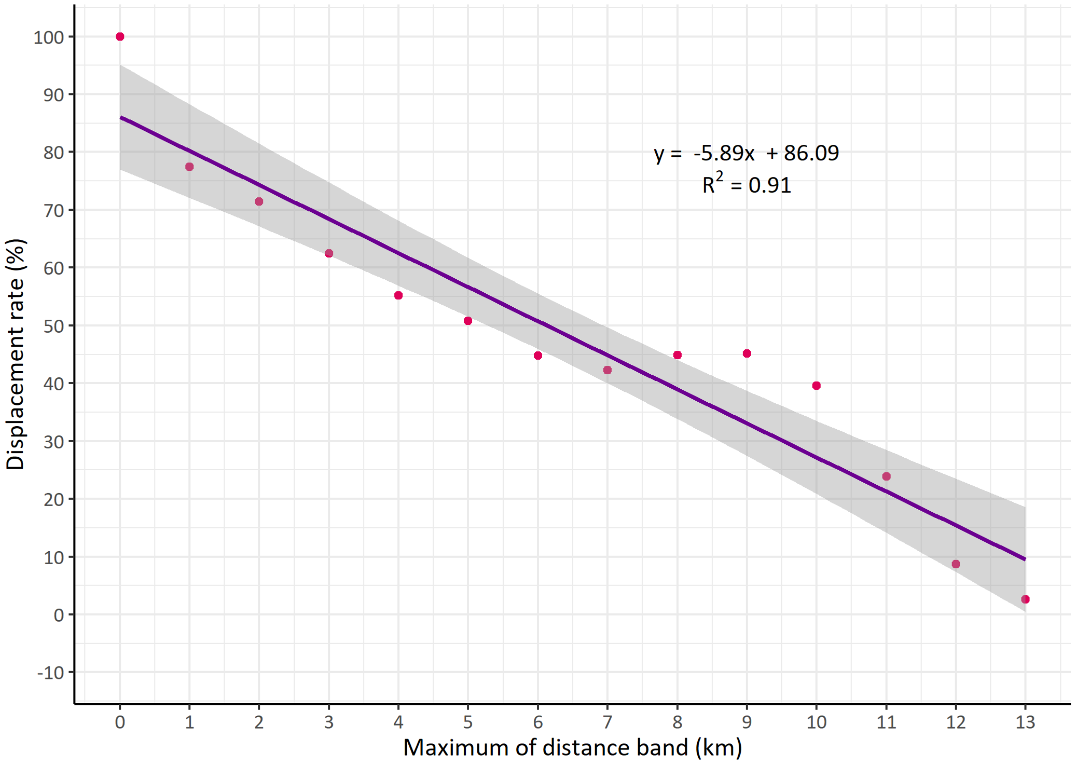

Figure 6.13. Linear regression using the "Maximum 1km" method of the maximum red-throated diver displacement rate within 1km distance bands with displacement distance from offshore wind farms.

Note: Shaded area = 95% confidence intervals.

The final method is more distinct than the previous three. As offshore wind farms found different displacement rates and different maximum displacement distances, fairly comparing them is troublesome. However, putting displacement rates and displacement distances into relative terms helps to better compare them. This has the advantage of accounting for different maximum displacement distances and prevents having many data points at some distance bands and very few at others. The other key advantage over the previous three methods is that the results are in relative terms, meaning the trendline can be easily applied to any maximum displacement distance. The displacement rate within each distance band is also relative to the displacement rate within the wind farm. Therefore, different within-wind farm displacement rates can be assumed, and the displacement rate within each distance band recalculated. There is still a disadvantage to this approach in that it is highly reliant on the maximum displacement distance actually being the furthest that displacement occurs. If displacement occurs beyond the maximum displacement distance, but there are no data points, then the relative data points are likely to be less accurate. The linear regression does not fully follow the data ($R^2 = 0.58$); therefore, caution is also warranted for this approach (Figure 6.14). The relationship can be described by Equation 6.10.

$$y = -0.60x + 91.17$$

Equation 6.10. "Relative" displacement gradient.

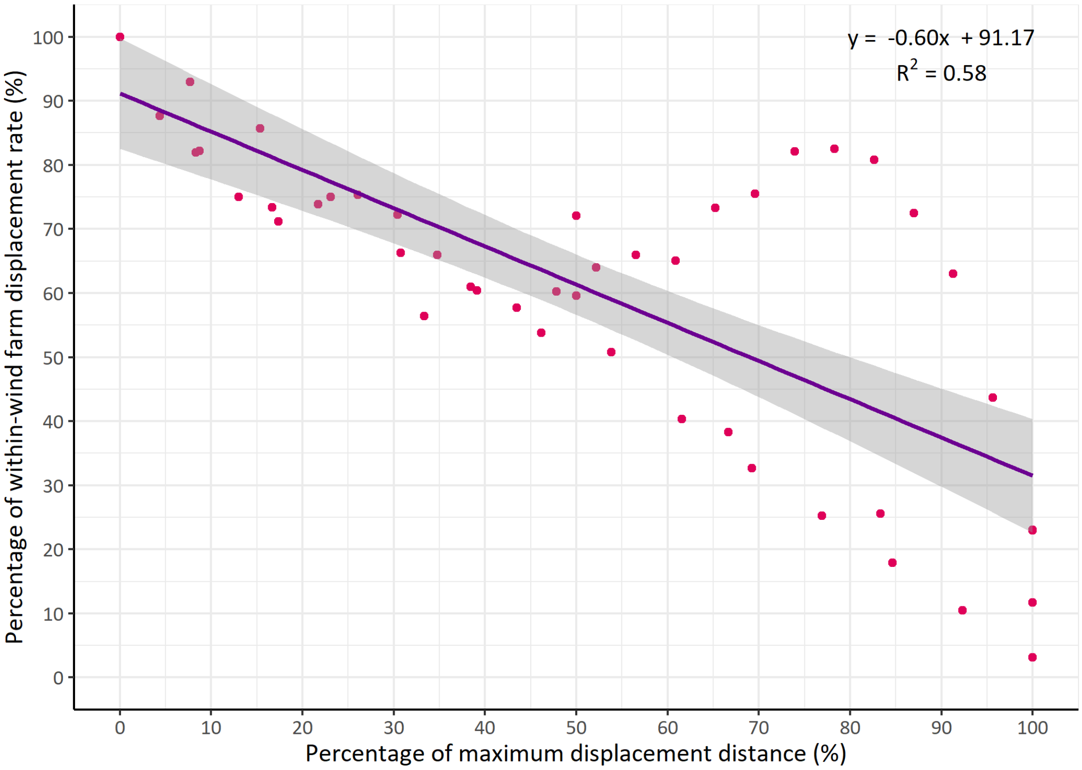

Figure 6.14. Linear regression using the "Relative" method of the relative red-throated diver displacement rate with relative displacement distance from offshore wind farms.

Note: Shaded area = 95% confidence intervals.

Table 6.5 shows the displacement rate within each distance band using the displacement gradient from the four methods, assuming a maximum displacement distance of 13km for all approaches. For the fourth method ("Relative"), the within-wind farm displacement rate is assumed to be 100%. The "All data" and "Average 1km" methods produce very similar displacement rates in each distance band, as may be expected. The "Maximum 1km" method results in higher displacement rates close to the wind farm but then declines to a lower displacement rate in the furthest distance band. i.e. a steeper gradient. The "Relative" method is not directly comparable to the other methods due to the different units of this method (% of maximum displacement distance and % of within-wind farm displacement rate, as opposed to distance bands in km and displacement rates in %). The "Relative" method is put into comparable units later in this chapter.

Table 6.5. Red-throated diver displacement rates within distance bands from a hypothetical wind farm based on a linear regression using four summarising methods.

	Displacement rate (%)			
Distance band	**All data (Figure 6.11)**	**Average 1km (Figure 6.12)**	**Maximum 1km (Figure 6.13)**	**Relative (Figure 6.14)**
Within OWF	69	65	86	100
0 — 1 km	64	60	80	87
1 — 2 km	59	56	74	82
2 — 3 km	55	52	68	77
3 — 4 km	50	48	62	73
4 — 5 km	46	43	57	68
5 — 6 km	41	39	51	63
6 — 7 km	36	35	45	59
7 — 8 km	32	31	19	54
8 — 9 km	27	27	33	50
9 — 10 km	22	22	27	45
10 — 11 km	18	18	22	40
11 — 12 km	13	14	15	36
12 — 13 km	9	10	10	31

Note: The “All data” method used all the displacement rates, the “Average 1km” method averaged the displacement rates within 1km distance bands, the “Maximum 1km” method took the maximum displacement rate within 1km distance bands, and the “Relative” method took the relative displacement rate and relative displacement distance band. The “Relative” displacement rates are in fact percentages of the within-wind farm displacement rate. If the within-wind farm displacement rate was 100%, then the figure is the table are also the displacement rates. If the within wind farm displacement rate was 60%, then the displacement rates in each distance band would be the listed percentages of 60%. So for example in the 12-13km distance band the displacement rate would be 31% of the within-wind farm displacement rate (60%), making the actual displacement rate 19%. In addition, if a different maximum displacement distance was used, the values would be scaled accordingly.

The “All data”, “Average 1km”, and “Maximum 1km” methods are all based on the red-throated diver displacement as stated in the literature. Each wind farm report presents different displacement gradients, including the maximum distance over which displacement is observed. The representative gradients are generated out to the maximum displacement distance observed at one wind farm, but all other wind farms only detected displacement at much smaller distances. Therefore, it is debatable that amalgamating displacement gradients from studies with different maximum displacement distances generates a truly representative displacement gradient. However, the “Relative” displacement gradient is the only method that could be used to calculate a gradient for a hypothetical wind farm with a large or small displacement rate within the wind farms or a large or small maximum displacement distance. Therefore, the “Relative” displacement gradient could be applied to an assessment of displacement at a future wind farm development by assuming a specific displacement rate within the wind farm and a specific maximum displacement distance or a range of displacement rates within the wind farm and a range of maximum displacement distances.

6.3.4 Results of using a representative displacement gradient to calculate total displacement impact

In order to apply the “Relative” displacement gradient to a range of scenarios of maximum displacement distance, first, the displacement rate within the wind farm is generated. Figure 6.10 shows that a lower displacement rate within the wind farm is associated with a larger maximum distance. Therefore, using Equation 6.6 a series of within-wind farm displacement rates are generated for a series of maximum displacement distances, from a minimum of within-wind farm only up to 13km from the wind farm boundary (Table 6.6). Using these combinations of within-wind farm displacement rates and maximum displacement distances in Table 6.6, and the displacement gradient from Equation 6.10, displacement gradients are generated (Figure 6.15).

Table 6.6. Simulated within-wind farm red-throated diver displacement rates based on the maximum displacement distance using Equation 6.6*.*

Maximum displacement distance (km)	**Within-wind farm displacement rate (%)**
0	98.53
1	96.35
2	94.17
3	91.99
4	89.81
5	87.63
6	85.45
7	83.27
8	81.09
9	78.91
10	76.73
11	74.55
12	72.37
13	70.19

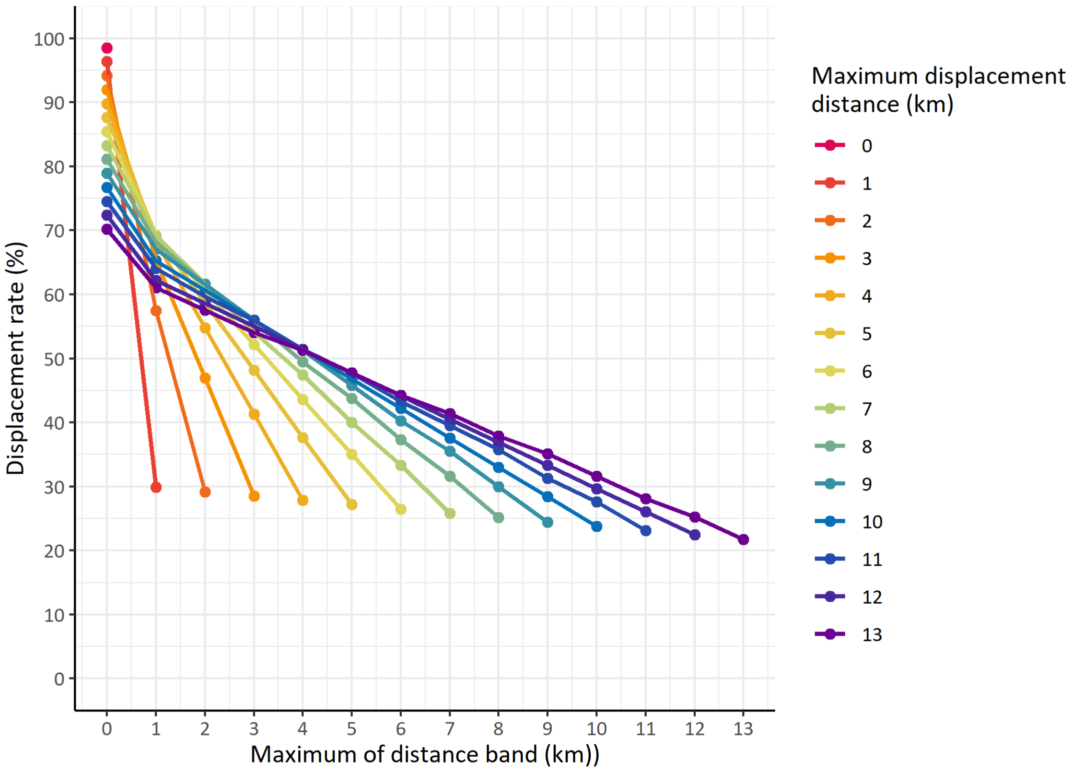

Figure 6.15. Simulated red-throated diver displacement rates across distance bands from a hypothetical wind farm for each scenario of maximum displacement distance (0km to 13km), generated from Equation 6.6 and Equation 6.10.

This method of generating a range of displacement gradients for different displacement rates within the wind farm and different maximum displacement distances could be replicated using any value of displacement rate within the wind farm and maximum displacement distance. Therefore, this could be used to generate simulations of the displacement effect of future wind farms.

6.3.5 Results of applying a representative displacement gradient to calculate the total displacement impact of wind farms in the Outer Thames Estuary Special Protection Area

The displacement rates within each of the scenarios of maximum displacement distance from 0km to 13km are then related to the red-throated diver density within the Outer Thames Estuary SPA. Calculation of the reduction in red-throated diver density, i.e. the overall displacement rate, within solely the areas affected by displacement in each of the maximum displacement distance scenarios is shown in Table 6.7. This shows that the lowest maximum displacement distance scenario (0km from the wind farm boundary) resulted in the largest overall displacement rate (98.53%).

Table 6.7. Simulated overall red-throated diver displacement rates at a hypothetical wind farm across the displacement-affected area for each maximum displacement distance scenario from 0km to 13km.

Maximum displacement distance (km)	**Displacement rate within affected area (%)**	**Size of affected area (km^2)**	**Number of birds displaced**
0	98.53	28	127
1	67.17	50	154
2	60.42	78	217
3	56.07	113	290
4	52.92	153	373
5	50.14	200	465
6	48.30	254	564
7	46.53	313	670
8	44.93	379	783
9	43.41	451	901
10	41.70	530	1016
11	40.42	614	1143
12	38.92	705	1263
13	37.68	803	1391

The scenario of a large displacement rate over a smaller area results in a low number of birds displaced, compared to smaller overall displacement rate over a larger area (Table 6.7). There is a non-linear relationship between the various parameters. This is due to the non-linear increase in the size of the affected area with maximum displacement distance (see Equation 6.4). Although the displacement rates across the entire affected area is smaller when maximum displacement distance is large, the overall loss of birds is much larger due to the size of the area affected.

Indeed, this can be seen if the displacement rates in distance bands reported for the four wind farms with displacement gradient information are used, along with a flat density of red-throated diver. Gunfleet Sands OWF has the second highest within-wind farm displacement rate (91.29%), smallest maximum displacement distance (2km), and smallest displacement-affected area (60km^2). Whilst this results in the largest displacement rate over this affected area (55%), the actual number of birds displaced was by far the lowest of the four wind farms (Table 6.8). Lincs, Lynn & Inner Dowsing OWF has the largest maximum displacement distance (13km), and largest displacement-affected area (928km^2). The displacement rate over the affected area is the smallest (34%), but the number of birds displaced is very large.

London Array OWF had the largest number of birds displaced, despite Lincs, Lynn & Inner Dowsing OWF having a larger affected area. This is due to the higher displacement rates within the smaller inner distance, and the comparatively lower displacement rates within the larger outer distance bands at Lincs, Lynn & Inner Dowsing OWF, compared to London Array OWF. This is in addition to London Array being almost twice the size of Lincs, Lynn & Inner Dowsing OWF (100km^2 and 55km^2, respectively), therefore each distance band around London Array contains more birds to be displaced. The 1km buffers around London Array and Lincs, Lynn & Inner Dowsing measure 39km^2 and 29km^2, respectively.

While Kentish Flats and London Array have very similar displacement rates (38.02% and 38.38%, respectively) over the whole affected area, the area affected (190km^2 versus 923km^2) and number of birds displaced (333 versus 1630) are vastly different.

Table 6.8. Overall red-throated diver displacement rates across the displacement-affected area, size of affected area, and number of hypothetical birds displaced at four offshore wind farms using displacement rates in the literature and monitoring reports.

Offshore wind farm	**Maximum displacement distance (km)**	**Displacement rate within affected area (%)**	**Size of affected area (km^2)**	**Number of birds displaced**
Gunfleet Sands	2	55.06	60	151
Kentish Flats	6	38.02	190	333
LLID	13	34.47	928	1471
London Array	11.5	38.38	923	1630

These differences show the importance of which metric, or more aptly the combination of metrics, of displacement is used in order to appropriately understand displacement effects and to compare wind farms. These results describe a scenario assuming a flat distribution of red-throated diver, but spatial fluctuation in densities is more likely to occur. Therefore, the actual density of red-throated divers in practice would also need to be considered to understand the implications for the Outer Thames Estuary SPA.

6.4 Discussion on red-throated diver displacement change with distance from offshore wind farms

These results have indicated that the larger area over which displacement occurs happens when there is a lower within-wind farm displacement rate. This may have implications for future wind farm design in relation to minimising the effect of displacement. If mitigation is to be put in place in order to reduce within-wind farm displacement rates, there is a possibility that doing so may cause a larger overall displacement effect if displacement spreads out over a wider area around the wind farm. This is a hypothesis at this stage, as there is no way of knowing whether changing wind farm parameters from those that might cause high within-wind farm displacement to those that lower within-wind farm displacement would have the effect of reducing or enlarging overall displacement.

There are many questions remaining because they directly relate to red-throated diver behaviour and being able to understand the driver of that behaviour, which cannot be obtained through a study of this sort. For instance, a question remains as to why some wind farms appear to have low displacement rates inside the wind farm whilst red-throated divers are also displaced from a vast distance surrounding the wind farm. One might assume that lower displacement within the wind farm might suggest some acceptance or habituation to the presence of turbines, but the fact that red-throated divers several kilometres outside the wind farm have redistributed even further from the wind farm suggests they are incredibly sensitive to the wind farm’s presence. Perhaps this is indicative of very individual-based behaviour.

These are the sorts of behavioural responses which a study of this nature cannot answer but can hypothesise a reason. Perhaps, in an area with high levels of anthropogenic activity just outside a wind farm, some birds perceive the wind farm to be the lesser source of disturbance, and so enter it, generating a relatively low displacement rate within the wind farm. Meanwhile, birds displaced from outside the wind farm are perhaps sufficiently sensitive to both the other sources of anthropogenic activity and the presence of a wind farm that they leave the wider area. This would result in a displacement effect over several kilometres outside the wind farm. In this case, it is the combination of the wind farm and other activities causing displacement rather than solely one source. Or perhaps in the event that there is a low density of turbines, there is sufficient space between turbines that birds are displaced away from individual turbines but not a whole wind farm. Meanwhile, other birds perceive the wind farm as a whole, and an attempt to remove oneself from the wind farm results in a large distance travelled in order to make the wind farm appear as small as possible against the backdrop of the seascape.

What red-throated diver habitat preferences are is a further question which needs to be considered, and may help to understand why and where birds move to. Red-throated divers prefer to utilise relatively shallow coastal areas up to around 20m deep (Black *et al.*, 2015; Duckworth *et al.*, 2020). They tend to associate with estuarine fronts where the likelihood of encountering prey is thought to be higher (Skov and Prins, 2001; Skov *et al.*, 2016). One way to predict where displaced birds may move to would be to model the current distributions of birds, the presence of anthropogenic activity, and depth contours. The removal of anthropogenic activities may present information on where birds would naturally occur, which may then help indicate where mitigation measures could be implemented to remove anthropogenic activity.

Empirical evidence of red-throated diver displacement has been described and presented in a range of different ways across reports in the literature. Displacement has been defined and calculated in different ways, from comparisons in density before and after the construction of wind farms to comparing assumed densities with and without the wind farm. Displacement rates have been quantified in discrete regions, for instance, in distance bands outside the wind farm and also across larger spatial scales, for instance, across a wind farm plus 10km outside of it. Discrete distance bands of different sizes, from 500m to several kilometres, have also been used. This non-standard approach to the presentation of displacement makes it difficult to understand the full extent of displacement, particularly when it is unknown whether the full spatial extent of displacement has been detected. It also presents a challenge when using the data collectively, for instance, to generate displacement rates or displacement gradients for use in impact assessments. Based on the disparities in current studies of red-throated diver displacement, an opinion on what standardised displacement studies could look like is provided in the conclusion.

Replicating this study once more comparative monitoring has been carried out is likely to provide more robust evidence of red-throated diver displacement. However, caution is noted with using data based on several factors.

- First, the method of surveying should be considered, particularly as boat-based surveys are more likely to result in a distribution modified by the survey itself (Briggs *et al.*, 1985; Henkel *et al.*, 2007; Fliessbach *et al.*, 2019).

- Detectability of species across survey methods also needs to be accounted for if there is a possibility that digital and visual aerial surveys produce different abundance estimates for different species (Žydelis *et al.*, 2019).
- Other aspects of survey design, such as the statistical power of detecting displacement and whether surveys covered the full spatial extent of displacement, should be scrutinised to ensure the full picture of displacement is presented.
- The method of translating raw survey data into modelled distribution is yet another factor that could influence the outcome of a displacement study, and differences across reports may need to be analysed.
- The very definition of displacement may also differ between studies; previous studies have used Before-After and Before-After-Control-Impact methods, assumed distribution without the wind farm, and comparisons in abundance inside and outside the wind farm. Whether these are all directly comparable ways of calculating could be questioned further in future studies.
- More obvious differences are also present between studies that should certainly be taken into consideration. The distance bands over which displacement is described in previous studies have varied widely, from small discrete distance bands to tens of kilometres covering the wind farm and surrounding area.
- The spatial extent of the study should also be scrutinised. Some studies focus solely on a particular wind farm, whilst others cover a larger area and account for the impact of multiple wind farms and sometimes other sources of disturbance as well. Teasing apart the influence of individual sources of displacement becomes difficult with larger-scale studies. However, the cumulative effect of multiple stressors may be more accurately viewed. Any future meta-analyses should consider this in the aims of the study.
- Whether the surveys have captured the full spatial extent of displacement should also be considered; for a couple of wind farms it would appear that displacement could have continued to occur beyond the extent of the surveys.
- For some studies, displacement rates are provided, whilst for others, they are not. For those not presenting displacement rates, displacement distances are often stated. However, without a displacement rate, half of the picture is missing; the spatial extent is provided, but the quantity is not.

- Some displacement results are statistically significant results, whilst others are not; therefore, perhaps a weighting could be applied to those statistically robust studies carrying more weight. Judgements may be needed across those insignificant results as to the validity of the displacement results presented.

It is possible that if the same site was studied, but each of these aspects of survey design, data analysis, and presentation of results were different, the outcome could indicate different displacement effects. A full investigation would be needed to determine if this is true, and maybe a worthwhile future work. This may also then enable more of the existing studies to be incorporated into a meta-analysis.

Future useful work would be to look at the data behind the displacement of other species to determine if the same issues are present. There may also be lessons from studies of other species, or indeed lessons from studies of red-throated diver displacement to apply to other species.

This chapter has suggested several ways to generate a representative displacement gradient for different applications. Each method has its own advantages and disadvantages, and may have different uses. The most easily translatable method was the “Relative” gradient, which preserves the relationship between maximum displacement distance and within-wind farm displacement rate, regardless of what these actual values are. The “All data” most accurately described the raw data, but can be quite easily skewed by outlying values. The “Average 1km” gradient most accurately captures the displacement rate within 1km distance bands, and is less susceptible to outliers. This advantage is also retained in the “Maximum 1km” gradient method, but provides a more precautionary approach by taking the maximum values in each 1km distance band. This method may therefore be best applied where a wort-case scenario is investigated, for instance within impact assessments.

6.5 Conclusion of the change in red-throated diver displacement with distance from offshore wind farms

This chapter has shown the differences in how displacement has been surveyed, calculated, and presented. These differences make direct comparison between studies difficult, and can lead to a lack of consensus of displacement effects. Therefore, a key recommendation for future research and future practice is to standardise displacement studies. Natural variability and inherent uncertainties within each dataset also exist, mean further reductions in data quantity and/or quality exacerbates difficulties in understanding the impact of displacement. Therefore, based on the learnings throughout this thesis, an opinion on a standardised displacement monitoring study is provided in Chapter 8.

This chapter has examined evidence of the extent of red-throated diver displacement from offshore wind farms and the different ways that displacement can be defined, quantified, and presented. The next chapter uses these findings and the findings of previous chapters to consider the different ways that cumulative displacement can be defined and quantified. This entails simulating the potential displacement effects of both existing and future wind farms.

Chapter 7 What might future cumulative red-throated diver displacement from offshore wind farms look like?

Abstract

The installation of offshore wind farm infrastructure is set to rise significantly following an already rapid rate of development. Minimising negative interactions is critical to aid progress. Understanding the current level of impact and being able to predict future impacts, particularly on a cumulative level, can play a role in minimising and mitigating impacts. Displacement of birds away from wind farms can mean large areas of foraging habitat is lost. Cumulative displacement could occur through several mechanisms, including birds being displaced solely due to the closest wind farm, birds being displaced solely by the first wind farm built, or birds being displaced multiple times over due to more than one wind farm. In this study, the impact of multiple scenarios of maximum displacement distance, gradient of displacement with distance from a wind farm, and method of calculating cumulative displacement was investigated. Red-throated diver distribution was overlain with operational and planned wind farms, then scenarios were simulated to investigate cumulative impacts on a Special Protection Areas in UK waters. The results indicate that existing wind farms have had a large cumulative displacement effect, leading to massive areas of habitat loss. Future wind farms will likely add a much smaller additional impact. Regardless, the method of calculating cumulative displacement can generate a wide range of results in terms of the area of impact and number of birds displaced. Each of the three methods of calculating cumulative displacement may be true to reality, therefore the method chosen could produce very different outcomes of an impact assessment. This highlights the need for better understanding of cumulative displacement effects and impacts to gain an accurate view of wind farm-wildlife interactions.

7.1 Introduction to future scenarios of seabird displacement at offshore wind farms

This thesis has so far examined how species are scoped into a cumulative displacement assessment, whether wind farm design can mitigate displacement, the influence of survey design on detecting displacement, and the extent of displacement. Given this knowledge of displacement from current offshore wind farms, the next step in addressing cumulative displacement would be to simulate potential future wind farms and their displacement effect.

However, the mechanism of cumulative displacement from multiple wind farms in close proximity is also not clear. For instance, are more birds displaced if two wind farms are present or displaced further from those wind farms? Is the effect of two wind farms twice the effect of one wind farm, more than twice, or less than twice? Therefore, this chapter explores three mechanisms of calculating cumulative displacement. Given the range of displacement rates and maximum distances over which displacement has been observed, this chapter also explores cumulative displacement through a series of displacement rates and maximum displacement distances. This is done for both existing wind farms and the addition of future wind farms in order to gauge the current extent of displacement and the impact of future development.

Different methods of calculating cumulative displacement have been used in impact assessments in the UK. For example, the Awel Y Mor offshore wind farm in Welsh waters, the buffer regions around the wind farm were cropped around the neighbouring operational Gwynt Y Mor offshore wind farm. This assumed that displacement was already occurring within Gwynt Y Mor, and no additional displacement would occur in the same location due to another wind farm being built nearby. It was established that displacement was only occurring within Gwynt Y Mor, and not beyond the boundary, so there was no need for considering how to calculate cumulative disturbance outside Gwynt Y Mor (Boa *et al.*, 2022). In contrast, the North Falls offshore wind farm in the southern North Sea, carried out a cumulative displacement assessment by merging buffers around operational neighbouring wind farms. This assumed that displacement occurs due to the closest wind farm. Then if wind farms or buffers of those not yet built or consented overlapped with operational wind farms, the operational wind farm or buffer was prioritised. This assumed that displacement was already occurring within those locations, and wouldn't additionally occur in an overlapping region due to the addition of a future wind farm (Royal HaskoningDHV, 2023).

The intention behind this chapter is not to solely consider which method is most likely to occur, or which is most real. Rather, it is to explore the potential implications of different methods of calculating cumulative displacement. Each method has advantages and disadvantages, different applications, and different levels of biological realism. Regardless, each could reasonably be applied to impact assessments of displacement, therefore this work aims to analyse how different the outcomes from each method may be. This may help to understand the consequence of using different ways to calculate cumulative displacement.

This chapter begins by describing the method used to simulate future scenarios of seabird displacement at offshore wind farms, including the use displacement rates within and outside wind farms, which were chosen based on the previous chapter. Due to the variety of displacement rates, maximum displacement distances, displacement gradients, and mechanisms of cumulative displacement that may exist, this chapter explores the impact of each combination of these variables using the same methods that would be carried out in an EIA. The results of these simulations, both for existing and future wind farms, are presented within the context of the Outer Thames Estuary Special Protection Area (SPA). Finally, the implications of the study, including recommendations for future practice and future research, are discussed.

7.2 Method to simulate future scenarios of seabird displacement at offshore wind farms

This section first defines the study area, then the datasets used within the simulations are detailed, followed by a description of how individual wind farm displacement was simulated, and finally, how cumulative wind farm displacement was simulated.

7.2.1 Study area – the Outer Thames Estuary Special Protection Area

The Outer Thames Estuary SPA and the red-throated diver qualifying feature of the SPA, as described in section 5.2.1, were again used as the context for this chapter. As mentioned throughout this thesis, the maximum extent of red-throated diver displacement from an offshore wind farm in the literature was 16km (Mendel *et al.*, 2019). Therefore, in order to examine the potential worst-case impact of future wind farms on the SPA, the entire SPA plus a 16km buffer was used as the study area.

7.2.2 Datasets used in simulating cumulative displacement of red-throated divers

Several publicly available datasets were used in this study and are described in Table 7.1:

- JNCC's Special Protection Areas (SPAs) with marine components (all UK waters) shapefile dataset, providing spatial information on marine protected areas for birds in UK waters.
- The Seabird Mapping and Sensitivity Tool (SeaMaST) provides seabird density and wind farm sensitivity maps for English waters.

In addition, The Crown Estate's Offshore Wind Site Agreements (England, Wales & NI) shapefile dataset was used, as described in Table 5.1.

Table 7.1. Datasets used to simulate the cumulative displacement of red-throated divers in the Outer Thames Estuary Special Protection Area (SPA).

Dataset	**JNCC's Special Protection Areas (SPAs) with marine components (all UK waters) shapefile**	**Seabird Mapping and Sensitivity Tool (SeaMaST)**
Overview	Spatial information on marine protected areas for birds	Seabird density and wind farm sensitivity maps
Spatial scale	UK Exclusive Economic Zone	English inshore (<12nm from coast) and offshore (>12nm from coast) waters
Temporal scale	Data as of March 2022. Covers all existing SPAs	Published 2019. Generated using survey data from 1979 to 2012
Detailed information	Contains boundaries of all SPAs with marine components across the UK, including the site code, site name, site status, and country. An associated spreadsheet contains further detail on the protected features at each SPA.	Tool mapping the density of seabirds and waterbirds and their sensitivity to offshore wind farms in England. Density distribution data was collated from aerial and boat-based surveys undertaken between 1979 and 2012, and a density surface was created through the use of a Generalised Additive Model (GAM) with distance to the coast as the primary covariate (further information in Bradbury *et al.* (2014). The density surface was mapped onto a 3km by 3km square grid, with bird density in each grid cell described in birds/km^2. Density distribution maps split by breeding and non-breeding season; data from aerial, boat-based, and both aerial and boat-based survey data; and birds flying, birds sitting on the water, and both birds flying and birds sitting on the water.

JNCC's Special Protection Areas (SPAs) with marine components (all UK waters) shapefile was used to obtain the boundary of the Outer Thames Estuary SPA. The density of non-breeding red-throated divers sitting on the water from aerial survey data from SeaMAST used as the baseline for analysing displacement is shown in Figure 7.1, along with the boundary of the Outer Thames Estuary SPA. As the red-throated diver was the species of interest, and the species is only present in the southern North Sea over the winter, the SeaMAST data covering the non-breeding season were used. Red-throated divers are particularly susceptible to disturbance by vessels, including boats carrying out surveys; the maps based on data from aerial surveys were selected as they are more likely to accurately capture the distribution of red-throated divers without the influence of the survey vessel.

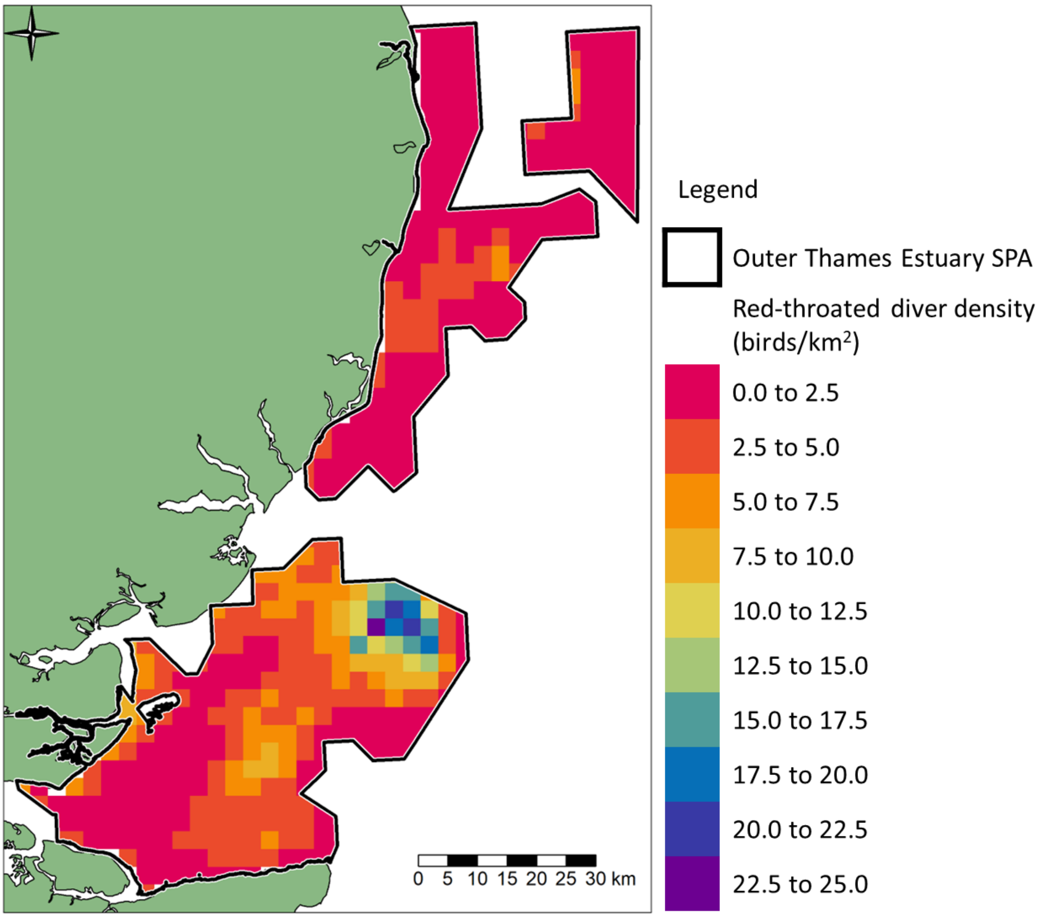

Figure 7.1. The total density of sitting and flying red-throated divers based on aerial survey data from 1979 and 2012, within the Outer Thames Estuary Special Protection Area (SPA), southern North Sea, UK.

Finally, maps based on birds sitting on the water and birds flying were used, as birds flying through a proposed wind farm area could be affected by either barrier effects or displacement. Flying birds may be transiting to another location and, therefore, potentially at risk of barrier effects due to the presence of a wind farm, or they may have been using the proposed wind farm area for foraging and, therefore, potentially at risk of displacement effects due to the presence of a wind farm. At present, the observation of a flying bird during an aerial survey does not give information on whether the bird was transiting or using the area for foraging. Therefore, it is assumed for this chapter that birds flying and sitting on the water are potentially subject to displacement, and both are often included in a displacement assessment.

From a methodological point of view, it is important to determine if the SeaMAST dataset gives a reasonable estimation of the wintering red-throated diver population for use in this thesis. The SeaMAST data showed that the red-throated diver population within the entire SPA was 15,195 individuals. This corroborates surveys from 2013 and 2018 showing populations of 14,161 and 21,997, respectively (APEM, 2013; Irwin *et al.*, 2019), giving assurances on the use of the SeaMAST dataset for this analysis.

7.2.3 Calculating wind farm displacement of red-throated divers

There were several stages to calculating wind farm displacement, from individual displacement due to existing wind farms to cumulative displacement from existing and future wind farms. The various stages of calculation are shown schematically in Figure 7.2 and explained in the subsequent sections. This section starts by describing how individual wind farm's displacement can be calculated, including how maximum displacement distances and displacement gradients are defined. The section concluded by describing the ways in which cumulative wind farm displacement can be calculated.

Individual wind farm displacement	Maximum displacement distance (km)	0km					
	Displacement gradient	100% within			Basic gradient		
Cumulative wind farm displacement	Calculating cumulative displacement	Impacted once in order	Impacted once from closest	Impacted multiple times	Impacted once in order	Impacted once from closest	Impacted multiple times

Figure 7.2. The variables included in simulating cumulative wind farm displacement of red-throated divers, showing the example of 0km maximum displacement distance.

Note: There were 17 variables of maximum displacement distance (0km shown, range 0-16km), two displacement gradients (“100% within” and “Basic gradient”), and three methods calculating cumulative displacement (“Impacted once in order”, “Impacted once from closest”, “Impacted multiple times”). The combination of 17 maximum displacement distances, two displacement gradients, and three methods of calculating cumulative displacement gives a total of 102 scenarios of individual wind farm displacement.

7.2.3.1 Calculating individual wind farm displacement

Calculating individual wind farm displacement was split into several steps, each with several variable values to model within them:

- First, the maximum displacement distance was determined, with 17 variables modelled

- Second, the displacement rates to use within and outside of the wind farms (termed displacement gradient) were calculated, with two displacement gradients modelled

For each of the 17 maximum displacement distances, there were two displacement gradient variables, resulting in a total of 34 scenarios of individual wind farm displacement. Red-throated diver densities within and surrounding each wind farm boundary were calculated in distance bands between the wind farms out to the maximum displacement distance. The displacement rates within each of the two displacement gradients were applied to the distance bands to calculate the full extent of displacement under each of the 17 scenarios of maximum displacement distance.

7.2.3.1.1 Maximum displacement distances

A worst-case scenario of displacement regarding spatial extent was based on the largest known cited displacement distance of 16km from a wind farm site in the German North Sea (Mendel *et al.*, 2019). Several slighter lower displacement distances have also been observed (10-15km in the German North Sea (Heinänen *et al.*, 2020) and 11.5km in the southern North Sea (APEM, 2021), making 16km a realistic maximum displacement distance. Therefore, offshore wind farms within 16km of the Outer Thames Estuary SPA boundary were selected for analysis and included wind farms at all stages of development. The location and status of wind farms, the Outer Thames Estuary SPA, and a 16km displacement distance around the SPA are shown in Figure 5.2.

A range of maximum displacement distances was simulated from within the wind farm only up to 16km, at intervals of 1km. Distance bands within each maximum displacement distance were generated, each with a width of 1km, to allow displacement rates to be applied to each distance band, enabling a displacement gradient to be formed. For example, for the scenario of maximum displacement distance of 3km, the impact areas were split into within wind farm, 0km-1km, 1km-2km, and 2km-3km distance bands. The value of 1km for distance bands was chosen as this has often been used by other studies when reporting red-throated diver displacement (see Table 4.2) and would also make these results comparable with the outputs of other studies. The non-breeding season red-throated diver density within the Outer Thames Estuary SPA was cropped to these rings so that displacement rates could be assigned.

7.2.3.1.2 Displacement rates within the wind farms

Two scenarios of displacement rates within the wind farm were used. The first was based on a worst-case scenario of a 100% displacement rate within the wind farm, and the second was based on the maximum displacement distance. In Chapter 5, it was established that studies of red-throated diver often report displacement rates within wind farms of 100%. Chapter 5 also established that there appears to be a trend in that the larger the maximum displacement distance, the lower the wind farm displacement rate. Therefore, both of these were taken forward as possible scenarios of displacement rates within wind farms to be simulated.

For the scenario of a trend in displacement rate within the wind farm with maximum displacement distance, as shown in Chapter 5, an equation was generated from the trend. Therefore, the within-wind farm displacement rate for each maximum displacement distance scenario was based on Equation 7.1.

$$y = -2.18x + 98.53$$

Equation 7.1. Trend in displacement rate within the wind farm with maximum displacement distance.

where

y = within wind farm displacement rate

x = maximum displacement distance

The displacement rates within the wind farm for each of the 17 maximum displacement distances are shown in Table 7.2.

Table 7.2. Example: red-throated diver displacement rates within the wind farm for 17 different maximum displacement distances to be applied to the case study of cumulative future displacement in the Outer Thames Estuary Special Protection Area (SPA).

Maximum displacement distance scenario	**Displacement rate within the wind farm (%)**
Within wind farm	98.53
1	96.35
2	94.17
3	91.99
4	89.81
5	87.63
6	85.45
7	83.27
8	81.09
9	78.91
10	76.73
11	74.55
12	72.37
13	70.19
14	68.01
15	65.83
16	63.65

7.2.3.1.3 Displacement rates outside the wind farms

Once the red-throated diver displacement rates within the wind farm had been simulated, the next step was to determine the gradient of displacement out to each of the maximum displacement distances. This was done for each scenario of maximum displacement from 0km to 16km and each scenario of either a 100% displacement rate within the wind farm or displacement rates within the wind farm determined by the maximum displacement distance, as shown in Table 7.2.

The displacement gradient was generated by applying the method of averaging a displacement gradient where relative distances and displacement rates are used, as outlined in Chapter 5. This method generated Equation 7.2, which can be used when different wind farm displacement rates and different maximum displacement distances are being simulated.

$$y = -0.60x + 91.17$$

Equation 7.2. Trend in percentage of within wind farm displacement rates with percentage of maximum displacement.

where

y = percentage of within wind farm displacement rate
x = percentage of maximum displacement distance

The red-throated diver displacement rates within the wind farm were either 100% under the first scenario or those within Table 7.2 under the second scenario. The displacement rates within each of the distance bands outside the wind farm could, therefore, be calculated from the proportion of the displacement rate within the wind farm at each distance band as a proportion of the maximum displacement distance. These two sets of displacement gradients were generated for each of the 17 maximum displacement distances. The two displacement gradients were named “100% within” for the scenario where the displacement rate within the wind farm was set at 100% and “Basic gradient” for the scenario where the displacement rate within the wind farm was based on the maximum displacement distance.

Examples of the rates of displacement within each distance band when the maximum displacement distance was 5km, 10km, and 16km, under either scenario of a “100% within” gradient or a “Basic gradient”, are shown in Table 7.3. Under the “100% within” scenario, the displacement rate within the outermost distance band, regardless of maximum displacement distance, was 31%. This was because the within wind farm displacement rate was always 100%, regardless of maximum displacement distance, and the displacement rate in each distance band was based on a proportion of the within wind farm displacement rate, depending on the distance band in question. Therefore, the displacement rate within the distance band was always the same proportion of the within the wind farm displacement rate (100%), and the displacement rate in interim distance bands differed as the maximum displacement distance differed. In comparison, the within wind farm displacement rate under the “Basic gradient” scenario differed with maximum displacement distance, and the displacement rate in each distance band was based on this value. Therefore, the outermost distance band always had a different displacement rate regardless of maximum displacement distance and was also, therefore, different from equivalent distance bands under the “100% within” scenario. Displacement rates used for all maximum displacement distances are shown in Appendix Table H1 and Appendix Table H2.

Table 7.3. Example red-throated diver displacement rates within each distance band, when maximum displacement was 5km, 10km, and 16km, assuming a 100% displacement rate within the wind farm ("100% within") and assuming the displacement rate within the wind farms is determined by on the maximum displacement distance ("Basic gradient").

	Displacement rate (%)					
	100% within			**Basic gradient**		
Distance band (km)	**5km max**	**10km max**	**16km max**	**5km max**	**10km max**	**16km max**
Within wind farm	100.00	100.00	100.00	87.63	76.73	63.65
0-1	79.00	85.00	87.00	69.23	65.22	55.38
1-2	67.00	79.00	83.00	58.71	60.62	53.47
2-3	55.00	73.00	79.00	48.20	56.01	50.92
3-4	43.00	67.00	76.00	37.68	51.41	48.37
4-5	31.00	61.00	72.00	27.17	46.81	45.83
5-6	N/A	55.00	68.00	N/A	42.20	43.92
6-7	N/A	49.00	64.00	N/A	37.60	41.37
7-8	N/A	43.00	61.00	N/A	32.99	38.83
8-9	N/A	37.00	57.00	N/A	28.39	36.28
9-10	N/A	31.00	53.00	N/A	23.79	34.37
10-11	N/A	N/A	49.00	N/A	N/A	31.83
11-12	N/A	N/A	46.00	N/A	N/A	29.28
12-13	N/A	N/A	42.00	N/A	N/A	26.73
13-14	N/A	N/A	38.00	N/A	N/A	24.82
14-15	N/A	N/A	34.00	N/A	N/A	22.28
15-16	N/A	N/A	31.00	N/A	N/A	19.73

7.2.3.2 Calculating cumulative wind farm displacement

Once displacement scenarios had been calculated, the next methods of calculating future cumulative displacement were explored. The 34 scenarios of individual wind farm displacement (see section 7.2.3.1) were taken through to then calculate cumulative wind farm displacement in the final stage, with three scenarios of simulating cumulative wind farm displacement described below. Therefore, 34 scenarios of individual displacement multiplied by three scenarios of cumulative displacement resulted in a total of 102 different scenarios were simulated.

The calculation of cumulative displacement from more than one wind farm was done in several ways, based on realistic and precautionary approaches, and all hypothetical at present. The scenarios were based on how the impact from multiple wind farms overlapping the same area of the sea was calculated:

- Cumulative displacement scenario 1: The first scenario assumed that overlapping areas of the sea were only impacted once, and due to the order in which wind farms were built. This was named “Impacted once in order” (Section 7.2.3.2.1)
- Cumulative displacement scenario 2: The second scenario also assumed areas of the sea could only be impacted once, but that the impact was due to the closest wind farm. This was named “Impacted once from closest” (Section 7.2.3.2.2)
- Cumulative displacement scenario 3: The third scenario allowed for multiple wind farms to each have an impact on an area of sea, such that impacts were additional. This was named “Impacted multiple times” (Section 7.2.3.2.3)

This was initially done for operational wind farms only, then with the addition of wind farms under construction, consented in the planning system and pre-planning application submission. Within and around the Outer Thames Estuary SPA, there were only operational, consented, and pre-planning application submission wind farms.

7.2.3.2.1 Cumulative displacement scenario 1: Impacted once in order

In this first scenario, it was assumed that the first offshore wind farm constructed had an impact on a particular area. A second offshore wind farm was built, and its impact covered a particular area. If there were overlapping regions of impact from the first and second wind farms, the area impacted by the first wind farm remained the same as if it alone was constructed. The impact of the second wind farm was the area that its impact covered minus the overlap with the existing OWF. Thus, there was no double counting within an overlapping impact area. It was assumed that any birds not displaced by the first wind farm were also not displaced by the second wind farm. To a degree, this may be true, as it may be that a bird not displaced by the first wind farm is not very sensitive to the presence of anthropogenic structures and, therefore, would not be displaced by a second wind farm. However, it may depend on how close the new wind farm is constructed relative to the bird in question, compared to the proximity of the first wind farm. A bird not displaced sitting on the water in the 16km distance band from the first wind farm may then also be sat on the water within the second wind farm when it is constructed. In that case, it would seem unlikely that a bird would not be displaced by a wind surrounding it, just because it was not displaced by a wind farm 16km away. The order in which operational OWFs were built is shown in Table 7.4 and shown along with distance bands in Figure 7.3.

Table 7.4. The order in which currently operational wind farms (as of July 2023) in and around the Outer Thames Estuary Special Protection Area (SPA) were built.

OWF number	**Offshore wind farm**	**Turbine construction started**	**Turbine construction finished**
1	Scroby Sands	2003	2004
2	Kentish Flats	2005	2005
3	Gunfleet Sands	2009	2010
4	Thanet	2009	2010
5	Greater Gabbard	2010	2012
6	London Array	2012	2012
7	Gunfleet Sands demo	2013	2013
8	Kentish Flats extension	2015	2015
9	East Anglia One	2019	2020

The order in which wind farms were constructed made a difference to the displacement rate applied at a particular at-sea location due to the distance band at that location. For instance, Wind Farm Number Two was built before Wind Farm Number Three, and there were overlapping areas of impact that were attributed to Wind Farm Number Two only. Therefore, the spatial extent of the impact from wind farm number three was reduced. Wind farm number six was built after several other wind farms nearby, making its attributable impact far smaller in spatial extent than if the other earlier wind farms were not built. The order in which future wind farms will be built was unknown and, therefore, was not modelled.

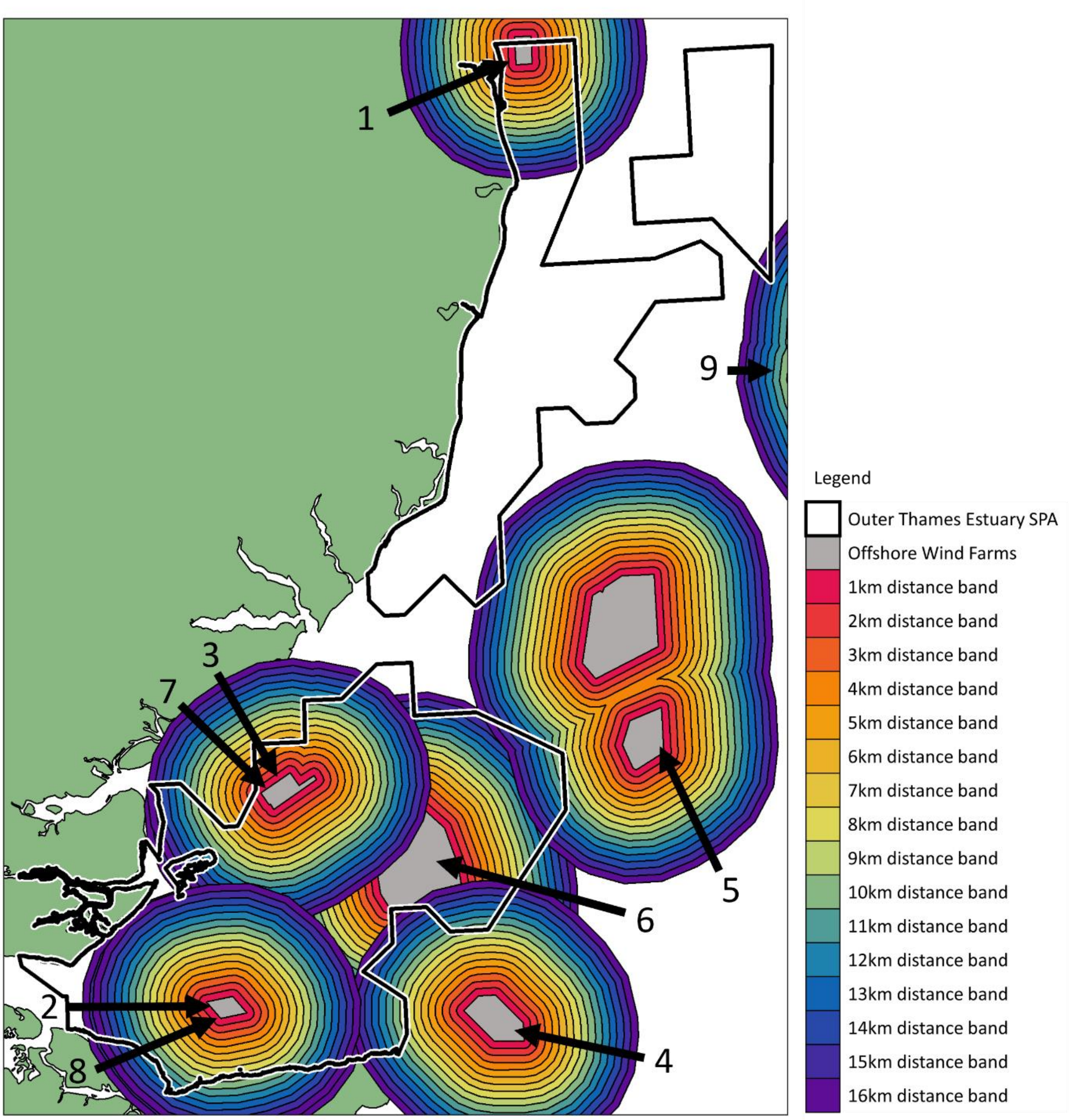

Figure 7.3. Map of how cumulative displacement was calculated under scenario 1: Impacted once in order for operational wind farms.

Note: The figure shows the impact of wind farms within 16km of the Outer Thames Estuary Special Protection Area (SPA), UK, and the distance bands around them that would be assigned to each wind farm. The order in which wind farms were built, and hence the number indicated in the figure, are shown in Table 7.4.

The same principle was then also applied separately to consented wind farms and pre-planning application wind farms. There were two consented wind farms within 16km of the Outer Thames Estuary SPA and one pre-planning application wind farm. It is reasonably safe to assume that the two consented wind farms will get built before the pre-planning application wind farm. However, it is far less certain which of the two consented wind farms would be built first. Therefore, when considering the consented wind farms, two scenarios were simulated, with either wind farm being built first. Then, when considering the of the pre-planning application wind farm, two scenarios were simulated, again with either consented wind farm being built first, followed by the second, then the pre-planning wind farms (Table 7.5). The order of operational consent and pre-planning application wind farms, along with distance bands, is shown in Figure 7.4.

Table 7.5. The order in which operational, consented, and pre-planning application wind farms in and around the Outer Thames Estuary Special Protection Area (SPA) were simulated to be built.

		Offshore wind farm order	
Stage	**Offshore wind farm**	**Consented build scenario 1**	**Consented build scenario 2**
Operational	Scroby Sands	1	1
Operational	Kentish Flats	2	2
Operational	Gunfleet Sands	3	3
Operational	Thanet	4	4
Operational	Greater Gabbard	5	5
Operational	London Array	6	6
Operational	Gunfleet Sands demo	7	7
Operational	Kentish Flats extension	8	8
Operational	East Anglia One	9	9
Consented	East Anglia One North	10	11
Consented	East Anglia Two	11	10
Pre-planning application	North Falls	12	12

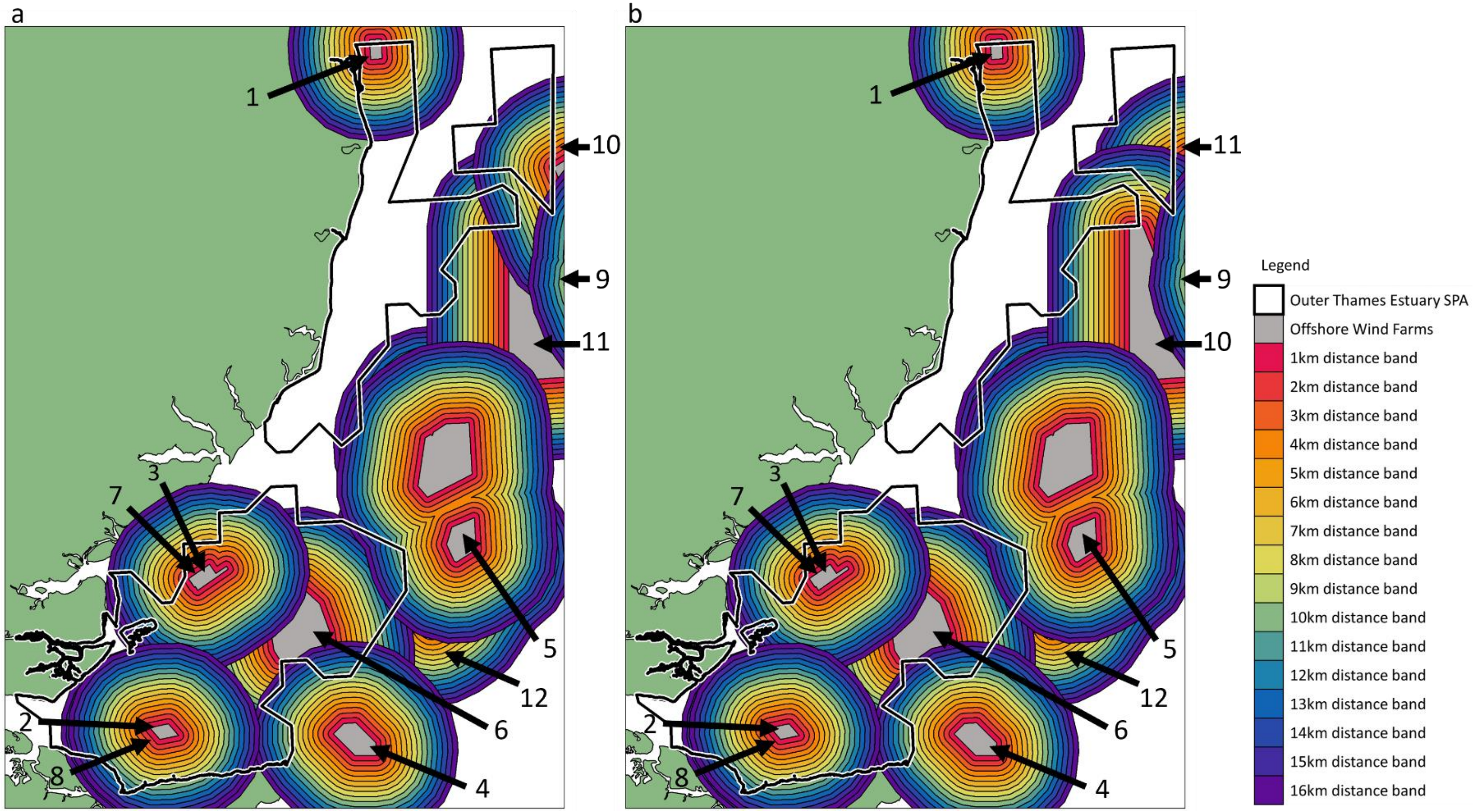

Figure 7.4. Map of how cumulative displacement was calculated under scenario 1: Impacted once in order for operational, consented, and pre-planning application wind farms. Figure 7.1.a assumes East Anglia One North is built first (number 10), followed by East Anglia Two (number 11). Figure 7.4.b assumes East Anglia Two is built first (number 10), followed by East Anglia One North (number 11).

Note: The figure shows the impact of wind farms within 16km of the Outer Thames Estuary Special Protection Area (SPA), UK, and the distance bands around them that would be assigned to each wind farm. The order in which wind farms were built, and hence the number indicated in the figure, are shown in Table 7.5.

7.2.3.2.2 Cumulative displacement scenario 2: Impacted once from the closest

In this second scenario, it was again assumed that only one wind farm had an impact on a particular area of the sea. However, in this scenario, where there were overlapping areas from multiple wind farms, the impact was attributed to the wind farm closest to that area of the sea. In practice, this meant that distance bands from different wind farms would merge together once they overlapped. Depending on the distance between wind farms, this meant different distance bands would be merged; for example, all distance bands up to and including the 5km distance bands from two wind farms 10km apart would not merge together, but the 6km distance bands and larger would merge together. The spatial extent of some wind farms was reduced in this scenario, where they were closer than 32km to another wind farm. The merged distance bands around operation wind farms, operational and consented wind farms, and operational, consented and pre-planning application wind farms are shown in Figure 7.5.

Since impacts were attributed to the closest wind farm and the displacement gradients were applied to distance bands until the distance bands from multiple wind farms merged, impacts at the same distance from each wind farm had the same displacement rate.

This is probably the most likely scenario to occur in reality, as it would make ecological sense that birds are most sensitive to and displaced by the wind farm closest to them. This scenario does not, however, account for any increased displacement rates due to the presence of multiple wind farms, particularly at locations which were mid-way between two wind farms. It is plausible that, at those locations, more birds are affected due to increased anthropogenic pressure.

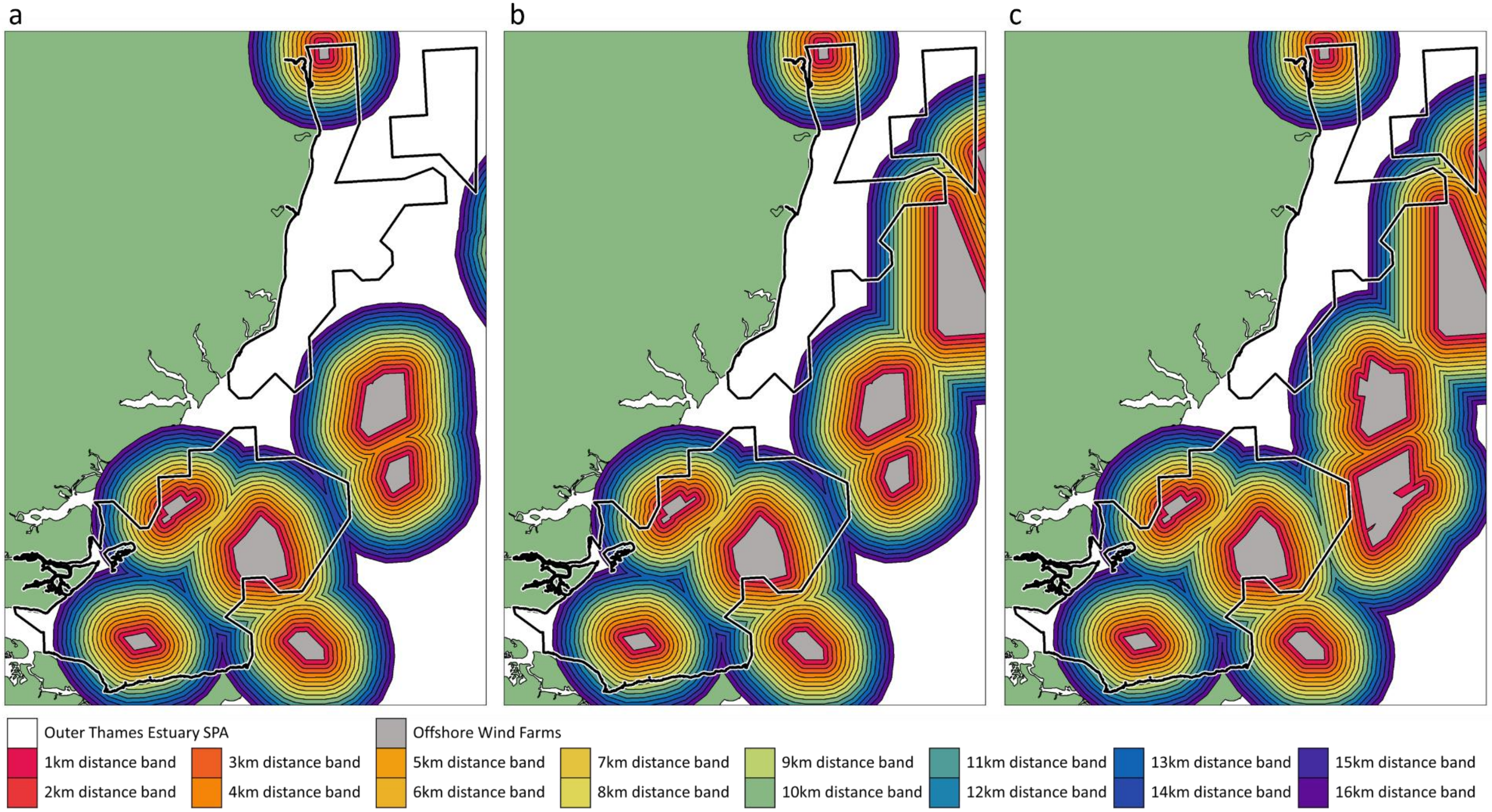

Figure 7.5. Map of how cumulative displacement was calculated under scenario 2: Impacted once from closest: Figure 7.5.a operational wind farms, Figure 7.5.b operational and consented wind farms, and Figure 7.5.c operational, consented, and pre-planning application wind farms.

Note: The figure shows the impact of wind farms within 16km of the Outer Thames Estuary Special Protection Area (SPA), UK, and the distance bands around them that would be assigned to each wind farm.

7.2.3.2.3 Cumulative displacement scenario 3: Impacted multiple times

In this final scenario, each wind farm had its own effect, regardless of the effect of other wind farms. Therefore, if there were overlapping areas of the sea due to the effect of multiple wind farms, the total impact on that area was the sum of the individual impacts. This can be seen in Figure 7.6, where distance bands from multiple wind farms overlapped, and displacement was assumed to occur in each distance band, regardless of whether displacement was also occurring in the same location due to another wind farm. Operational consent, pre-planning application wind farms, and distance bands associated with them are all shown in Figure 7.6. This was the sole scenario for calculating cumulative displacement in which the impact from each wind farm was not affected by the impact from another wind farm nor by the addition of further wind farms.

In this scenario, more than 100% of the birds could theoretically have been displaced if the displacement rate in overlapping areas of impact was summed to more than 100%. This may have been possible if there was an increase in the population between the construction of the first and second wind farms, and the baseline for assessing the second wind farm was different to the baseline for assessing the first wind farm. The spatial extent of each wind farm was the maximum displacement distance in every direction. This scenario, the worst-case, may also be likely to occur in reality if birds not displaced by only one wind farm are displaced by more than one wind farm due to this increased pressure.

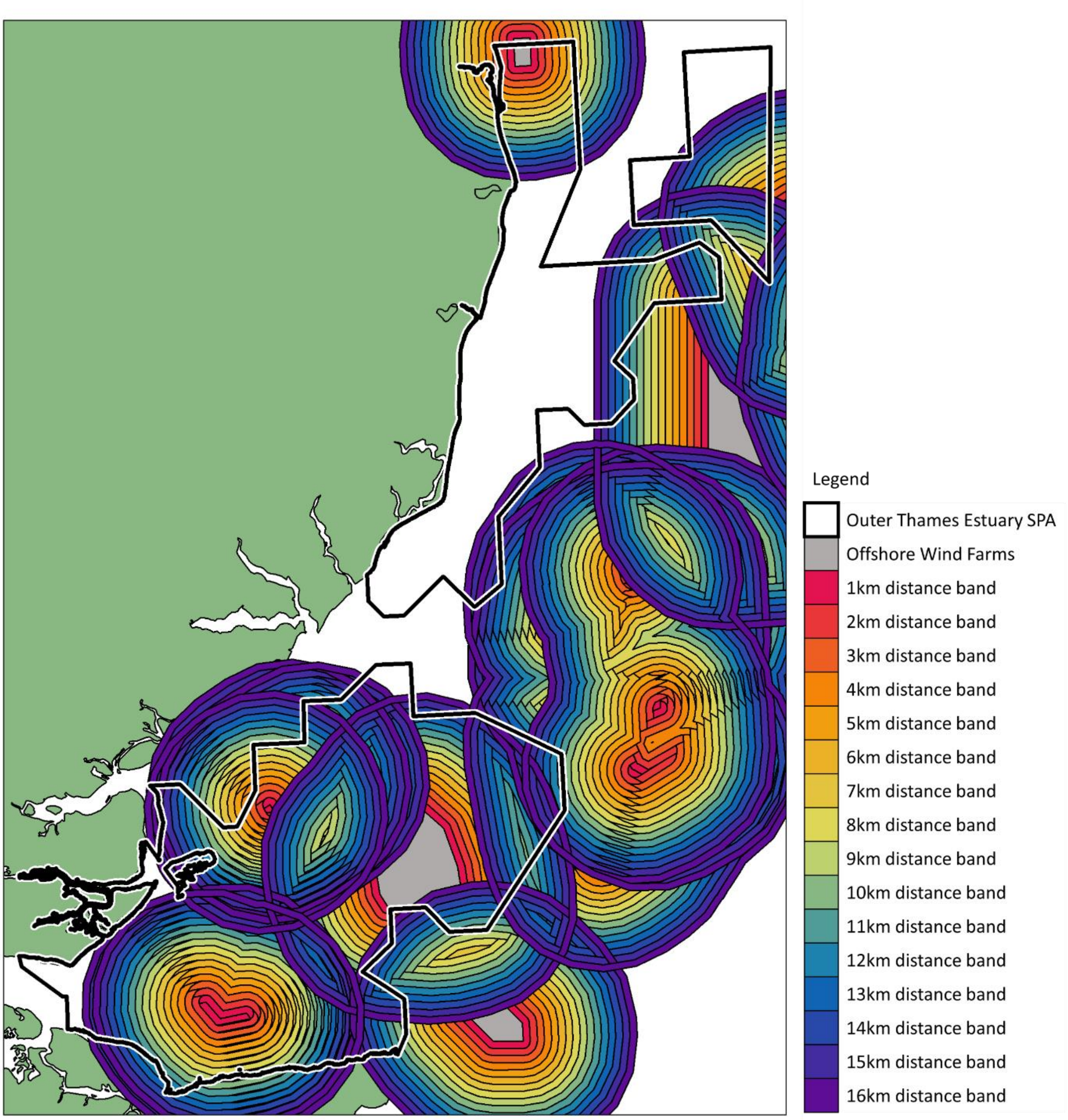

Figure 7.6. Map of how cumulative displacement was calculated under scenario 3: Impacted multiple times for operational, consented, and pre-planning application wind farms.

Note: The figure shows the impact of wind farms within 16km of the Outer Thames Estuary Special Protection Area (SPA), UK, and the distance bands around them that would be assigned to each wind farm.

The analysis was carried out in R (R Core Team, 2022). The R markdown code is available in Appendix I.

7.3 Results of simulating future scenarios of red-throated diver displacement at operational offshore wind farms

The results of simulating each of the scenarios of seabird displacement are presented in this section. First, the area of impact is presented for the operational wind farms, the consented wind farms, the pre-planning application wind farms, and finally, the total of all existing and future wind farms. The influence of the difference in maximum displacement distances and scenarios of calculating cumulative displacement are described. The number of displaced red-throated divers is then presented, again for the operational wind farms, the consented wind farms, the pre-planning application wind farms, and finally, the total of all existing and future wind farms. The influence of the difference in maximum displacement distances, displacement gradients, and scenarios of calculating cumulative displacement are described.

7.3.1 The simulated area impacted by displacement from cumulative wind farm development

First, the results of the area impacted by the operational wind farms are presented, followed by the contribution of the consented and pre-planning application wind farms, followed by the full cumulative effect of all operational consented and pre-planning application wind farms.

7.3.1.1 The simulated area impacted by existing (operational) wind farms only

When considering operational wind farms only, the total affected area under the “Impacted once in order” and “Impacted once from closest” scenarios are equal because impacts are only counted once. In comparison, the total affected area under the “Impacted multiple times” scenario is far greater as impacts from multiple wind farms are summed. If the maximum displacement distance is 16km, under the “Impacted once in order” and “Impacted once from closest”, the total affected area is 2436km^2, whilst under the “Impacted multiple times” scenarios, the total affected area is 5427km^2. Under this latter scenario, the same regions of the SPA are impacted multiple times; therefore, the calculation of the impacted area is far larger than the area of the sea purely. The area of Outer Thames Estuary SPA is 3,924km^2. Therefore, under the two scenarios where birds are affected once, depending on the maximum displacement distance, up to 62% of the SPA area is affected. This is compared to the area of the wind farms alone, which only covers around 5% of the SPA, showing just how much displacement at distances from a wind farm makes a difference to the spatial effect of displacement, particularly in a protected area.

The area of each of the distance bands under each of the three scenarios is different due to the method of calculating cumulative displacement (Figure 7.7). This is an important aspect as different displacement rates are applied to each distance band. Therefore, although the total area affected under the "Impacted once in order" and "Impacted once from closest" scenarios are the same, the number of displaced birds is different. The number of displaced birds under the "Impacted multiple times" scenario is also different, but due to the summing of impacts as well as the displacement rates. The area of the 0km distance band (i.e. within the wind farm) is always larger than the 1km distance band due to the comparatively large size of the wind farms themselves.

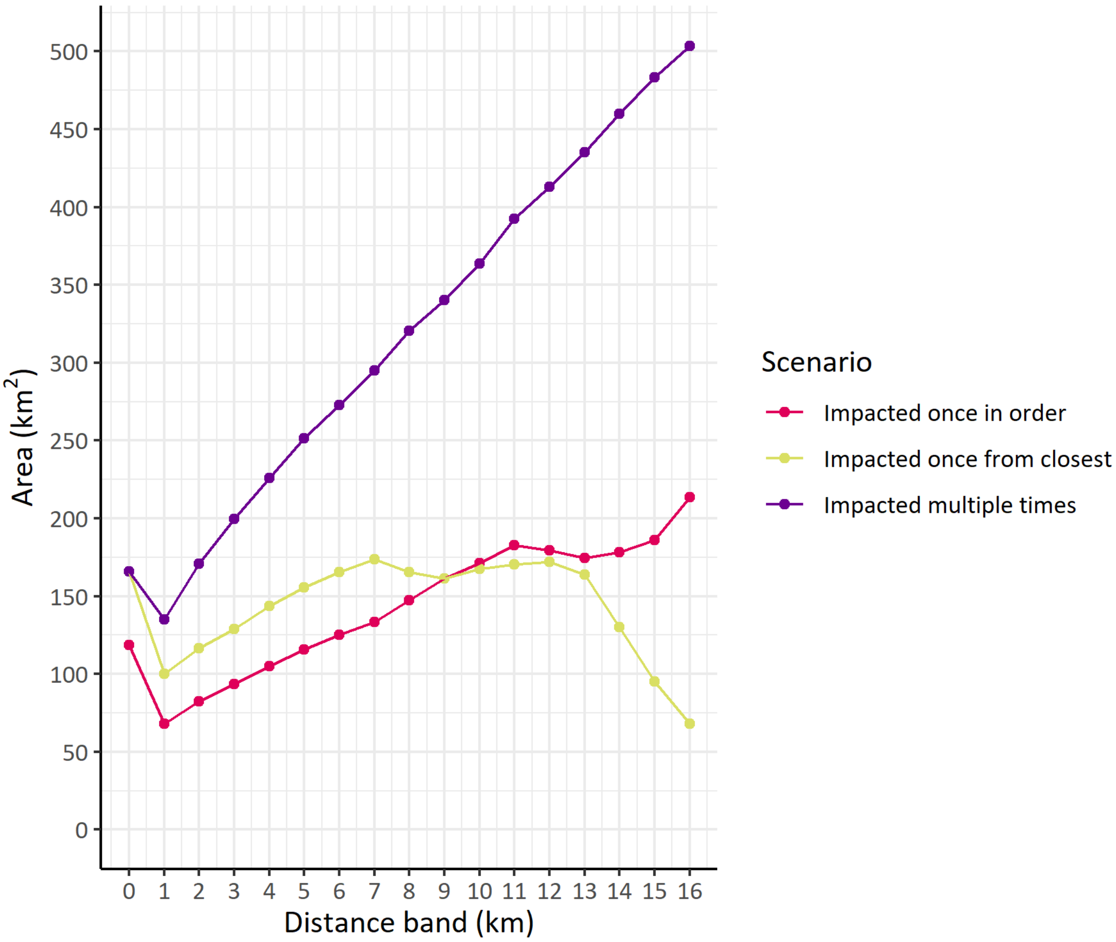

Figure 7.7. The area of each distance band under three scenarios of calculating cumulative displacement from operational offshore wind farms, assuming the maximum displacement distance was 16km.

Under the “Impacted once in order” scenario, the area of each distance band is dependent on the order in which wind farms were built, but also the maximum displacement distance. For example, when the maximum displacement distance is 16km, the impacted area within wind farms (0km distance band) is less than that under the “Impacted once from closest” scenario. This is because the 16km distance band from wind farms built first overlaps the 0km distance band of wind farms built later. Therefore, the impact within that overlapping region has already been assigned to the wind farms built first, thereby removing the impact from the later wind farms. This can be seen in Figure 7.7, where the area within each distance band under the “Impacted once in order” scenario is smaller compared to the “Impacted once from closest” scenario because distance bands from wind farms built first cut away distance bands from later wind farms.

Under the “Impacted once from closest” scenario, several of the wind farms in the southern part of the SPA are around 14km from one another, meaning that distance bands of 7km and over are merged. But as there are multiple wind farms, these outer distance bands merge such that they are only present around the outside edge of the collection of wind farms. Only the smaller distance bands are present between wind farms, as can be seen in Figure 7.5a. This means that the area of distance bands 7km and over is smaller than the other scenarios. This can be seen in Figure 7.7 as the “Impacted once from closest” area line does not increase beyond the 7km distance band. The area even decreases from the 14km distance band where more wind farms are within 28km of one another, again meaning these outer distance bands are only present around the outside edge of the collection of wind farms.

The largest distance bands are under the “Impacted multiple times” scenario because there is no merging or reducing overlapping distance bands. Therefore, the area of each distance band is the sum of each wind farm, and distance bands further from the wind farm increase in size.

7.3.1.2 The simulated area impacted by future (consented and pre-planning application) wind farms only

Although displacement was modelled using operational wind farms as well as consented and pre-planning application wind farms, such that the influence of all wind farms was accounted for, the results presented are solely the contribution of the consented or pre-planning application wind farms. Results are also presented separately for consented wind farms and pre-planning wind farms. This all allows a better indication of the influence of future wind farms.

The area of each distance band and total area affected is calculated separately for wind farms with consent to build and for wind farms yet to submit a planning application. The wind farms with consent to build are located 1km outside the Outer Thames Estuary SPA boundary, meaning there is no impact on the SPA from the displacement within the wind farms themselves, and hence, the area of impact is zero. As previously stated, the order in which the two consented wind farms would be built is unknown; therefore, two scenarios are generated to account for either wind farm being built first under the “Impacted once in order” scenario. Only one scenario is required for the pre-planning application of wind farms, as there is only one wind farm within 16km of the SPA; therefore, there is no ordering of wind farms to consider. Further, the distance bands on the pre-planning wind farm only overlap with one of the consented wind farms’ distance bands. Therefore, the order in which the two consented wind farms are built does not make a difference to the impact of the pre-application wind farm.

The area of impact from consented wind farms under all scenarios of calculating cumulative displacement increases in the further distance bands. Again, the “Impacted multiple times” scenario affects a much larger area (602km^2, the sum of all the “Impacted multiple times” points in Figure 7.8) than the “Impacted once in order” and “Impacted once from closest” scenarios (446km^2). However, these areas are all much smaller compared to those from operational wind farms. This is due to the location of consented wind farms outside rather than within the SPA, the SPA being narrower and closer to the consented wind farms, and there are fewer consented wind farms compared to operational wind farms. The “Impacted once from closest” and “Impacted multiple times” scenarios both have the same area in the 0km to 6km distance bands because those distance bands of the two consented wind farms do not overlap. Therefore, there is no double-counting of the same location under the “Impacted multiple times” scenario. The 0km to 9km distance bands each have smaller areas under the “Impacted once in order” scenario than the “Impacted once from closest”, but the 10km to 16km distance of the “Impacted once from closest” scenario are larger than the “Impacted once in order” scenario. Under the “Impacted once in order” scenario, there is a similar trajectory of area with distance band regardless of whether it is assumed that East Anglia One North or East Anglia Two is built first. The area of each distance band is slightly different if different consented wind farms are built first, but not by any more than 5km^2 (Figure 7.8).

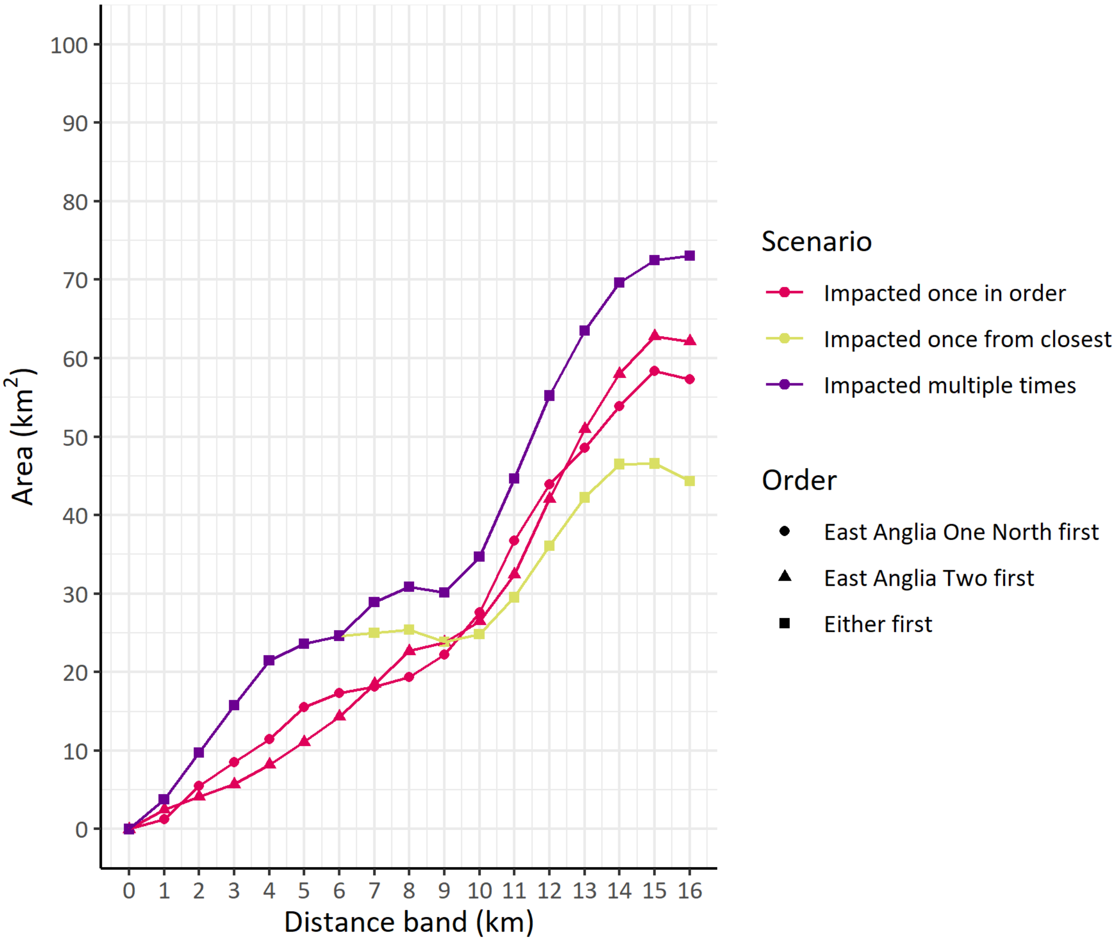

Figure 7.8. The area of each distance band under three scenarios of calculating cumulative displacement from consented offshore wind farms and assuming the maximum displacement distance was 16km.

There is only one pre-planning application wind farm within 16km of the Outer Thames Estuary SPA, and it is situated 2km from the SPA boundary. Therefore, under all three scenarios of calculating cumulative displacement, the impacted area of the smaller distance bands is zero, as these distance bands do not overlap with the SPA.

The area of individual distance bands under the “Impacted once in order” scenario gradually increases in distance bands further from the wind farm. However, the area of the 11km distance band to the 16km distance band declines. This is due to interaction at those points with operational and consented wind farms. The impact in those regions is already attributed to said operational or consented wind farms, removing them from association with the pre-planning wind farms. The total area affected is 93km^3 when the maximum displacement distance is 10km, and 41km^2 when the maximum displacement distance is 16km.

The “Impacted once from closest” scenario has a markedly different pattern of affected area within distance bands beyond the 10km distance band. The 11km, 12k, 13km, 14km, and 15km distance bands all have negative areas (Figure 7.9). This is because the area of each distance band is calculated as the area under the equivalent distance band when operational, consented, and pre-planning application wind farms is included minus the area when operational and consented wind farms are included. As this scenario merges distance bands from different wind farms, the merging of the outer distance band when operational and consented wind farms are included was larger than when pre-planning application wind farm is also included. Figure 7.9 shows the contribution of the pre-planning application wind farm area to the total area of the SPA impacted. Therefore, although this figure shows negative areas for some distance bands, the actual area impacted by all operational, consented, and pre-planning application wind farms is above zero. The total area of impact under the “Impacted once from closest” scenario is 10km^2 when the maximum displacement distance is 16km.

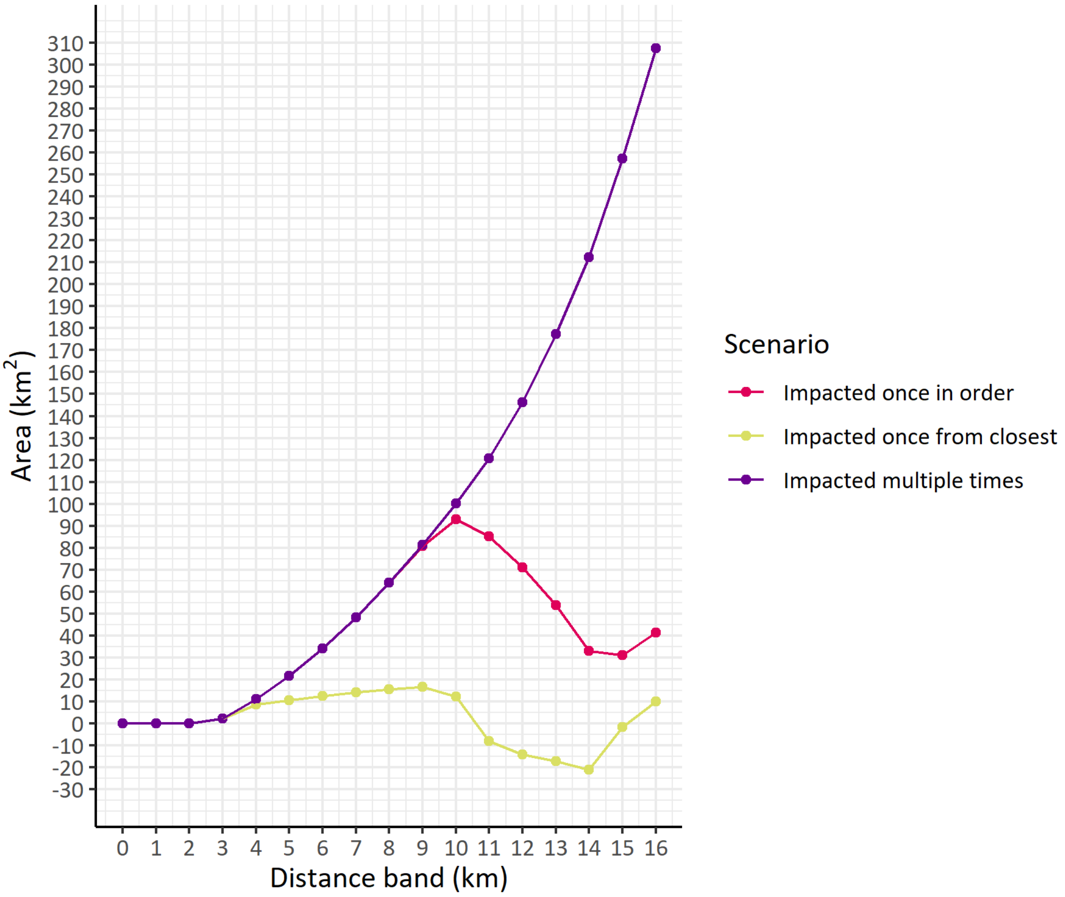

Figure 7.9. The area of each distance band under three scenarios of calculating cumulative displacement from pre-planning application offshore wind farms, assuming the maximum displacement distance was 16km.

The area of individual distance bands under the "Impacted multiple times" scenario for the pre-planning application wind farm sees a similar trend to those for consented wind farms, albeit a smaller area affected. This is mainly because there is only one pre-planning application wind farm affecting the SPA. The total area affected is 307km^2 when the maximum displacement distance is 16km.

7.3.1.3 The simulated area impacted by all existing and future wind farms

The total area impacted by each stage and scenario of calculating cumulative displacement can be seen in Figure 7.10. It is clear that operational wind farms have already caused the largest impact on the SPA in terms of area of impact, with consented and pre-planning application wind farms having a much smaller additional impact. Although these latter wind farms may have a lesser impact, when combined with the existing impact from operational wind farms, the result of adding more wind farms may, in fact, be detrimental.

For instance, under the “Impacted once in order” scenario, 2,436km^2 is impacted if the maximum displacement distance is 16km. Adding the 446km^2 from the consented wind farms and the 671km^2 from the pre-planning application wind farms results in a total of 3,553km^2. This is an increase of 46%, assuming all wind farms are built.

Under the “Impacted once from closest” scenario, 2,443km^2 is impacted if the maximum displacement distance is 16km. Adding the 443km^2 from the consented wind farms and the 42km^2 from the pre-planning application wind farms results in a total of 2,928km^2. This is an increase of 20%, assuming all wind farms are built.

Finally, under the “Impacted multiple times” scenario, 5,427km^2 is impacted if the maximum displacement distance is 16km. Adding the 602km^2 from the consented wind farms and the 1,585km^2 from the pre-planning application wind farms results in a total of 7,614km^2. This is an increase of 40%, assuming all wind farms are built.

The addition of these yet-to-be-built wind farms may, therefore, appear insignificant on their own, but when combined with the already large impact from existing wind farms, may generate sufficient impact beyond a set threshold or tipping point.

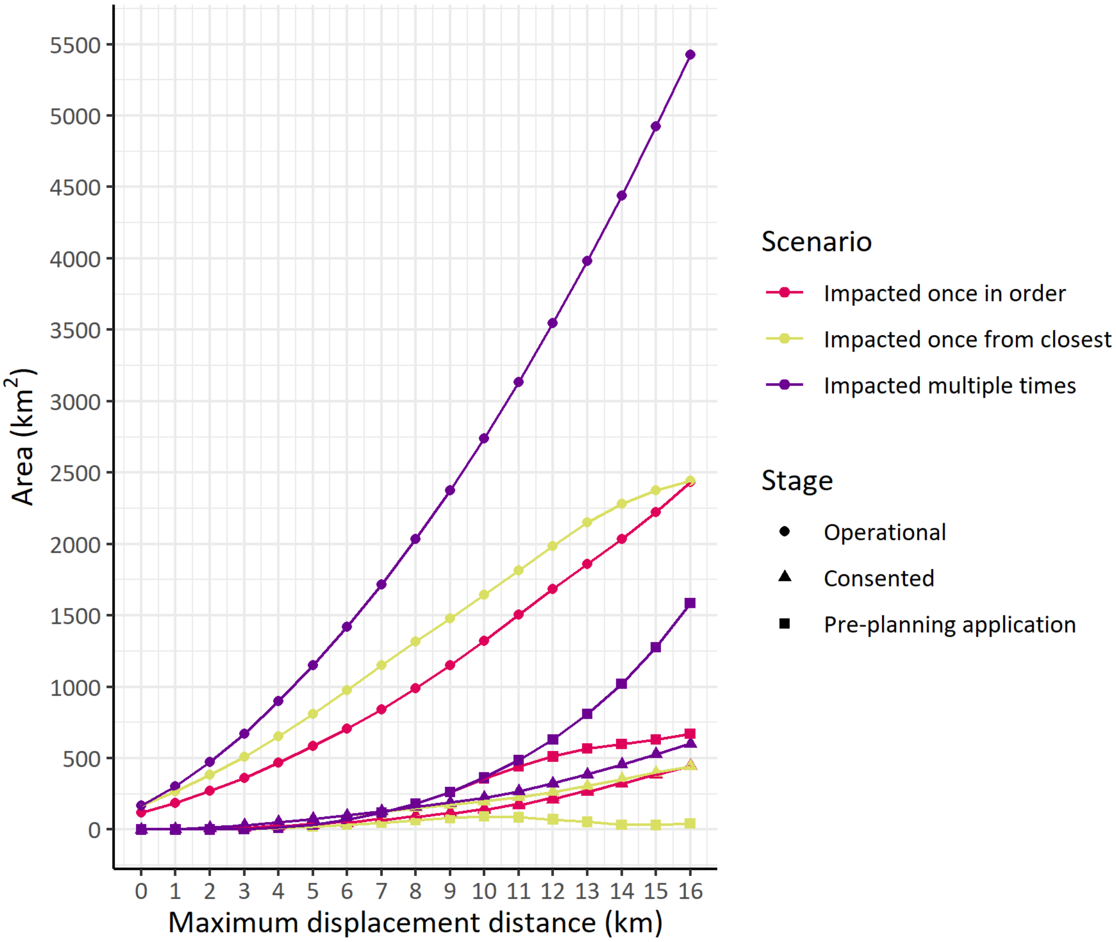

Figure 7.10. The area of the Outer Thames Estuary Special Protection Area (SPA) impacted by displacement by operational consented and pre-planning application wind farms based on a range of maximum displacement distances (0-16km) and three scenarios of calculating cumulative displacement.

7.3.2 The simulated number of red-throated divers displaced from cumulative wind farm development

First, the results of the number of displaced birds for the operational wind farms are presented, followed by the contribution of the consented and pre-planning application wind farms, followed by the full cumulative effect of all operational consented and pre-planning application wind farms.

7.3.2.1 The simulated number of red-throated divers displaced from existing (operational) wind farms only

There are two displacement gradients to apply to the distance bands within each of the maximum displacement distances under each of the scenarios of calculating cumulative displacement. The smallest number of birds are displaced under the “Impacted once in order” scenario, using the “Basic gradient”. The number of birds displaced increases from 448 up to 3,525 birds when the maximum displacement distance is 15km, before dropping slightly to 3,497 birds when the maximum displacement distance is 16km. A similar trajectory is seen under the “Impacted once from closest” scenario whereby the number of birds displaced gradually increases the plateaus to 3,826 birds when the maximum displacement distance is 16km. The combination of lower displacement rates in the “Basic gradient” and the smaller area of outer distance bands results in the levelling of displaced birds when the maximum displacement distance is very large (Figure 7.11).

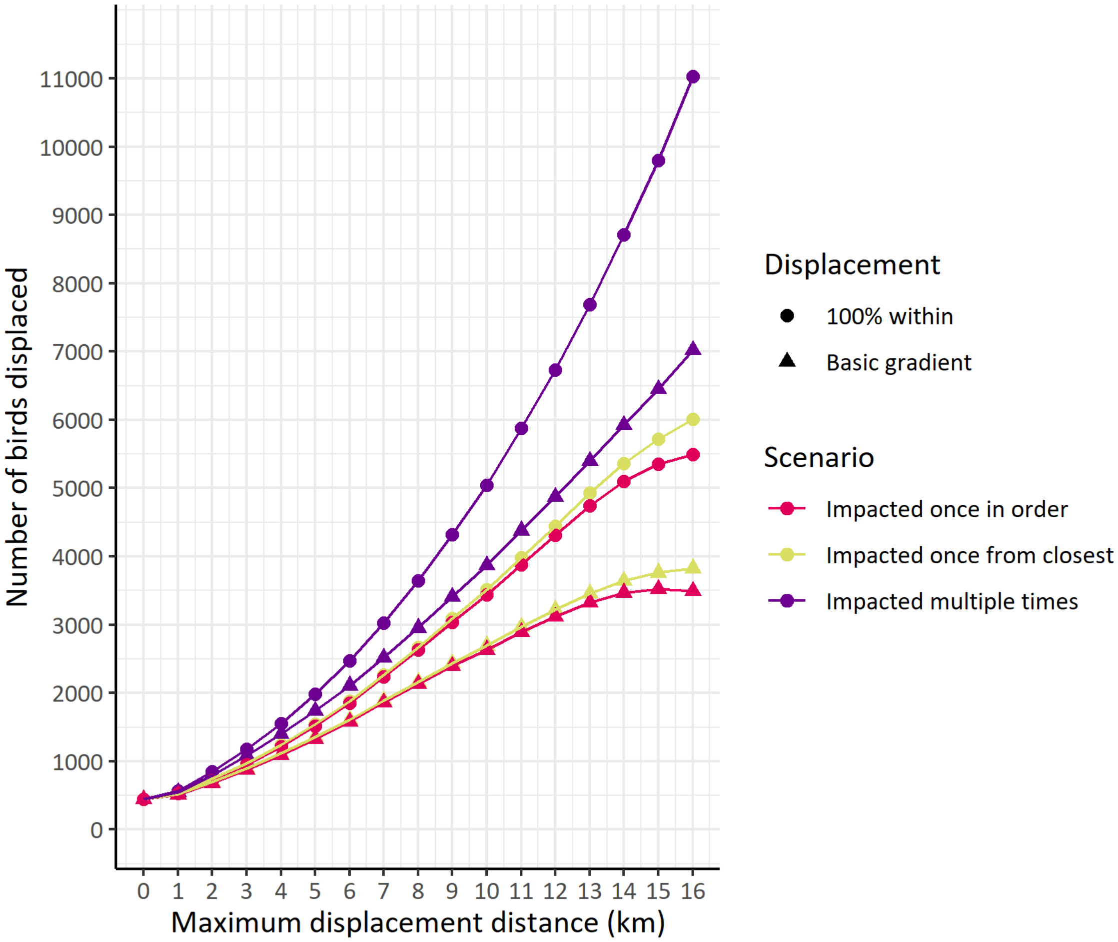

Figure 7.11. The number of red-throated divers within the Outer Thames Estuary Special Protection Area (SPA) displaced by operational wind farms based on a range of maximum displacement distances (0-16km), two displacement gradients, and three scenarios of calculating cumulative displacement.

Meanwhile, under the “Impacted once in order” scenario using the “100% within” gradient, the number of birds displaced increases from 448 up to 5,494 birds when the maximum displacement distance is 16km. Similarly, under the “Impacted once from closest” scenario, the number of birds displaced increases from 448 to 6,012 when the maximum displacement distance is 16km.

Of the three scenarios of calculating cumulative displacement, the “Impacted multiple times” scenario generates the largest number of displaced birds under both displacement gradients. Using the “Basic gradient”, the number of displaced birds gradually increases to 7,018 birds when the maximum displacement distance is 16km. Using the “100% within” displacement gradient, this gradually increases to 11,026 birds when the maximum displacement distance is 16km.

7.3.2.2 The simulated number of red-throated divers displaced from future (consented and pre-planning) wind farms

Again, there are two displacement gradients to apply to the distance bands within each of the maximum displacement distances under each of the scenarios of calculating cumulative displacement. In addition, there are two scenarios of the order in which consented wind farms are built.

When considering displacement from consented wind farms, the smallest number of birds are displaced under the “Impacted once in order” scenario, using the “Basic gradient” (Figure 7.12). There is a marginal difference in the number of displaced birds depending on whether East Anglia One North or East Anglia Two is built (as seen in the 15km and 16km maximum displacement distance in Figure 7.13). Assuming a maximum displacement distance of 16km, under the “Basic gradient”, 212 birds are displaced if East Anglia One North is built first, and 209 birds are displaced if East Anglia Two is built first. Under the “100% within” gradient, 333 birds are displaced if East Anglia One North is built first, and 328 birds are displaced if East Anglia Two is built first.

Under the “Impacted once from closest” scenario, using the “Basic gradient”, the number of birds displaced increases from 0 within the wind farms and one bird at 1km maximum displacement distance up to 224 birds when the maximum displacement distance is 16km. For the “100% within” displacement gradient, a sharper increase in the number of displaced birds is seen, with up to 352 birds displaced with a maximum displacement distance of 16km. Similar trajectories are seen under the “Impacted multiple times” scenario, with up to 270 birds displaced using the “Basic gradient” and up to 424 birds displaced using the

“100% within” displacement gradient, both when the maximum displacement distance is 16km (Figure 7.12).

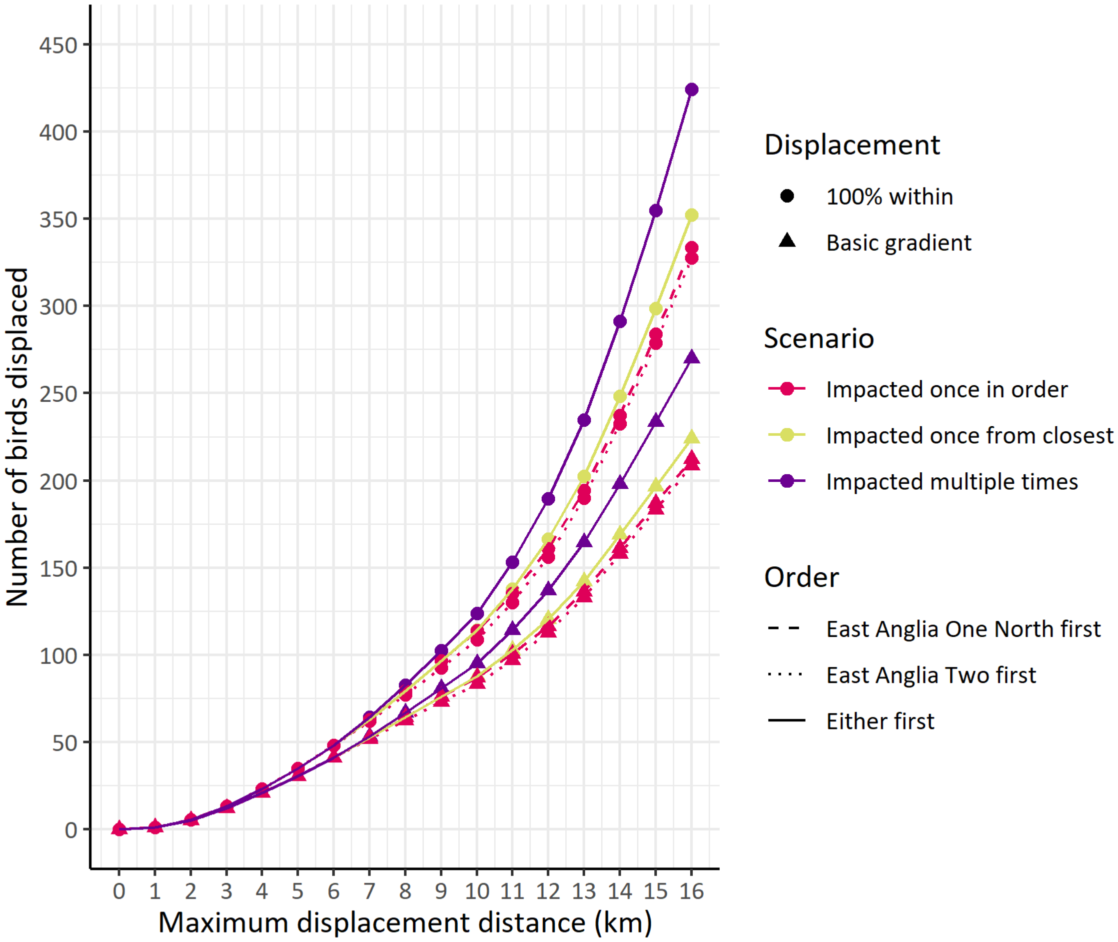

Figure 7.12. The number of red-throated divers within the Outer Thames Estuary Special Protection Area (SPA) displaced by consented wind farms, based on a range of maximum displacement distances (0-16km), two displacement gradients, and three scenarios of calculating cumulative displacement.

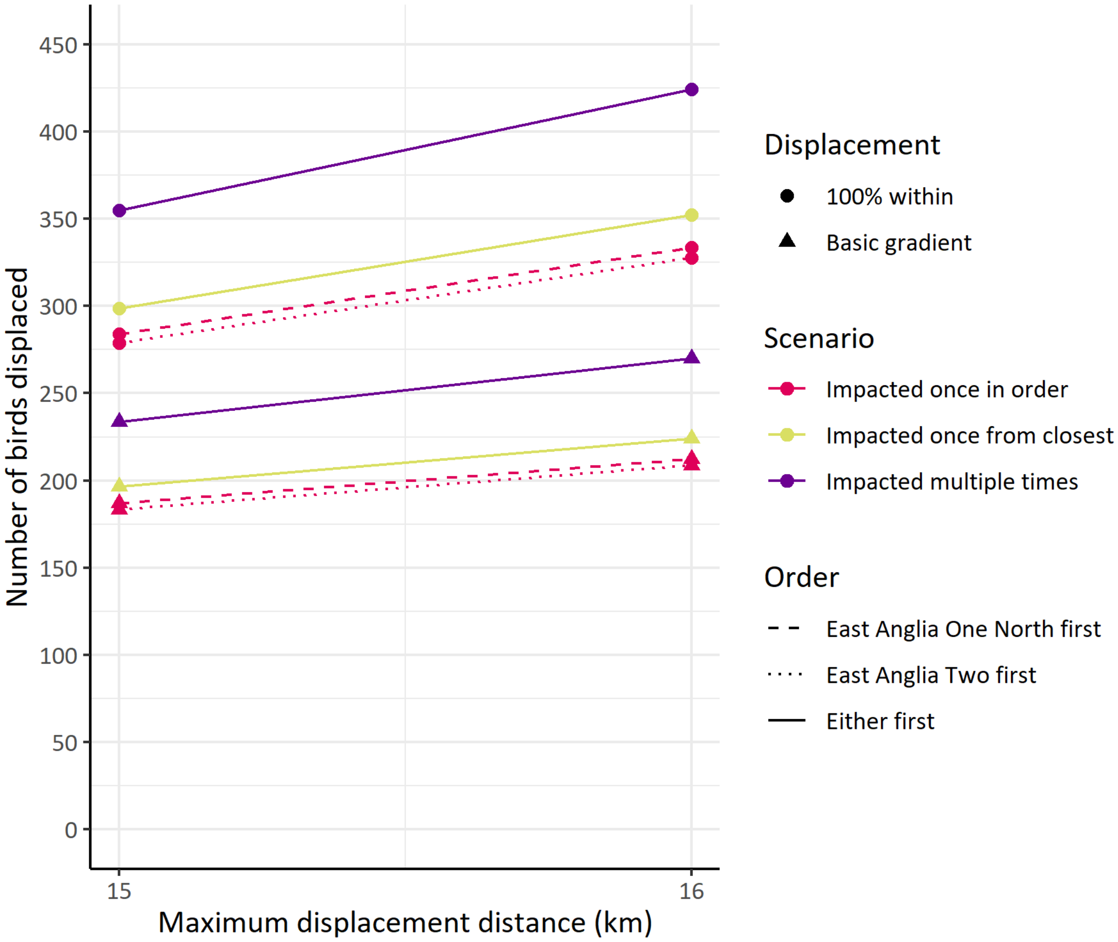

Figure 7.13. The number of red-throated divers within the Outer Thames Estuary Special Protection Area (SPA) displaced by consented wind farms, based on two displacement gradients and three scenarios of calculating cumulative displacement, but with maximum displacement distances of 15km and 16km, showing the small difference in number of displaced birds depending on whether East Anglia One North or East Anglia Two were built first.

When considering displacement from pre-planning application wind farms, the largest number of birds are displaced under the “Impacted multiple times” scenario, using the “100% within” displacement gradient. The number of birds displaced increases from zero within the wind farms and one bird at a 3km maximum displacement distance up to 1,134 birds when the maximum displacement distance is 16km. For the “Basic gradient”, a shallower increase in the number of displaced birds is seen, with up to 722 birds displaced with a maximum displacement distance of 16km.

Meanwhile, the trajectory of the number of displaced birds with maximum displacement distance is markedly different under the “Impacted once in order” and “Impacted once from closest” scenarios.

Under the “Impacted once in order” scenario, the number of displaced birds increases up to a maximum at a maximum displacement distance of 11km, with 312 and 232 birds displaced, respectively (Figure 7.14). Beyond this distance, the number of birds fell rapidly, down to 7 birds and 11 birds displaced under the “100% within” gradient and the “Basic gradient”, respectively. This is due to the large outermost distance bands from pre-planning application wind farms overlapping with operational and consented wind farms. Through this method of calculating cumulative displacement, displacement is already attributed to those earlier wind farms, therefore the little of these distance bands are attributed to pre-planning application wind farms.

Under the “Impacted once from closest” scenario, with both the “100% within” gradient and the “Basic gradient”, the number of displaced birds increases up to a maximum at a maximum displacement distance of 11km, with 324 and 241 birds displaced, respectively (Figure 7.14). Larger maximum displacement distances result in lower numbers of birds being displaced, down to 155 and 99 birds displaced, again with the “100% within” and basic displacement gradients. This is reflective of the area of this scenario of calculating cumulative displacement, whereby when the maximum displacement distance is very large, the distance bands are merged with those from operational and consented wind farms. Therefore, the total impacted area attributed to the pre-planning wind farm is much smaller.

When the maximum displacement distance is 16km, the total impacted area is smaller under the “Impacted once from closest” scenario compared to the “Impacted once in order” scenario, yet more birds are displaced. This is likely due to the distance bands within those two scenarios being in different locations across the SPA due to the different methods of calculating cumulative displacement. Therefore, there are different numbers of birds present to be displaced, even though the displacement rate is the same in the equivalent distance bands.

The number of displaced birds is based on the density of birds across the displacement-affected area, the area of each distance band, and the displacement rate within it. This combination, therefore, means that a smaller overall displacement-affected area could have a larger number of birds displaced compared to a larger overall displacement-affected area.

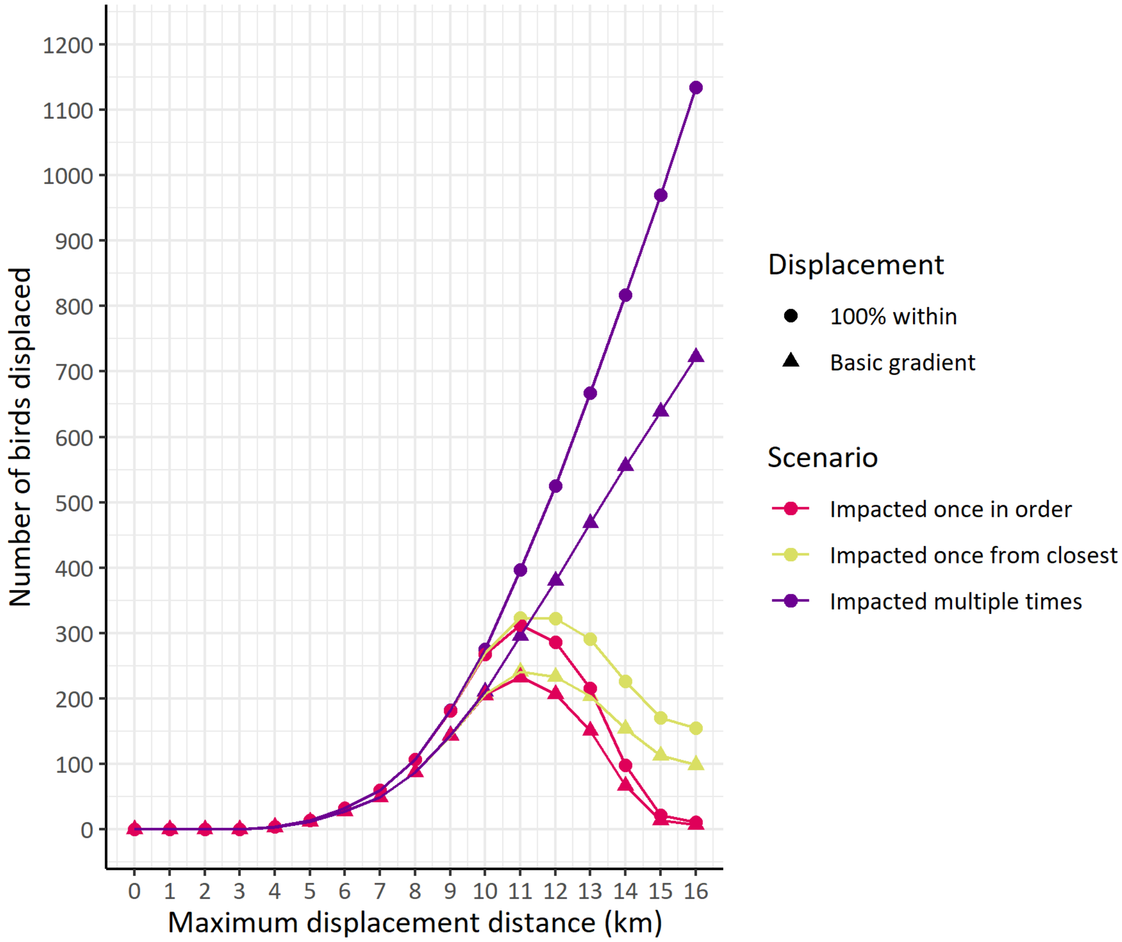

Figure 7.14. The number of red-throated divers within the Outer Thames Estuary Special Protection Area (SPA) displaced by pre-planning application wind farms based on a range of maximum displacement distances (0-16km), two displacement gradients, and three scenarios of calculating cumulative displacement.

7.3.2.3 The simulated number of red-throated divers displaced from all existing and future wind farms

Considering all stages of development together (operational, consented, and pre-planning application wind farms), the full extent of possible displacement is seen. It is clear that operational wind farms have already caused the largest impact on the SPA in terms of the number of birds displaced, with consented and pre-planning application wind farms having a much smaller additional impact. Although these latter wind farms may have a lesser impact when combined with the existing impact from operational wind farms, the result of adding more wind farms may, in fact, be detrimental.

Under the “Impacted once in order” scenario and either the “100% within” or “Basic gradient” displacement gradient scenarios, assuming all future wind farms are built there would be 7% more birds displaced compared to the effect of only the operational wind farms. Under the “Impacted once from closest” scenario and again either displacement gradient scenario, assuming all future wind farms are built there would be 8% more birds displaced compared to the effect of only the operational wind farms. Meanwhile, under the “Impacted multiple times” scenario, regardless of the displacement gradient scenario, assuming all future wind farms are built there would be 12% more birds displaced compared to the effect of only the operational wind farms.

The mean peak population of red-throated divers within the SPA is estimated to be 18,079 individuals (Natural England, 2013). Assuming the worst-case scenario of 16km maximum displacement distance and the “100% within” displacement gradient and under the “Impacted once in order” scenario, the total cumulative displacement from all current and future wind farms (5,838 birds) amounts to 32% of the SPA population. Under the “Impacted once from closest” scenario, the total cumulative displacement of 6,519 birds is 36% of the SPA population. Finally, the 12,584 birds displaced under the “Impacted multiple times” scenario is 70% of the SPA population.

7.4 Discussion on future scenarios of red-throated diver displacement at offshore wind farms

There are many variations of maximum displacement distances, displacement gradients, and methods of calculating cumulative displacement used in this analysis. Some are probably more likely to occur than others, but with so little known about the reasons that red-throated divers move in response to offshore wind farms, these are all plausible. Each of these methods of calculating cumulative displacement could therefore be reasonably applied to displacement impact assessments, and indeed some of them have.

The “Impacted multiple times” method represents the worst-case scenario, with values of area and number of birds effected far outweighing those from the other two methods. Although more than 100% of birds cannot be impacted, it is entirely reasonable to suggest that a higher proportion of birds may be impacted due to multiple wind farms compared to one wind farm. Therefore, although a worst-case scenario, this method may not overestimate reality.

The “Impacted once from closest” would seem to be the most sensible way for birds to be displaced, with only the nearest wind farm causing the displacement. This seems to be the likely mechanism for displacement of birds, or at least for those close to a wind farm. Further from a wind farm it is possible that more than one wind farm cause displacement.

The “Impacted once in order” method could also be biologically realistic, as birds not displaced by one wind farm may be sufficiently resilient to wind farm presence that it is not displaced by a second wind farm, even if the second wind farm is closer than the first. Therefore there could be no additional displacement in overlapping buffers. In the extreme scenario of a second wind farm built within the outermost distance band of an existing wind farm (where displacement rate are likely very low), it is probable that the second wind farm does cause more displacement than is caused by the first wind farm. The parameters of wind farms design could play a part, however. For instance, if the first wind farm consists of many large turbines close to the sea surface, whilst the second consists of fewer smaller turbines then it is plausible that the second wind farm, regardless of distance to a bird, causes less displacement than the first. Note, however, that just because displacement may not occur, or occur to a lesser extent, due to a second wind farm, it may cause additional stress. This could have implications for body condition and knock-on effects to reproduction or survival. At present, there is no established approach to analysing the effects of stress response wind farms for marine birds. Displacement rate alone may not be sufficient to establish the impact to an individual, and much more research is needed on this front.

In terms of the most likely method of calculating cumulative displacement, it is probably a combination of the impacted once from the closest scenario and the impacted multiple times scenario. The impacted once from the closest scenario may apply close to wind farms (i.e. birds only impacted by the closest wind farm), with the impacted multiple times scenario occurring further from wind farms (i.e. birds impacted from multiple wind farms mid-way between wind farms).

What does this mean for future planning of wind farms? Wind farms located close to each other such that the maximum displacement distances from each wind farm overlap mean that the total area impacted is lower than if the wind farms were further apart. This may be advantageous in that the impact is more localised, freeing up areas of the sea that are not impacted. The total number of birds displaced is also likely to be lower within the overlapping impacted regions compared to separate impacted regions. Therefore, it may seem obvious to build wind farms as close together as possible, bearing in mind other considerations such as locating turbines so that they receive as much wind as possible, which may be more difficult when turbines are closer together. However, the suitability of both the impacted and unimpacted habitat for red-throated divers must also be considered. The total number of birds displaced is a combination of factors of displacement due to the wind farm and the density of birds present. Therefore, building wind farms close together to reduce displacement rates in a location with high densities of red-throated divers may, in fact, be more detrimental than building only one wind farm in that location and another further away where fewer red-throated divers are present. Of course, the ideal scenario would be to build all wind farms in areas of least suitable habitat for red-throated divers, but where this is not possible due to other constraints, all of these factors must be accounted for. This also includes the suitability of habitat for red-throated divers in the areas left unimpacted.

In large areas of sea, such as the Outer Thames Estuary SPA, much of the site has existing anthropogenic activity occurring, so a level of displacement from other activities is likely already happening. Therefore, areas of the most suitable habitat which could be left unimpacted by offshore wind farms may not actually be useable by red-throated divers if there are other pressures being exerted at those locations, for instance, shipping lanes, aggregate dredging, and recreational water sports. There may indeed be a disconnect between the ideal suitable habitat for red-throated divers and their densities. A holistic approach to marine spatial planning is needed to fully appreciate the cumulative pressures on red-throated divers, as well as other seabirds and other marine life.

These results may also have an implication of monitoring of seabird displacement where wind farms are located close together. If it is the case that multiple wind farms can have an impact on displacement rates, some consideration of this fact needs to be given when reporting displacement results. Reporting a maximum displacement distance due to impacts that are actually due to another wind farm may artificially inflate the impact of a wind farm, whilst assuming an impact is due to one wind farm when it is actually due to the combination of multiple wind farms may artificially decrease the impact of a wind farm. Indeed, some displacement studies present only the impact of multiple wind farms on a region rather than trying to attribute impacts to specific wind farms (Burt *et al.*, 2017; Mendel *et al.*, 2019; Heinänen *et al.*, 2020; Vilela *et al.*, 2020). Similarly, the timing of displacement monitoring relative to the development of wind farms is important. Monitoring at a built wind farm may be occurring whilst a neighbouring wind farm is being built, with potentially overlapping impacts, so the built wind farm would need to consider the influence of a wind farm under construction on displacement.

7.5 Conclusion of future scenarios of red-throated diver displacement at offshore wind farms

This chapter has analysed a range of scenarios of current and future wind farms and the potential displacement impact to red-throated divers in the Outer Thames Estuary SPA. The results show that operational wind farms have had the largest impact on red-throated diver displacement, and that future consented and pre-planning application wind farms will likely add a much smaller additional impact. However, depending on the method of calculating cumulative wind farm displacement, the contribution of both operational and future wind farms may be quite different. Each of the three methods of calculating cumulative displacement may be true to reality, or a combination of calculation methods may in fact best describe the actual displacement effect. This wide variety of potential cumulative effects indicate that caution is needed when assessing cumulative effects due to the uncertainty in results. This demonstrates why better understanding of displacement effects and impacts is needed to obtain an accurate view of wind farm-wildlife interactions.

This chapter has simulated the potential displacement effects from future offshore wind farms using information from previous chapters. The forecasting of future displacement is the last stage in the process of considering the cumulative displacement effects of offshore wind farms by using the results of previous stages to make accurate predictions. However, this is a circular process, and it also now becomes the first stage by providing information on wind farms that have not yet been built or obtaining consent. This can then aid the siting of future wind farms by considering both the impact of existing and new developments. Any new developments will then be designed, and displacement surveys will provide further evidence of red-throated diver displacement. Overall, this circular process should allow evidence of negative and positive impacts to be fed into decision-making regarding the best and worst locations and designs for wind farms and how to mitigate against negative impacts and enhance positive impacts.

Chapter 8 Conclusions and recommendations

This research aimed to contribute to the understanding of the effects of offshore wind farms on seabirds by analysing how cumulative seabird displacement from offshore wind farms is assessed and verified, and exploring what current and future cumulative displacement might look like.

The research was translated into six objectives investigated by reviewing Environmental Impact Assessments, statistical analysis, and exploring spatial data. The research contributed to the understanding of the effects of offshore wind farms on seabirds by:

a) reviewing the methods used to predict cumulative seabird displacement and the empirical evidence of red-throated diver displacement from offshore wind farms
b) investigating which species and impacts are assessed for displacement in offshore wind farm cumulative assessments
c) exploring how offshore wind farm design influences red-throated diver displacement
d) investigating how much monitoring is sufficient to detect red-throated diver displacement from offshore wind farms
e) determining how red-throated diver displacement changes with distance from offshore wind farms, and
f) exploring what future cumulative red-throated diver displacement from offshore wind farms might look like

This chapter first summarises the main findings, before suggesting actions for future practice. It then describes the future research which would follow and complement this work, before finally summarising the key achievements.

8.1 Summary of key findings

When it comes to scoping species and impacts for a displacement assessment of offshore wind farms, different wind farm developments scope them differently. Then, when it comes to a cumulative assessment, again, developments appear to have a range of reasons for scoping in species and other wind farm developments. This sometimes comes down to whether or not there is data or an assessment at other wind farms for a particular species and impact. Occasionally, the result of one wind farm's individual assessment is modified by another wind farm's assessment, taking a lack of assessment of a species to mean a "negligible" effect.

These various approaches and issues with assessment further the uncertainty already associated with largely unknown cumulative effects. The combination of species and other wind farms included in a cumulative assessment varied widely across the six wind farms studied. Some developments took the approach of including every other wind farm in a cumulative assessment, whilst in return, those other wind farms did not include the focal wind farm in their cumulative assessments.

A range of other scenarios was seen, including approaches to classifying the level of cumulative effect from the individual effect levels. For example, two wind farms assess the cumulative effect of one another yet come to different conclusions on the level of cumulative effect. Inconsistencies in approaches such as these are just some of a multitude of uncertainties regarding cumulative assessments; shifting baselines, use of threshold levels of impact, and whether additive calculations are accurate to reality are just a few others. These all support the need for a more consistent approach and doing so in a strategic way such that more robust assessments of cumulative effects can be made.

When looking to detect and verify predictions made during the EIA, survey design is crucial. Multiple aspects of survey design interact with baseline red-throated diver densities and levels of impact to influence the statistical power to detect changes in red-throated diver densities as a result of displacement from offshore wind farms. The further transects are spaced apart and less area covered by surveys, the lower the power to detect displacement. Similarly, fewer survey days and densities of red-throated divers make it more difficult to detect changes between the pre-construction and post-construction phases of offshore wind farm development. The displacement rate to be detected also plays a role, with lower rates of change being more difficult to detect.

The combination of these factors all needs to be accounted for early when planning monitoring studies in order to obtain sufficiently powerful surveys prior to carrying them out. This is particularly pertinent at the pre-construction phase of development but also during Environmental Impact Assessments such that impacts can be verified post-construction. The highly dependent nature of survey attributes on the detectability of change within one species shows how case-specific this issue is. The research has been illustrated using a specific species, yet the method is replicable for others, as well as different locations and causes of change. This work has shown how power analysis can be used to tailor surveys such that the goal of the survey can be achieved and contingencies accounted for.

There are vast differences in the extent of displacement and the ways that displacement is described. There appear to be several elements of offshore wind farm design which may influence the extent of red-throated diver displacement. Turbine diameter, the distance between turbines, and the density of turbines all correlated with the displacement rate within wind farms, with larger turbines spaced further apart over an area, resulting in lower displacement within the wind farm boundary. In addition, the number of turbines was correlated with the area over which displacement was observed to take place, with more turbines resulting in a larger overall area affected by displacement. Other parameters of wind farm design did not appear to have had an influence on displacement rates of the area impacted. Wind farm design parameters are not usually accounted for in a displacement assessment, though this research suggests it may have an influence on the extent of displacement of red-throated diver. It also opens the door for the potential to minimise red-throated diver displacement, which, given the species' sensitivity to offshore wind farms, maybe a substantial advantage to building new or repowering existing wind farms.

The investigation into red-throated diver displacement rates at distances from offshore wind farms found that a large variety of displacement effects have been seen, from small to large areas affected and from small to large displacement rates within wind farms. There appeared to be a general trend that displacement rates reduced further from wind farms. There also appeared to be a trend that larger areas over which displacement was observed were linked with smaller displacement rates within wind farms. This may indicate individual bird behaviour, with some birds remaining within wind farms whilst others move a substantial distance away. Meanwhile, the opposite can also be true, with most birds displaced from within wind farms, but only by a short distance from the wind farm. Multiple methods of generating a representative gradient of displacement with distance from a wind farm were explored, with a general gradient that could be applied to a range of circumstances followed through to the application of a real-world scenario. This method using relative values to generate a displacement gradient had the advantage of being usable on a range of maximum displacement distances and displacement rates within wind farms, making it widely applicable.

Investigations into reports of red-throated diver displacement have revealed the disparities in how studies have sought to survey, analyse, and present results. Non-standardised approaches to these studies may have resulted in a mixed picture regarding the full extent of red-throated diver displacement. Results have shown to be incredibly varied across locations and wind farms. This may be due to individual behaviour, site-specific impacts, the design of studies, or indeed a combination of these factors. Using the data collectively is also an issue which needs to be carefully handled due to the difference in approaches. In order to aid this in the future, an opinion on what standardised displacement studies could look like is provided in the conclusion (Chapter 8).

When considering how cumulative red-throated diver displacement may actually occur in practice, a range of simulated hypothetical scenarios of both current and future cumulative displacement of red-throated diver showed that the mechanism of cumulative displacement could result in markedly different results. The implication for the true cumulative effect is that the current approach to cumulative assessments may vastly underestimate or overestimate the extent of displacement. When considering the Outer Thames Estuary SPA, much of the SPA, in terms of both area and number of birds, has already been impacted by operational offshore wind farms. The building of future wind farms, due to their proposed location outside the SPA, is likely to only add a small additional impact. The study has highlighted the need to consider how multiple wind farms in close proximity may have a cumulative displacement impact to fully understand the impact on a population.

Therefore, when designing and carrying out studies of wind farm displacement, it is recommended that consideration is given to how best to either assign an impact to a particular wind farm or assume that impacts cannot be assigned to specific wind farms and instead consider the wider impact to a population. The former approach is often taken by individual wind farms; however, the latter approach is likely to be more useful in terms of understanding pressures on seabirds and quantifying the total impact. Standard practice for displacement monitoring when multiple wind farms are present would be useful to ensure comparable studies are carried out and results presented. Spatial marine planning of offshore renewables may also want to consider the mechanism of cumulative displacement to implement the best layout of multiple wind farms.

8.2 Recommendations for future practice

This research has resulted in several recommendations for future practice. These are partly based on the process of searching for, using, and improving data. They are also centred around methods of assessing impacts in terms of scoping of species and impacts and how to calculate cumulative displacement. Each would need careful consideration before being tackled, including stakeholder engagement in the process and implementation to ensure success. These recommendations are split into the advice that is needed from regulators and SNCBs, the practice to be implemented by developers, and the development of new standards. These practical steps can be taken in any order, and each set of recommendations has different organisations responsible for their implementation. Some steps require input from multiple organisations, some are multi-step, and some are directly transferrable with little extra research.

8.2.1 Recommendations for provision of advice

The second recommendation is to clarify how to use the outcomes from other offshore wind farm assessments in a cumulative assessment, for instance, the meaning of a “negligible” effect and how to deal with offshore wind farms with no data on the presence of a particular species, or where a displacement assessment has not been carried out for a particular species at another offshore wind farm. This again requires advice from SNCBs and engagement with offshore wind farm developers to implement this advice.

Another recommendation is for advice to be provided on how to combine results from individual projects in a cumulative assessment and how to assess the significance of a cumulative effect. Multiple wind farms appear to have used data, or lack of data, from other wind farms’ individual assessments inconsistently. This prompts the notion that guidance is required as the method of undertaking a cumulative assessment. This may also need to cover how to calculate the significance of a cumulative effect and how to appropriately convey the level of certainty in an outcome. This could perhaps include more clarity on thresholds for a particular level of impact. Note should be given, however, that receptor-specific impact assessments still exclude any analysis of the impact on the ecosystem as a whole. Ways of doing these are being explored and may be implemented in the future (Isaksson *et al.*, 2023).

A further recommendation is to begin considering whether offshore wind farm design influences the extent of displacement and whether this should be accounted for in impact assessments and implemented into mitigation measures. This requires further research prior to implementation, both for red-throated divers and other species. It would also require consideration of how to optimise the design to minimise impacts to all species and receptors, including outside of seabirds. SNCBs may have a role in commissioning projects to fill these knowledge gaps or carrying out further research prior to providing advice on how wind farm design may be used in mitigation and impact assessments. Engagement with research organisations and offshore wind farm developers is likely to be needed to provide further research into the influence of wind farm design on displacement and implement any new advice on practice.

8.2.2 Recommendations for practice to be implemented by developers

New evidence on displacement, as well as other sources of disturbance and impacts, are constantly being presented. Therefore, it is recommended that cumulative assessments be revisited when new evidence or post-construction monitoring has been carried out. This would give the most up-to-date picture of the status of seabird populations in relation to the impact of anthropogenic activity (though again noting the lack of ecosystem analysis). This would likely need to be done with each new development impacting seabirds. However, SNCBs and regulators would also have a role to play in understanding the most recent status of cumulative impacts to inform decisions about future developments and management and conservation measures.

A better assessment of cumulative impacts is needed to predict and mitigate them, not just across offshore wind farms but also in combination with other sources of disturbance. However, the current state of knowledge, particularly in the mechanism of cumulative displacement, is not in a position to allow this. Therefore, future research is first needed.

8.2.3 Recommendations for implementation of standards

The first recommendation is to standardise, where applicable, the scoping of species for both an individual and a cumulative displacement assessment. This would enable each cumulative displacement assessment to consider the same set of impacts on particular species and a true representation of the potential cumulative displacement effect. This would require advice from Statutory Nature Conservation Bodies (SNCB) and SNCB engagement with offshore wind farm developers to implement this advice.

When considering surveys to confirm the extent of displacement, it is recommended that the use of power analysis becomes standard practice, including the approach to power analysis. This means first having an understanding of either the displacement rate likely to occur or the displacement rate which would ideally be detectable. The number of surveys which would be needed to detect such a change can then be calculated, with either the same or a different number of surveys undertaken before and after the construction of a wind farm (see Chapter 4 for more details on the interaction between power analysis input parameters). This is needed prior to surveys commencing and will give confidence that surveys will achieve a certain standard, be statistically significant, and provide robust evidence of the extent of displacement. This will require advice from SNCBs and engagement with offshore wind farm developers to implement.

Finally, standardised methodology is recommended for studies of displacement, including data collection, analysis, and presentation of results. Throughout this research, empirical evidence of red-throated diver displacement has been collated from the literature and used. Investigations into the data have revealed a range of ways in which the data has been collected, analysed, and presented in reports. These differences mean that each dataset or report needs to be carefully considered before they are used and interpreted. It also means that results are not always directly comparable. This can result in a reduced dataset of comparable data. Given that uncertainties with each dataset and natural variability also exist, any reductions in data quantity and/or quality can hamper efforts to understand the impact of displacement. Consequently, based on the learnings throughout this thesis, an opinion on a standardised displacement monitoring study is provided.

The first overarching recommendation is to design a study from the outset, considering each stage of the study, from the aims through data collection and analysis to the presentation of results. The definition of displacement is one of the first aspects to consider, as this will inform the method of detecting and calculating displacement. Displacement as a comparison of densities in the study area before and after the construction of an offshore wind farm is the most direct method of detecting displacement. Adding a control area outside of the main study area to track natural variation in distribution would provide more clarity on the likelihood that changes in distribution are due to the presence of a wind farm. Only surveying after wind farm construction is a less direct way of detecting displacement. Comparisons would need to be made to the assumed distribution without the wind farm present, using modelling. However, this is likely to give a less accurate result in contrast to a Before-and-After study. Alternative methods of detecting bird presence could be used, for instance, using GPS trackers to understand the utilisation of a particular area. This would not likely constitute a Before-and-After study unless trackers were fitted over a long time period, which is probably not feasible. However, a tracking study would provide other information, such as how birds in flight manoeuvre in and around wind farms. It could also display other types of behaviour in response to wind farms, such as rafting and foraging. Comparisons would, therefore, be made between densities and behaviours close to and far from wind farms. This would not, however, give a comparable displacement rate to that from a Before-After study. Ideally, both a Before-and-After study and tracking would be implemented. The former would provide data on distributional changes in birds, whilst the latter would provide behavioural information. The remainder of this conclusion will focus on a Before-and-After study in an attempt to inform standardisation of the more frequently used method of studying displacement.

Setting an aim for a Before-and-After style study is first required. This would likely include the species to be included and an estimate of both the displacement rates to be detected and the spatial extent of the study. A power analysis is to be carried out to determine whether the study design is appropriate. Consideration should be given to a number of factors influencing the statistical power to detect displacement:

- The number of transects, transect spacing, and coverage of the study area
- The number of surveys during each phase of development
- The likely displacement rate during each phase of development
- The likely density of birds during each phase of development
- The likely variability in density within each survey and phase of development

The type of survey should also be a consideration. The most accurate method of surveying seabird distribution is to use digital aerial surveys, followed by visual aerial and then boat-based surveys. Digital aerial surveys, at an appropriate altitude, also prevent the introduction of attraction or disturbance and, hence, the alteration of distribution that boat-based surveys usually cause. Therefore, digital aerial surveys are recommended.

The survey area should be designed from the outset and continued through the entire survey period. The survey needs to cover the likely displacement-affected area. From existing evidence of red-throated diver displacement, this could be up to 16km from a wind farm boundary. Therefore, a potential maximum displacement distance needs to be estimated. This could potentially be extended to allow detection of the maximum extent of displacement, in other words, surveying the surrounding area where displacement has not occurred. Surveys may want to go one step further and survey outside of the displacement-affected area in order to gauge where birds have been displaced. This may be useful where wind farms are built in or close to designated areas. It may be important to understand whether birds are redistributed within or outside of the designated areas, as this may make a difference to the feature's population size.

How the raw data will be used to generate abundance and distribution estimates would also be useful to understand at the outset. Basic statistics can be performed to generate abundance estimates from raw data; however, this would not generate a density distribution map. In order to understand the gradient in displacement or even displacement inside and outside a wind farm, would be better calculated my modelling to generate a spatial distribution of seabird presence. The best technique to achieve this is likely to be at least partly dependent on the data collected. Techniques used in the literature include, for example, MRSea and inlabru, which are two tools which take raw observation data and covariates to generate spatial distribution maps (Scott-Hayward *et al.*, 2017; Bachl *et al.*, 2019). Choosing a modelling technique early on in survey planning will also help with collecting data in a suitable format for inputting into a model. It is also important to consider other data that may go into a model, such as environmental covariate data, and whether this will need to be collected with the surveys or sourced elsewhere. However, testing how well different covariates in a model describe the raw data may still be needed after data collection.

Once distribution maps have been generated, displacement rates can be calculated. A consistent format for describing displacement across the study area may be the most useful aspect of standardising surveys. A displacement rate within the wind farm boundary should be presented as a minimum. Displacement outside the wind farm can then also be calculated. This should be in discrete distance bands of an appropriate size, ideally 1km (see Figure 4.1 for an example). Distance bands should be extended out to cover the survey area.

However, caution is noted with the displacement rates that are calculated in distance bands at great distances from the wind farm boundary. The farther from the boundary a distance band is, the further apart opposite sides of the distance band are from one another. For instance, the western extent of the 1km-2km distance band, around a wind farm with a radius of 4km, would be 12km from the eastern extent of the distance band. Meanwhile, the western extent of the 9km-10km distance band would be 28km from the eastern extent of the distance band. Whether a single displacement rate should be given covering a region so far apart from one another is debatable, and there is still work to do on this front.

A sensitivity analysis of splitting the survey area into directions from a wind farm may be a first step to determine the most appropriate segments to split the survey area into (see examples of splitting the survey area by 90° and 45° in Figure 8.1 and Figure 8.2, respectively). This may be especially appropriate where other sources of disturbance are present in certain directions from the focal wind farm. The disadvantage to this is that the segments may be site-specific, reducing the direct comparability across displacement studies. However, if segments are used, this would generate a range of displacement rates per distance. Therefore, summary statistics on these data points could be undertaken in a standardised way for each displacement study, reintroducing comparability.

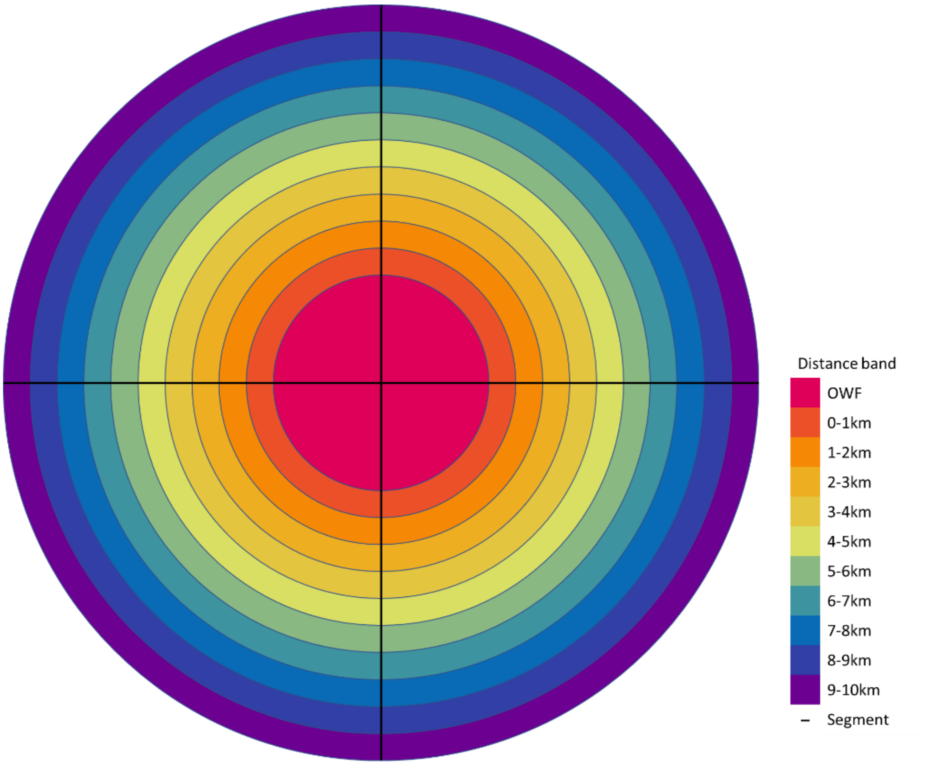

Figure 8.1. Example wind farm and buffers split by 90° segments for analysing seabird displacement at different directions from the wind farm.

Statistics on the significance of displacement results also need to be consistent across studies, with values such as a displacement rate and the significance value needed as a minimum. Studies where it is not possible to do statistics or where statistics show insignificant results should also present these results clearly so there is no ambiguity. Visual inspection of distribution maps may suggest displacement has occurred, although statistics suggest an insignificant result. Where this is the case, it should be clearly stated, including the results of the statistical tests.

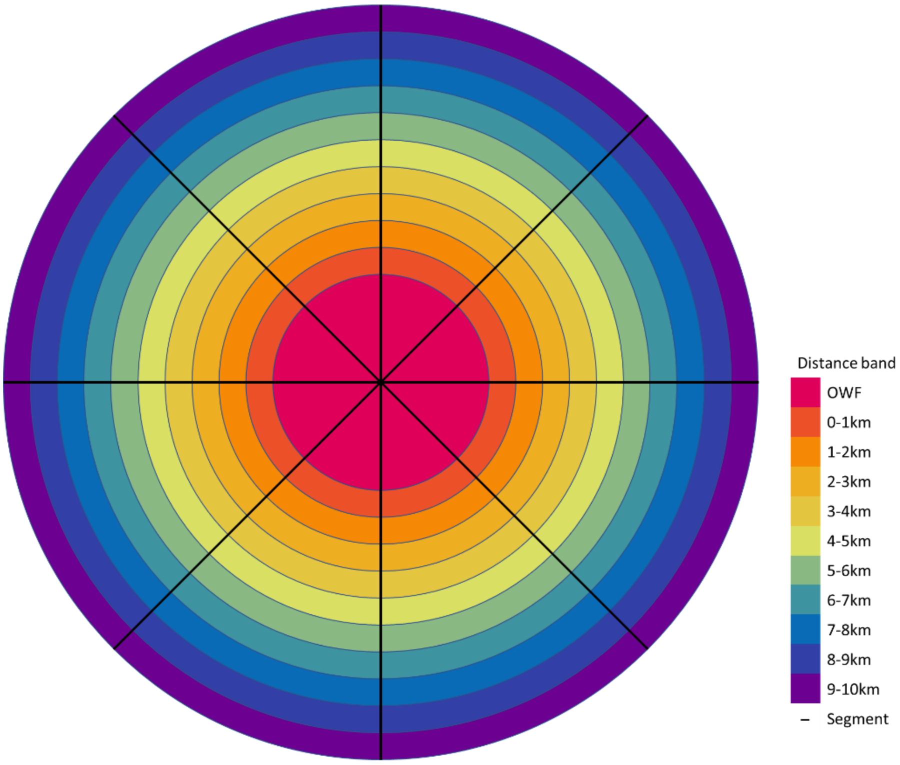

Figure 8.2. Example wind farm and buffers split by 45° segments for analysing seabird displacement at different directions from the wind farm.

Finally, the other sources of disturbance, particularly other operational wind farms or those under construction during the period of the surveys, should be clearly presented in maps. The distance between wind farms and the date and status of their development should be noted. Consideration is needed as to whether other wind farms are included in modelling the distribution from raw data and also whether they are included in the calculation of displacement rates. Existing wind farms close to the focal wind farm of the study may have already had a displacement effect. If a displacement study has already been carried out, its results may help inform or suggest the effect of the additional focal wind farm. A study covering the displacement-affected area of the focal wind farm plus the existing wind farm would then provide additional data on the displacement of the existing wind farm. Comparisons between the initial study and the second may reveal whether displacement rates in overlapping regions of displacement from the two wind farms are lower or larger than the sum of the two.

The aspects of survey design mentioned here could all be considered before undertaking the first survey pre-construction of a wind farm and carried through the last survey post-wind farm construction. This would help ensure the aims of the survey are met, and the study is carried out in a manner comparable to other studies. Consequently, this will enhance the understanding of seabird displacement to enable better citing of wind farms and minimisation and mitigation of impacts.

8.3 Recommendations for future research

The majority of this study has focussed on red-throated divers and, in some cases, specific locations. Therefore, some of its outcomes are not necessarily directly applicable to other locations and species. However, the basic principles such as modifying aspects of survey design to change the power of being able to detect changes are likely to be applicable to other locations and species. Furthermore, given the interplay between different parameters of survey design, the concept of running a power analysis prior to undertaking surveys is recommended regardless of species and location.

Displacement rates within and outside of wind farms and the spatial extent of displacement are likely to differ per species. The red-throated diver was chosen for this study as evidence suggests this species to be the most sensitive to displacement from offshore wind farms. Other species are more likely to have a less severe behavioural response to wind farm avoidance. However, as seabirds face a range of other pressures, displacement effects should also be considered for other species. The knock-on impact of displacement on both individuals and populations also needs further consideration, both for red-throated divers and other species. Red-throated divers are often affected by displacement during the wintering period, but the consequence on productivity in the following breeding season is unknown (Dierschke *et al.*, 2017).

Individual birds, though they are the same species, appear to respond very differently to offshore wind farms. At particular wind farms, some red-throated divers remain within wind farms, whilst others move a substantial distance away. Meanwhile, at other wind farms, most birds are displaced from within wind farms and only a small surrounding area. Further research is needed to fully understand why red-throated divers respond to wind farms in terms of maximum displacement distance and displacement gradients, how they respond to multiple wind farms, and whether maximum displacement distance and displacement gradients differ when many wind farms are present. The reasons for all of these differences are not understood. Therefore, appropriately locating, designing, and otherwise mitigating the impact of wind farms is problematic.

Mitigation of displacement effects may come in the guise of wind farm design. However, extensive testing and validation of alternative wind farm designs would be needed before this becomes routine. Red-throated divers' apparent site-specific responses to wind farms may somewhat complicate the picture. If responses are different across wind farms, perhaps wind farm-specific design is the answer. Any mitigation would also need to carefully monitor any impacts to other receptors in order to ensure new negative impacts are not inadvertently generated; the overall best outcome should be achieved.

Finally, more research is needed to understand the mechanism of cumulative displacement from offshore wind farms and other sources of disturbance. One way to achieve this could be to carry out long-term monitoring surveys of offshore wind farms spatially close together. This would include surveys carried out before and after the construction of each wind farm in order to track the movement of birds over a long time period. A control area could also be surveyed with the aim of recording natural variation. Data collection, analysis, and presentation of results should follow a standardised protocol, such as that suggested in the conclusion (Chapter 8).

8.4 Key achievements

From start to finish, individual and cumulative displacement from offshore wind farms is predicted and evidenced differently. This thesis has highlighted these differences and hypothesised reasons for disparities and whether these are warranted or not. Research has also suggested where standardisation could be implemented and what this might look like. This thesis has contributed to knowledge regarding aspects of survey design, wind farm design, and mitigation measures. A forward view has been presented on the potential cumulative impact of offshore wind, which could be used as the basis for understanding the implications of decisions for future developments.

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Appendix A – More detail on the context of how the research for this thesis has been carried out

Throughout this thesis, the research has been influenced by the context in which it was carried out. The research was started as a full-time PhD student at the University of Strathclyde, covering 16 months. Following this, a role as a full-time marine ornithologist at the Joint Nature Conservation Committee (JNCC) was taken. Therefore, the thesis research was undertaken part-time whilst working full-time at JNCC.

There are multiple ways in which this arrangement has impacted the research. However, it is first important to understand the work at JNCC. The Joint Nature Conservation Committee is the public body that advises the UK government and devolved administrations to UK-wide and international nature conservation. JNCC, as a Statutory Nature Conservation Body (SNCB), is responsible for providing nature conservation advice in offshore areas, from the edge of territorial waters to the UK Continental Shelf. The purpose is to support the management of activities to ensure the overall sustainability of the use of the marine environment.

The role of a marine ornithologist is to provide advice to statutory bodies, regulators, and industry on the potential impacts of marine industries on seabird populations, as well as working jointly with the government, industry, NGOs and academia to obtain evidence on impacts. The evidence required to make informed decisions that ensure sustainable use of the marine environment is a focus of the work. This includes synthesising existing evidence and brokering engagement between different sectors. Typically, through collaboration, the most relevant new evidence required to fulfil conservation ambitions is identified against a backdrop of reducing uncertainty in evidence relevant to offshore developments.

One of the first learnings from working at JNCC is the role that SNCBs have with regard to how impact assessments and seabird monitoring studies are carried out. SNCBs provide advice on everything from baseline characterisation surveys through the parameters to use in impact assessments to monitoring impacts after wind farm construction. Therefore, insights have been gained into the evidence used to inform advice and how the advice is formed. Scrutiny of empirical evidence is a critical part of generating an up-to-date understanding of the impacts of human activity on seabirds. Evidence of a particular effect can be very site-specific and contain many other interacting factors such that, at times, it seems almost impossible to compare outcomes from study to study. Negotiating which evidence to use within a meta-analysis can be very tricky because of this. This insight aided the research with regard to analysing which data to include in meta-analyses and why in Chapters 4 and 6. Research into the generation of a representative displacement gradient in Chapter 6 was undertaken whilst leading a group of SNCBs specifically tasked with providing formal advice on displacement assessments. The final method used to generate a representative displacement gradient in Chapter 6 is currently used by SNCBs across the UK as an example of the displacement rates to use in an assessment of red-throated diver displacement from offshore wind farms.

Insights have been gained into where some of the main evidence gaps are. The displacement of red-throated divers is one such knowledge gap and a crucial one across the UK. Multiple SPAs are designed for wintering red-throated divers, but these areas are also busy with multiple sources of anthropogenic disturbance, including existing and planned offshore wind farms. Two of the three largest red-throated diver SPAs have conservation objectives to reduce the sources of disturbance within and around the SPA. This, therefore, gave weight and importance to investigating the displacement of this species, both individually and cumulatively. Calculating cumulative displacement is also seen as a knowledge gap by SNCBs, with ongoing conversations around appropriate methods. Several offshore wind farm impact assessments have begun to assess cumulative displacement, including using the “Impacted once from closest” and “Impacts multiplied times” methods used in Chapter 7.

During the first period of full-time research, a 3-month internship with and designed by JNCC was undertaken. The aim was to investigate various aspects of survey design to be able to detect red-throated diver displacement. Working with marine ornithologists from JNCC and other SNCBs, the project was designed and carried out, which resulted in the work contained within Chapter 5.

The need for standardisation in approaches to impact assessment and monitoring, where appropriate, is a clear objective for SNCBs. Although SNCBs provide advice to a range of industries, developers often present impacts using alternative methods and parameters. These alternatives are quite easily perpetuated throughout impact assessments. After a method or parameter is used, it can become precedent-setting, even if it is just done once. Aspects of impact assessments are sometimes modified once a planning application has been submitted and examination and consultation have begun. Changes can be very difficult to track, meaning the first full draft of an ES is often taken as the final impact assessment, and results are used in subsequent cumulative assessments.

The Cumulative Effects Framework (CEF) is a tool currently in development with input from SNCBs. This will include a platform where all plans and projects can run individual and cumulative assessments in a standardised manner. In addition, the CEF will have the capacity to recalculate the impacts from all plans and projects each time it is used, meaning if standard methods or parameters are changed in the future, the impact from all existing wind farms can be recalculated based on these new methods or parameters. These factors have all fed into the thesis in that it has aimed to highlight inconsistencies in approaches within different aspects of the impact of cumulative seabird displacement. It has also sought to note why the inconsistencies may be present, as well as providing recommendations for standardisation.

Appendix B - Survey, modelling, and displacement calculation methods from offshore wind farms which have red-throated diver displacement

Table B1. Survey, modelling, and displacement calculation methods from individual offshore wind farms in Denmark which used aerial surveys which have red-throated diver displacement.

Parameter	**Horns Rev I**	**Nysted**	**Horns Rev II**
Location	North Sea - Denmark	North Sea – Denmark	North Sea - Denmark
Type of survey	Visual aerial	Visual aerial	Visual aerial
Survey altitude	76m	76m	75m
Transect orientation	North to south	North to south	Unknown
Transect spacing	2km	2km	2km
Transects within the wind farm	Three transects each 4km long	Three transects each 4km long	21 transects placed 2km apart within the wind farm
Transects outside the wind farm	Ten transects to the west (up to 20km from the wind farm) and 17 transects to the east (up to 32km from the wind farm). 14km north of the wind farm and 14km south of the wind farm surveyed	23 transects, some west up to 16km from the wind farm some east up to 28km from the wind farm. 7km north of the wind farm and 7km south of the wind farm surveyed	21 transects placed 4km apart outside the wind farm. 16km to the west, 28km to the east, and 10km to the north and south
Number and date of surveys	Thirty-four surveys were carried out between August 1999 and December 2005, with 16 of these occurring before construction of the wind farm and 15 after construction was complete	Twenty-one preconstruction surveys were carried out between August 1999 and December 2005, and five post-construction surveys were carried out between September 2003 and November 2005. In addition, three surveys were carried out between January 2003 to August 2003 during the construction phase	Pre-construction six surveys between November 2005 and May 2006 and four surveys between January and April 2007. Post-construction, ten surveys between spring 2011 and spring 2012
Other surveys	None	None	None
Modelling method	Density of birds	Density of birds	Generalized Linear Model (GLM)

Parameter	Horns Rev I	Nysted	Horns Rev II
Data period	Pre-construction Post-construction	Pre-construction Post-construction	Pre-construction Post-construction
Displacement method	BACI	BACI	BACI
Reference	Petersen et al. (2006)	Petersen et al. (2006)	Petersen et al. (2014)

Table B2. Survey, modelling, and displacement calculation methods from individual offshore wind farms in the UK which used aerial surveys which have red-throated diver displacement.

Offshore wind farm	Lincs, Lynn, and Inner Dowsing	London Array
Location	North Sea – UK	North Sea - UK
Type of survey	Visual aerial and digital aerial	Digital aerial
Survey altitude	610m between January 2010 and February 2012. 550m from November 2012 onwards	Unknown
Transect orientation	Unknown	Unknown
Transect spacing	1.25km apart from January 2010 to February 2012. 3.25km apart from November 2012 onwards	Grid-based system with grid size of 500m by 500m
Transects within the wind farm	Unknown	Unknown
Transects outside the wind farm	Unknown	A region around the wind farm was surveyed, though the region around the wind farm was not equal in every direction from the wind farm boundary. The minimum distance surveyed outside the wind farm was 2km to the north and south, whilst up to 16km was surveyed outside the wind farm to the northeast

Offshore wind farm	**Lincs, Lynn, and Inner Dowsing**	**London Array**
Number and date of surveys	Sixty pre-construction surveys were conducted between November 2003 and August 2006. Between November 2007 and February 2013, the Lynn & Inner Dowsing wind farm and Lincs wind farm were constructed, one after the other; therefore, this whole period was termed the construction phase for the sake of a displacement study, with 24 surveys 25 conducted. From April 2013 onwards, this post-construction phase began, with 66 surveys conducted until March 2016	Twelve pre-construction surveys between November 2010 and February 2011. During the construction of the wind farm, 27 surveys between November 2011 and February 2013. Operational surveys between November 2013 and February 2016, consisting of 24 surveys
Other surveys	A control area was surveyed to the east of the wind farm with transects 6.5km apart	Control area to up to 16km the southwest which abutted the boundary of the wind farm
Modelling method	MRSea (CReSS spatial modelling with Spatially Adaptive Local Smoothing Algorithm (“SALSA”) based model selection)	MRSea (CReSS spatial modelling with Spatially Adaptive Local Smoothing Algorithm (“SALSA”) based model selection)
Data period	Pre-construction Post-construction	Pre-construction Post-construction
Displacement method	Before-After	BACI
Reference	Webb et al (2017)	APEM (2021)

Table B3. Survey, modelling, and displacement calculation methods from multiple offshore wind farms which used aerial surveys which have red-throated diver displacement.

Parameter	**German North Sea I**	**German Bight**	**Liverpool Bay**
Location	North Sea - Germany	North Sea - Germany	Irish Sea - Wales
Type of survey	Visual aerial and digital aerial	Digital aerial and telemetry (used separately)	Digital aerial
Survey altitude	Unknown	549m	Unknown
Transect orientation	Unknown	Unknown	Unknown
Transect spacing	Unknown	8km	Unknown
Transects within the wind farm	Unknown	17 transects covering within and around wind farms.	Unknown

Parameter	German North Sea I	German Bight	Liverpool Bay
Transects outside the wind farm	Unknown	17 transects covering within and around wind farms.	Unknown
Number and date of surveys	2001 to 2018	6 telemetry tags fitted in 2015, 20 in 2016, and 9 in 2017. 4 digital aerial surveys conducted, two in 2016 and two in 2017	1 in February 201, 3 in March 2011, 1 in January 2015, and 1 in February 2015
Other surveys	None	None	None
Modelling method	Integrated Nested Laplace Approximation with Stochastic Partial Differential Equation	Generalised Additive Mixed Model (GAMM)	MRSea (CReSS spatial modelling with Spatially Adaptive Local Smoothing Algorithm ("SALSA") based model selection)
Data period	Pre-construction Post-construction	Post-construction	Post-construction
Displacement method	Before-After	Comparison to assumed distribution without OWF	Comparison of red-throated divers within and outside the wind farm
Reference	Vilela et al. (2020)	Heinänen et al. (2020)	Burt et al (2017)

Table B4. Survey, modelling, and displacement calculation methods from single offshore wind farms in the UK which used boat-based surveys which have red-throated diver displacement.

Parameter	Gunfleet Sands	Kentish Flats	Thanet
Location	North Sea - UK	North Sea - UK	North Sea - UK
Type of survey	Boat-based	Boat-based	Boat-based
Survey altitude	N/A	N/A	N/A
Transect orientation	West-SouthWest to North-NorthWest	Unknown	East to West
Transect spacing	Unknown	1km apart from 2002 to spring 2011. From autumn 2011 onwards, transects were spaced 2km apart	1km
Transects within the wind farm	2 transects	Four transects	During the pre-construction surveys, 7 transects.

Parameter	**Gunfleet Sands**	**Kentish Flats**	**Thanet**
Transects outside the wind farm	3 transects outside the windfarm, no information on the distance either side of the wind farm nor how many transects either side	Until spring 2009, four transects extending 2km beyond the wind farm in every direction. From autumn 2009 to spring 2011, a further transect was added to the west, meaning the survey covered 3km from the western edge of the wind farm. From autumn 2011 onwards, transects covered 5km to the west and 4km to the north, east, and south.	During the pre-construction surveys, the wind farm plus a 1km buffer was covered, by two transects, one either side of the wind farm, amounting to 67km2. During construction and post-construction the wind farm plus a 2km buffer was surveyed by 4 transects, two either side of the wind farm, covering 111km2.
Number and date of surveys	13 pre-construction surveys between October 2007 and March 2008, 20 surveys between October 2008 and March 2010 during the construction of the wind farm, and 30 post-construction surveys between October 2010 and March 2013	Pre-construction surveys between 2002 and 2004, surveys during construction from 2004 to 2005, and post-construction between 2005 and 2013.	Twelve boat-based surveys between November 2004 and October 2005 and four aerial surveys between November 2004 and March 2005 made up the pre-construction data. For the construction phase, there were three boat-based surveys between February and March 2009 and 12 between October 2009 and March 2010. Finally, 12 boat-based surveys were carried out between October 2010 and March 2011, 12 between October 2011 and March 2012, and 12 between October 2012 and March 2013.
Other surveys	None	A control area several kilometres southeast of the wind farm was surveyed from 2002 to 2013 using a 1km transect spacing, covering an approximate 3km by 3km area.	A control area to south covering 33km2 was surveyed by 4 transects during pre-construction surveys. This was increased to cover 38kms by 2 more surveys during the construction and post-construction phases.
Modelling method	Mean density of birds	Mean density of birds	Mean density of birds
Data period	Pre-construction Post-construction	Pre-construction Post-construction	Pre-construction Post-construction

Parameter	**Gunfleet Sands**	**Kentish Flats**	**Thanet**
Displacement method	BACI	BACI	BACI
Reference	NIRAS (2015)	Percival (2014)	Percival (2013)

Table B5. Survey, modelling, and displacement calculation methods from single offshore wind farms in Germany which used boat-based surveys which have red-throated diver displacement.

Parameter	**Alpha Ventus**
Location	North Sea - Germany
Type of survey	Boat-based
Survey altitude	N/A
Transect orientation	North to south
Transect spacing	3km
Transects within the wind farm	1 transect
Transects outside the wind farm	10 transects, each 13.6km in length. Not clear how far north and south of the wind farm the transects extended. Similarly, it was not obvious how far the transects extended east and west of the wind farm
Number and date of surveys	Seventy-seven surveys were carried out between January 2010 and March 2013, during which time the wind farm was operational
Other surveys	None
Modelling method	(Generalised Additive Model GAM)
Data period	Post-construction
Displacement method	Comparison of red-throated divers within and outside the wind farm
Reference	Welcker and Nehls (2016)

Table B6. Survey, modelling, and displacement calculation methods from single offshore wind farms which used both aerial and boat-based surveys which have red-throated diver displacement.

Parameter	**North Hoyle**	**Butendiek & Helgoland Cluster**	**German North Sea II**
Single or multiple OWFs	Single	Multiple	Multiple
Location	Irish Sea - Wales	North Sea - Germany	North Sea - Germany
Type of survey	Boat-based and aerial surveys	Visual aerial and boat-based pre-construction. Digital aerial post-construction.	Visual aerial, digital aerial, and boat-based.
Survey altitude	Unknown	Unknown	Unknown
Transect orientation	Unknown	Unknown	Unknown
Transect spacing	Unknown	Unknown	Unknown
Transects within the wind farm	Unknown	Unknown	Unknown
Transects outside the wind farm	Unknown	Unknown	Unknown
Number and date of surveys	Eight boat-based surveys between November 2002 and March 2003 and five aerial surveys between August 2002 and February 2003 made up the pre-construction surveys. Eleven boat-based surveys between February 2003 and February 2004 and four aerial surveys between May 2003 and March 2004 made up the construction surveys. Thirty-six boat-based surveys between March 2004 and March 2007 and 27 aerial surveys between May 2004 and February 2007 made up the post-construction surveys	Pre-construction from 2000 to 2013. Post-construction from 2015 to 2017	2000 to 2017
Other surveys	None	None	None
Modelling method	Unknown	Generalised Additive Mixed Model (GAMM)	Generalised Additive Model (GAM)
Data period	Unknown	Pre-construction Post-construction	Pre-construction Post-construction

Parameter	**North Hoyle**	**Butendiek & Helgoland Cluster**	**German North Sea II**
Displacement method	Unknown	Before-After	BACI
Reference	May (2008)	Mendel et al. (2019)	Garthe et al. (2023)

Table B7. Survey, modelling, and displacement calculation methods from offshore wind farms which used methods other than aerial and boat-based surveys which have red-throated diver displacement.

Parameter	**Egmond aan Zee**
Single or multiple OWFs	Single
Location	North Sea - Denmark
Type of survey	Visual observations were taken from a met mast located at the west edge of the wind farm, with observers doing scans of the sea surface to survey for species distributions and abundance within and outside of the wind farm.
Survey altitude	N/A
Transect orientation	N/A
Transect spacing	N/A
Transects within the wind farm	Most of the wind farm was observed
Transects outside the wind farm	The limit of observation was 3km from the met mast, meaning the maximum extent of observation outside the wind farm was 3km to the southwest. The north, east, and south of the wind farm were not surveyed.
Number and date of surveys	53 days from spring 2007 to December 2009
Other surveys	A bird radar system mounted on the met mast was used to track the flights of birds in and around the wind farm. A horizontal surveillance radar was used, which covered approximately 5km from the met mast location.
Modelling method	Number of birds
Data period	Post-construction
Displacement method	Comparison to assumed distribution without OWF.
Reference	Krijgsveld et al. (2011)

Appendix C - Results of questions used to analyse EIAs of offshore wind farms in the UK to compare the different ways that individual and cumulative wind farm assessments have been carried out

Table C1. Results of questions used to analyse EIAs of Aberdeen, Barrow, Beatrice, and Burbo Bank offshore wind farms in the UK to compare the different ways that individual and cumulative wind farm assessments have been carried out.

Question	**Aberdeen**	**Barrow**	**Beatrice**	**Burbo Bank**
Is there a section dedicated to cumulative effects?	Within species section	Independent section	· Within species section · Appendix	· Within species section · Appendix
Was the scoping of species the same as or different to that within the main impact assessment?	Same	Different	Different	Different
In what way was the scoping of species different to the main impact assessment?	N/A	Outcome of impact assessment found no significant impact therefore CIA not required	Impact assessment included other species. Some species data were not available from other sites	Impact assessment included other species. Some species data were not available from other sites
Was a reason given for scoping the species that were assessed?	Yes	Yes: all	Yes: all	Yes: all
Was the scoping of impacts the same as main impact assessment or different?	Different	N/A	Same	Same

Question	Aberdeen	Barrow	Beatrice	Burbo Bank
In what way was the scoping of impacts different to the main impact assessment?	Individual impact assessment separated impacts. CEA mostly assessed cumulative effects as a whole, not different types of cumulative impacts	N/A	N/A	N/A
Were all species scoped in analysed with respect to every impact?	Species-specific impacts	N/A	Species-specific impacts	All species and all impacts
Were potential impacts considered at different stages of the project?	Two · Construction · Operation	N/A	All · Construction · Operation · Decommissioning	One · Operation

Question	**Aberdeen**	**Barrow**	**Beatrice**	**Burbo Bank**
Were the types of potential impacts specified?	Generally not specified Construction · Disturbance Operation · Displacement · Collision	N/A	Construction · Disturbance and potential displacement due to boat traffic · Disturbance and potential displacement due to construction activity · Indirect impacts upon prey Operation · Disturbance due to maintenance activity · Avoidance of turbines and displacement · Barrier effects · Collision risk · Indirect effects on distribution of prey and habitat Decommissioning · Disturbance and potential displacement due to boat traffic · Disturbance and potential displacement due to decommissioning activity · Indirect impacts upon prey	Construction · Disturbance
Did the assessment include operational displacement?	Generally not specified Yes	No	No	No
If no information was available from another windfarm site, what action was taken?	No assessment was carried out	N/A	No assessment was carried out	No assessment was carried out
How are cumulative impacts calculated?	Unknown	N/A	Summed	Summed

Table C2. Results of questions used to analyse EIAs of Burbo Bank Extension, Dudgeon, Galloper, and Greater Gabbard offshore wind farms in the UK to compare the different ways that individual and cumulative wind farm assessments have been carried out.

Question	**Burbo Bank Extension**	**Dudgeon**	**Galloper**	**Greater Gabbard**
Is there a section dedicated to cumulative effects?	· Within species section · Appendix	· Within species section · Appendix	· Within species section · Appendix · Independent section	Independent section
Was the scoping of species the same as or different to that within the main impact assessment?	Same	Different	Same	Different
In what way was the scoping of species different to the main impact assessment?	N/A	Species scoped in were sensitive at more than one site, where one site was windfarm in question	N/A	Only one species analysed for one impact Unknown species analysed for other impact
Was a reason given for scoping the species that were assessed?	Yes	Yes	Yes	Yes: some
Was the scoping of impacts the same as main impact assessment or different?	Same	Same	Same	Same
In what way was the scoping of impacts different to the main impact assessment?	N/A	N/A	N/A	N/A
Were all species scoped in analysed with respect to every impact?	Species-specific impacts	Species-specific impacts	Species-specific impacts	Species-specific impacts
Were potential impacts considered at different stages of the project?	All · Construction · Operation · Decommissioning	All · Construction · Operation · Decommissioning	All · Construction · Operation · Decommissioning	Two · Construction · Operation

Question	**Burbo Bank Extension**	**Dudgeon**	**Galloper**	**Greater Gabbard**
Were the types of potential impacts specified?	Construction · Disturbance by boat activity · Disturbance by construction · Direct impacts on prey Operation · Disturbance due to maintenance activity · Avoidance and displacement · Barrier effects · Collision risk · Indirect impacts on prey species Decommissioning · Disturbance by boat activity · Direct impacts on prey	Construction · Disturbance and displacement by boat activity · Disturbance and displacement by construction noise · Direct impacts on prey and habitat Operation · Disturbance due to maintenance activity · Avoidance and displacement · Barrier effects · Collision risk · Indirect impacts on prey and habitat Decommissioning · Disturbance and displacement by boat activity · Disturbance and displacement by construction noise · Direct impacts on prey and habitat	Construction · Direct disturbance · Indirect disturbance Operation · Disturbance due to maintenance activities · Displacement and avoidance · Barrier effects · Collision risk Decommissioning · Direct disturbance · Indirect disturbance	Construction · Indirect habitat loss/Disruption of flight-lines Operation · Indirect habitat loss/disruption of flight-lines · Collision risk
Did the assessment include operational displacement?	Yes	Yes	Yes	No
If no information was available from another windfarm site, what action was taken?	Data sourced elsewhere: use of designated site population data to	N/A	Where no quantitative data was available, a qualitative assessment was made	N/A

Question	Burbo Bank Extension	Dudgeon	Galloper	Greater Gabbard
	calculate values for other sites			
How are cumulative impacts calculated?	Summed	Summed	Summed	Unknown

Table C3. Results of questions used to analyse EIAs of Gunfleet Sands, Gwynt Y Mor, Humber Gateway, and Inch Cape offshore wind farms in the UK to compare the different ways that individual and cumulative wind farm assessments have been carried out.

Question	Gunfleet Sands	Gwynt Y Mor	Humber Gateway	Inch Cape
Is there a section dedicated to cumulative effects?	Within species section	Independent section	Independent section	Within species section
Was the scoping of species the same as or different to that within the main impact assessment?	Different	Different	Different	Same
In what way was the scoping of species different to the main impact assessment?	No species scoped into CEA	Species not specifically identified as being assessed in main impact assessment nor CEA	Not all species included in impact assessment analysed in CEA, without explanation as to the removal	All Valued Ornithological Receptors (VOR) analysed
Was a reason given for scoping the species that were assessed?	No	No	No	Yes
Was the scoping of impacts the same as main impact assessment or different?	Different	Different	Same	Same
In what way was the scoping of impacts different to the main impact assessment?	No impacts scoped into CEA	Not all main impacts included in CEA	N/A	N/A
Were all species scoped in analysed with respect to every impact?	No species and no impacts	Species-specific impacts	Species-specific impacts	Species-specific impacts

Question	**Gunfleet Sands**	**Gwynt Y Mor**	**Humber Gateway**	**Inch Cape**
Were potential impacts considered at different stages of the project?	No	Two · Construction · Operation	Two · Construction · Operation	All · Construction · Operation · Decommissioning
Were the types of potential impacts specified?	None	Construction · Disturbance Operation · Direct habitat loss · Avoidance · Barrier effect · Collision risk	Construction · Disturbance Operation · Direct habitat loss · Collision risk · Displacement · Flight lines	Construction · Direct habitat loss · Disturbance · Indirect impacts on prey Operation · Direct habitat loss · Direct disturbance · Indirect impacts on prey · Displacement · Barrier effect · Collision risk Decommissioning · Direct habitat loss · Disturbance · Indirect impacts on prey
Did the assessment include operational displacement?	No	No	Yes	Yes
If no information was available from another windfarm site, what action was taken?	No assessment was carried out	Where no quantitative data was available, a qualitative assessment was made	N/A	N/A
How are cumulative impacts calculated?	N/A	Unknown	Summed	

Table C4. Results of questions used to analyse EIAs of Kentish Flats, Kentish Flats Extension, Lincs, and Moray East offshore wind farms in the UK to compare the different ways that individual and cumulative wind farm assessments have been carried out.

Question	**Kentish Flats**	**Kentish Flats Extension**	**Lincs**	**Moray East**
Is there a section dedicated to cumulative effects?	Independent section	· Within species section · Independent section	Within species section	Independent section
Was the scoping of species the same as or different to that within the main impact assessment?	Different	Different	Different	Different
In what way was the scoping of species different to the main impact assessment?	No species scoped into CEA	Species scoped into main impact assessment explained. Not all species included in impact assessment analysed in CEA, without explanation as to the removal	Species specific assessment in main impact assessment, but all species and all impacts assessed in CEA	CEA included sensitive species at other sites
Was a reason given for scoping the species that were assessed?	No	No	No	Yes
Was the scoping of impacts the same as main impact assessment or different?	Different	Different	Different	Different
In what way was the scoping of impacts different to the main impact assessment?	No impacts scoped into CEA	Less impacts scoped into CEA. No explanation for removal of impacts	Not all impacts included in impact assessment analysed in CEA, without explanation as to the removal	Not all impacts included in impact assessment analysed in CEA, without explanation as to the removal
Were all species scoped in analysed with respect to every impact?	No species and no impacts	Species-specific impacts	All species and all impacts	All species and all impacts
Were potential impacts considered at different stages of the project?	No	All · Construction · Operation · Decommissioning	All · Construction · Operation · Decommissioning	One · Operation

Question	Kentish Flats	Kentish Flats Extension	Lincs	Moray East
Were the types of potential impacts specified?	None	Construction · Disturbance and displacement Operation · Collision risk · Disturbance and displacement · Indirect - loss of habitat · Indirect - impact on prey Decommissioning · Disturbance and displacement	Construction · Disturbance Operation · Displacement · Collision risk Decommissioning · Disturbance	Operation · Disturbance/displacement · Collision risk
Did the assessment include operational displacement?	No	Yes	Yes	Yes
If no information was available from another windfarm site, what action was taken?	No assessment was carried out	Site not assessed	"Negligible impact" was assumed	"Negligible impact" was assumed
How are cumulative impacts calculated?	N/A	Unknown	Summed	Unknown

Table C5. Results of questions used to analyse EIAs of Neart na Gaoithe and Seagreen offshore wind farms in the UK to compare the different ways that individual and cumulative wind farm assessments have been carried out.

Question	Neart na Gaoithe	Seagreen
Is there a section dedicated to cumulative effects?	Within species section	Within species section
Was the scoping of species the same as or different to that within the main impact assessment?	Different	Same
In what way was the scoping of species different to the main impact assessment?	Species scoped into main impact assessment explained. Not all species included in impact assessment analysed in CEA, without explanation as to the removal	N/A
Was a reason given for scoping the species that were assessed?	Yes	Yes

Question	**Neart na Gaoithe**	**Seagreen**
Was the scoping of impacts the same as main impact assessment or different?	Different	Same
In what way was the scoping of impacts different to the main impact assessment?	Not all impacts included in impact assessment analysed in CEA, without explanation as to the removal	N/A
Were all species scoped in analysed with respect to every impact?	All species and all impacts	Species-specific
Were potential impacts considered at different stages of the project?	One · Operation	Two · Construction · Operation
Were the types of potential impacts specified?	Operation · Displacement · Collision risk	Construction · Disturbance Operation · Collision risk · Displacement
Did the assessment include operational displacement?	Yes	Yes
If no information was available from another windfarm site, what action was taken?	N/A	Where no quantitative data was available, a qualitative assessment was made
How are cumulative impacts calculated?	Summed	Summed

Appendix D – Parameters of and calculations of displacement from offshore wind farms which have red-throated diver displacement evidence

Table D1. Parameters of built wind farms which have associated red-throated diver displacement evidence associated with individual wind farms.

Location	Wind farm	Number of turbines	Wind farm area (km²)	Avg. turbine spacing blade (m)	Avg. turbine spacing tower (m)	Rotor diameter (m)	Rotor swept area (m²)	Turbine height (m)	Air gap (m)	Density of rotor swept area (%)	Density of turbines (turbines/km²)	Capacity (MW)	Distance to coast (km)
Den	Horns Rev I	80	20	560	640	80	5,027	110	30	2.0	4.0	160	14
Den	Horns Rev II	91	35	660	753	93	6,793	115	22	1.8	2.6	209.3	30
Den	Nysted	72	21	624	704	80	5,027	109	29	1.7	3.4	165.6	11
Ger	Alpha Ventus	12	4	844	970	126	12,469	156	30	3.7	3.0	60	45
Ned	Egmond aan Zee	36	27	846	936	90	6,362	115	25	0.8	1.3	108	10
UK	Gunfleet Sands	48	18	621	728	107	8,992	129	22	2.5	2.7	172.8	7
UK	Kentish Flats	30	10	612	702	90	6,362	115	25	1.9	3.0	90	8.9
UK	Lincs	75	35	500	620	120	11,310	160	40	2.4	2.1	270	8
UK	Lynn & Inner Dowsing	54	20	500	607	107	8,992	134	27	2.4	2.7	194.4	5.2
UK	London Array	175	100	804	924	120	11,310	147	27	2.0	1.8	630	20
UK	North Hoyle	30	10	570	650	80	5,027	107	27	1.5	3.0	60	7.5
UK	Thanet	100	35	642	732	90	6,362	115	25	1.8	2.9	300	12

Table D2. Parameters of built wind farms which have associated red-throated diver displacement evidence associated with multiple wind farms.

Study no.*	Wind farm	Number of turbines	Wind farm area (km^2)	Avg. turbine spacing blade (m)	Avg. turbine spacing tower (m)	Rotor diameter (m)	Rotor swept area (m^2)	Turbine height (m)	Air gap (m)	Density of rotor swept area (%)	Density of turbines (turbines/km^2)	Capacity (MW)	Distance to coast (km)
1, 2, 3	Amrumbank West	80	32	696	816	120	11,310	150	30	2.8	2.5	288	35
1, 2, 3	Butendiek	80	33	696	816	120	11,310	180	60	2.7	2.4	288	32
1, 2, 3	Dan Tysk	80	70	1068	1188	120	11,310	148	28	1.3	1.1	288	70
1, 2, 3	Meerwind Sud/Ost	80	42	840	960	120	11,310	149	29	2.2	1.9	288	23
1, 2, 3	Nordsee Ost	48	24	1021	1147	126	12,469	155	29	2.5	2.0	295	60
1, 3	Sandbank	72	60	1027	1157	130	13,273	160	30	1.6	1.2	288	90
1	Alpha Ventus	12	4	844	970	126	12,469	156	30	3.7	3.0	60	45
1	BARD Offshore 1	80	60	964	1086	122	11,690	151	29	1.6	1.3	400	100
1	Borkum Riffgrund 1	78	36	756	876	120	11,310	143	23	2.5	2.2	312	55
1	Borkum Riffgrund 2	56	25	984	1148	164	21,124	187	23	4.7	2.2	448	54
1	Deutsche Bucht	31	23	Unknown	Unknown	164	21,124	182	18	2.9	1.4	248	100
1	Global Tech I	80	41	789	905	116	10,568	148	32	2.1	2.0	400	180
1	Gode Wind 01 & 02	97	73	970	1124	154	18,627	188	34	2.5	1.3	582	33
1	Hohe See	71	42	Unknown	Unknown	154	18,627	182	28	3.1	1.7	497	95
1	Merkur Offshore	66	47	870	1020	150	17,671	175	25	2.5	1.4	396	45
1	Nordergrunde	18	4	580	706	126	12,469	147	21	6.4	5.1	111	16
1	Nordsee One	54	41	832	958	126	12,469	153	27	1.6	1.3	332	40

Study no.*	**Wind farm**	**Number of turbines**	**Wind farm area (km^2)**	**Avg. turbine spacing blade (m)**	**Avg. turbine spacing tower (m)**	**Rotor diameter (m)**	**Rotor swept area (m^2)**	**Turbine height (m)**	**Air gap (m)**	**Density of rotor swept area (%)**	**Density of turbines (turbines/km^2)**	**Capacity (MW)**	**Distance to coast (km)**
1	Riffgat	30	6	576	696	120	11,310	150	30	5.7	5.0	108	15
1	Trianel Windpark Borkum	40	56	928	1044	116	10,568	148	32	0.8	0.7	200	45
1	Veja Mate	67	51	1016	1170	154	18,627	180	26	2.4	1.3	402	95

*Study no. 1 = Vilela *et al.* (2020), study no. 2 = (Mendel *et al.*, 2019), study no. 3 = (Heinänen *et al.*, 2020)

Table D3. Survey, modelling, and displacement calculation methods from individual wind farms which have red-throated diver displacement.

Wind farm	**Survey method**	**Modelling method**	**Data period**	**Displacement method**
Alpha Ventus	Boat-based	(Generalised Additive Model GAM)	Post-construction	Comparison to outside OWF
Butendiek & Helgoland Cluster	Boat-based and visual aerial (pre-construction) and digital aerial (post-construction)	Generalised Additive Mixed Model (GAMM)	Pre-construction Post-construction	BACI
Egmond aan Zee	Radar and met-mast-based observation	Number of birds	Post-construction	Comparison to assumed distribution without OWF
German Bight	Telemetry and digital aerial (used separately)	Generalised Additive Mixed Model (GAMM)	Post-construction	Comparison to assumed distribution without OWF
German North Sea	Visual aerial and digital aerial	Integrated Nested Laplace Approximation with Stochastic Partial Differential Equation	Pre-construction Post-construction	BACI
Gunfleet Sands	Boat-based	Mean density of birds	Pre-construction Post-construction	BACI
Horns Rev I and Nysted	Visual aerial	Density of birds	Pre-construction Post-construction	BACI
Horns Rev II	Visual aerial	Generalized Linear Model (GLM)	Pre-construction Post-construction	BACI
Kentish Flats	Boat-based	Mean density of birds	Pre-construction Post-construction	BACI
Lincs, Lynn and Inner Dowsing	Visual aerial and digital aerial	MRSea (CReSS spatial modelling with Spatially Adaptive Local Smoothing Algorithm ("SALSA") based model selection)	Pre-construction Post-construction	BACI
London Array	Digital aerial	MRSea (CReSS spatial modelling with Spatially Adaptive Local Smoothing Algorithm ("SALSA") based model selection)	Pre-construction Post-construction	BACI
Thanet	Boat-based and aerial	Mean density of birds	Pre-construction Post-construction	BACI

Appendix E – R markdown code used in the analysis of Chapter 4

Packages required

```
library("ggpubr")
library("readxl")
library("dgof")
library(dplyr)
library(ppcor)
library(extrafont)
loadfonts(device = "win")
```

Import data

```
#Set working directory
setwd("C:/Users/44755/OneDrive - University of Strathclyde/5. OWF design and displacement/")

#Import displ spreadsheet
Displ_values <- read_excel("Main displ spreadsheet.xlsx", sheet = 1)
#Remove qualitative data
Displ_values <- Displ_values[Displ_values$`Results Quantitative/Qualitative?` != "Qualitative",]
#Import OWF spreadsheet
All_OWF_values <- read_excel("Main displ spreadsheet.xlsx", sheet = 2)
#Select only individual OWFs
OWF_values <- All_OWF_values[1:16,]
#Remove rows not required
Many_OWF_values <- All_OWF_values[17:47,]
#Make numbers numeric
OWF_values$`No. turbines` <- as.numeric(OWF_values$`No. turbines`)
OWF_values$`Height (m)` <- as.numeric(OWF_values$`Height (m)`)
OWF_values$`Area (km2)` <- as.numeric(OWF_values$`Area (km2)`)
OWF_values$`Spacing row (m)` <- as.numeric(OWF_values$`Spacing row (m)`)
OWF_values$`Spacing column (m)` <- as.numeric(OWF_values$`Spacing column (m)`)
OWF_values$`Density (turbines/km2)` <- as.numeric(OWF_values$`Density (turbines/km2)`)
OWF_values$`Swept area (m2)` <- as.numeric(OWF_values$`Swept area (m2)`)
OWF_values$`Distance to coast (km)` <- as.numeric(OWF_values$`Distance to coast (km)`)
OWF_values$`Capacity (MW)` <- as.numeric(OWF_values$`Capacity (MW)`)
OWF_values$`Air gap (m)` <- as.numeric(OWF_values$`Air gap (m)`)
OWF_values$`Diameter (m)` <- as.numeric(OWF_values$`Diameter (m)`)
OWF_values$`Density (%)` <- as.numeric(OWF_values$`Density (%)`)
OWF_values$`Avg spacing (diameters)` <- as.numeric(OWF_values$`Avg spacing (diameters)`)
```

```r
OWF_values$`Avg spacing (m)` <- as.numeric(OWF_values$`Avg spacing (m)`)
OWF_values$`Avg spacing to tower (m)` <- as.numeric(OWF_values$`Avg spacing to tower (m)`)
OWF_values$`Max displ area` <- as.numeric(OWF_values$`Max displ area`)

#Average and sum Lincs, Lynn & Inner Dowsing
OWF_values[nrow(OWF_values)+1,]<-list("UK", "Lincs, L & ID",as.numeric(dplyr::select(filter(OWF_values, `OWF` == "Lincs"),c(`No. turbines`)))+as.numeric(dplyr::select(filter(OWF_values, `OWF` == "L & ID"),c(`No. turbines`))),mean(c(as.numeric(dplyr::select(filter(OWF_values, `OWF` == "Lincs"),c(`Height (m)`))),as.numeric(dplyr::select(filter(OWF_values, `OWF` == "L & ID"),c(`Height (m)`))))),as.numeric(dplyr::select(filter(OWF_values, `OWF` == "Lincs"),c(`Area (km2)`)))+as.numeric(dplyr::select(filter(OWF_values, `OWF` == "L & ID"),c(`Area (km2)`))),mean(c(as.numeric(dplyr::select(filter(OWF_values, `OWF` == "Lincs"),c(`Spacing row (m)`))),as.numeric(dplyr::select(filter(OWF_values, `OWF` == "L & ID"),c(`Spacing row (m)`))))),mean(c(as.numeric(dplyr::select(filter(OWF_values, `OWF` == "Lincs"),c(`Spacing column (m)`))),as.numeric(dplyr::select(filter(OWF_values, `OWF` == "L & ID"),c(`Spacing column (m)`))))),(as.numeric(dplyr::select(filter(OWF_values, `OWF` == "Lincs"),c(`No. turbines`)))+as.numeric(dplyr::select(filter(OWF_values, `OWF` == "L & ID"),c(`No. turbines`))))/(as.numeric(dplyr::select(filter(OWF_values, `OWF` == "Lincs"),c(`Area (km2)`)))+as.numeric(dplyr::select(filter(OWF_values, `OWF` == "L & ID"),c(`Area (km2)`)))),mean(c(as.numeric(dplyr::select(filter(OWF_values, `OWF` == "Lincs"),c(`Swept area (m2)`))),as.numeric(dplyr::select(filter(OWF_values, `OWF` == "L & ID"),c(`Swept area (m2)`))))),mean(c(as.numeric(dplyr::select(filter(OWF_values, `OWF` == "Lincs"),c(`Distance to coast (km)`))),as.numeric(dplyr::select(filter(OWF_values, `OWF` == "L & ID"),c(`Distance to coast (km)`))))),as.numeric(dplyr::select(filter(OWF_values, `OWF` == "Lincs"),c(`Capacity (MW)`)))+as.numeric(dplyr::select(filter(OWF_values, `OWF` == "L & ID"),c(`Capacity (MW)`))),mean(c(as.numeric(dplyr::select(filter(OWF_values, `OWF` == "Lincs"),c(`Air gap (m)`))),as.numeric(dplyr::select(filter(OWF_values, `OWF` == "L & ID"),c(`Air gap (m)`))))),mean(c(as.numeric(dplyr::select(filter(OWF_values, `OWF` == "Lincs"),c(`Diameter (m)`))),as.numeric(dplyr::select(filter(OWF_values, `OWF` == "L & ID"),c(`Diameter (m)`))))),mean(c(as.numeric(dplyr::select(filter(OWF_values, `OWF` == "Lincs"),c(`Density (%)`))),as.numeric(dplyr::select(filter(OWF_values, `OWF` == "L & ID"),c(`Density (%)`))))),mean(c(as.numeric(dplyr::select(filter(OWF_values, `OWF` == "Lincs"),c(`Avg spacing (diameters)`))),as.numeric(dplyr::select(filter(OWF_values, `OWF` == "L & ID"),c(`Avg spacing (diameters)`))))),mean(c(as.numeric(dplyr::select(filter(OWF_values, `OWF` == "Lincs"),c(`Avg spacing (m)`))),as.numeric(dplyr::select(filter(OWF_values, `OWF` == "L & ID"),c(`Avg spacing (m)`))))),mean(c(as.numeric(dplyr::select(filter(OWF_values, `OWF` == "Lincs"),c(`Avg spacing to tower (m)`))),as.numeric(dplyr::select(filter(OWF_values, `OWF` == "L & ID"),c(`Avg spacing to tower (m)`))))),as.numeric(dplyr::select(filter(OWF_values, `OWF` == "Lincs"),c(`Max displ area`))))
#Remove old Lincs, L & ID rows not required
OWF_values <- OWF_values[OWF_values$OWF != "Lincs",]
OWF_values <- OWF_values[OWF_values$OWF != "L & ID",]

#Import histogram values
Histo_values <- read_excel("Main displ spreadsheet.xlsx", sheet = 3)
Histo_values <- Histo_values[1:35,11:12]
#Import displ rate in buffers
Displ_rate_buffers <- read_excel("Main displ spreadsheet.xlsx", sheet = 4)
Displ_rate_buffers <- Displ_rate_buffers[,11:14]
#Import displ rate in buffers accounting for width of buffer region
```

```
Displ_rate_buffers_width <- read_excel("Main displ spreadsheet.xlsx", sheet = 5)
#Import displ rate in buffers accounting for width of buffer region
Displ_rate_buffers_prop <- read_excel("Main displ spreadsheet.xlsx", sheet = 6)
#Import buffer area data
Displ_values_buffer <- read_excel("OWF and buffer areas.xlsx", sheet = 1)
```

Test for normal distribution

```
#Displ
shapiro.test(Displ_values$`% displ`)
ggqqplot(Displ_values$`% displ`, ylab = "Displ rate")
shapiro.test(Displ_values$`Displ distance`)
ggqqplot(Displ_values$`Displ distance`, ylab = "Displ distance")

#OWF
shapiro.test(OWF_values$`No. turbines`)
shapiro.test(OWF_values$`Height (m)`)
shapiro.test(OWF_values$`Area (km2)`)
shapiro.test(OWF_values$`Spacing row (m)`)
shapiro.test(OWF_values$`Spacing column (m)`)
shapiro.test(OWF_values$`Density (turbines/km2)`)
shapiro.test(OWF_values$`Swept area (m2)`)
shapiro.test(OWF_values$`Distance to coast (km)`)
shapiro.test(OWF_values$`Capacity (MW)`)
shapiro.test(OWF_values$`Air gap (m)`)
shapiro.test(OWF_values$`Diameter (m)`)
shapiro.test(OWF_values$`Density (%)`)

#Mostly non-normal distributions
```

Select values - Displacement rate within OWF

```
#Select % displ within OWF
Displ_within_OWF <- dplyr::select(filter(Displ_values, `Displ distance` == 0),c(OWF,`% displ`)
)
#Select corresponding OWF info
Displ_within_OWF_OWFs <- subset(OWF_values, OWF %in% Displ_within_OWF$OWF)
#Merge tables
Displ_within_OWF_merge <- merge(Displ_within_OWF, Displ_within_OWF_OWFs, by="OW
F")
```

Kendall stats - Displacement rate within OWF

```
#Kendall stats
Displ_rate_No_turb <- cor.test(Displ_within_OWF_merge$`% displ`, Displ_within_OWF_me
rge$`No. turbines`,  method = "kendall")
Displ_rate_Height <- cor.test(Displ_within_OWF_merge$`% displ`, Displ_within_OWF_merg
e$`Height (m)`,  method = "kendall")
Displ_rate_Area <- cor.test(Displ_within_OWF_merge$`% displ`, Displ_within_OWF_merge
$`Area (km2)`,  method = "kendall")
```

```
Displ_rate_Spac_row <- cor.test(Displ_within_OWF_merge$`% displ`, Displ_within_OWF_merge$`Spacing row (m)`,  method = "kendall")
Displ_rate_Spac_col <- cor.test(Displ_within_OWF_merge$`% displ`, Displ_within_OWF_merge$`Spacing column (m)`,  method = "kendall")
Displ_rate_Density_turb <- cor.test(Displ_within_OWF_merge$`% displ`, Displ_within_OWF_merge$`Density (turbines/km2)`,  method = "kendall")
Displ_rate_Swept <- cor.test(Displ_within_OWF_merge$`% displ`, Displ_within_OWF_merge$`Swept area (m2)`,  method = "kendall")
Displ_rate_Coast <- cor.test(Displ_within_OWF_merge$`% displ`, Displ_within_OWF_merge$`Distance to coast (km)`,  method = "kendall")
Displ_rate_Capacity <- cor.test(Displ_within_OWF_merge$`% displ`, Displ_within_OWF_merge$`Capacity (MW)`,  method = "kendall")
Displ_rate_Air_gap <- cor.test(Displ_within_OWF_merge$`% displ`, Displ_within_OWF_merge$`Air gap (m)`,  method = "kendall")
Displ_rate_Diameter <- cor.test(Displ_within_OWF_merge$`% displ`, Displ_within_OWF_merge$`Diameter (m)`,  method = "kendall")
Displ_rate_Density_perc <- cor.test(Displ_within_OWF_merge$`% displ`, Displ_within_OWF_merge$`Density (%)`,  method = "kendall")
Displ_rate_Avg_spac_D <- cor.test(Displ_within_OWF_merge$`% displ`, Displ_within_OWF_merge$`Avg spacing (diameters)`,  method = "kendall")
Displ_rate_Avg_spac_m <- cor.test(Displ_within_OWF_merge$`% displ`, Displ_within_OWF_merge$`Avg spacing (m)`,  method = "kendall")
Displ_rate_Avg_spac_tower <- cor.test(Displ_within_OWF_merge$`% displ`, Displ_within_OWF_merge$`Avg spacing to tower (m)`,  method = "kendall")

#Plot stats
#Density turb
Density_vs_displ_within <- ggplot(Displ_within_OWF_merge, aes(x=`Density (turbines/km2)`, y=`% displ`))+
  geom_point(col="#DF0059")+
  theme_bw()+
  theme(panel.border = element_blank(), axis.line = element_line(colour = "black"),
        legend.position = "bottom", legend.direction = "vertical",
        text=element_text(size=12,  family="Calibri"))+
  xlab(expression(paste("Density (turbines/k", m^2, ")")))+
  ylab("Displacement rate (%)")+
  stat_cor(method="kendall", aes(family="Calibri"))+
  geom_smooth(method='lm', formula= y~x, col="#6C0091")
#Swept area
Swept_vs_displ_within <- ggplot(Displ_within_OWF_merge, aes(x=`Swept area (m2)`, y=`% displ`))+
  geom_point(col="#DF0059")+
  theme_bw()+
  theme(panel.border = element_blank(), axis.line = element_line(colour = "black"),
        legend.position = "bottom", legend.direction = "vertical",
        text=element_text(size=12,  family="Calibri"))+
  xlab(expression(paste("Swept area (", m^2, ")")))+
  ylab("Displacement rate (%)")+
  stat_cor(method="kendall", aes(family="Calibri"), label.y.npc=1, label.x.npc=0.5)+
  geom_smooth(method='lm', formula= y~x, col="#6C0091")
```

```
#Column spacing
Column_spacing_vs_displ_within <- ggplot(Displ_within_OWF_merge, aes(x=`Spacing column (m)`, y=`% displ`))+
  geom_point(col="#DF0059")+
  theme_bw()+
  theme(panel.border = element_blank(), axis.line = element_line(colour = "black"),
        legend.position = "bottom", legend.direction = "vertical",
        text=element_text(size=12,  family="Calibri"))+
  xlab("Maximum turbine spacing (m)")+
  ylab("Displacement rate (%)")+
  stat_cor(method="kendall", aes(family="Calibri"), label.y.npc=1, label.x.npc=0.5)+
  geom_smooth(method='lm', formula= y~x, col="#6C0091")
#Diameter
Diameter_vs_displ_within <- ggplot(Displ_within_OWF_merge, aes(x=`Diameter (m)`, y=`% displ`))+
  geom_point(col="#DF0059")+
  theme_bw()+
  theme(panel.border = element_blank(), axis.line = element_line(colour = "black"),
        legend.position = "bottom", legend.direction = "vertical",
        text=element_text(size=12,  family="Calibri"))+
  xlab("Diameter (m)")+
  ylab("Displacement rate (%)")+
  stat_cor(method="kendall", aes(family="Calibri"), label.y.npc=1, label.x.npc=0.5)+
  geom_smooth(method='lm', formula= y~x, col="#6C0091")
#Avg spacing
Avg_spacing_vs_displ_within <- ggplot(Displ_within_OWF_merge, aes(x=`Avg spacing (m)`, y=`% displ`))+
  geom_point(col="#DF0059")+
  theme_bw()+
  theme(panel.border = element_blank(), axis.line = element_line(colour = "black"),
        legend.position = "bottom", legend.direction = "vertical",
        text=element_text(size=12,  family="Calibri"))+
  xlab("Average spacing blade to blade (m)")+
  ylab("Displacement rate (%)")+
  stat_cor(method="kendall", aes(family="Calibri"), label.y.npc=1, label.x.npc=0.5)+
  geom_smooth(method='lm', formula= y~x, col="#6C0091")
#Avg spacing to tower (m)
Avg_spacing_tower_vs_displ_within <- ggplot(Displ_within_OWF_merge, aes(x=`Avg spacing to tower (m)`, y=`% displ`))+
  geom_point(col="#DF0059")+
  theme_bw()+
  theme(panel.border = element_blank(), axis.line = element_line(colour = "black"),
        legend.position = "bottom", legend.direction = "vertical",
        text=element_text(size=12,  family="Calibri"))+
  xlab("Average spacing tower to tower (m)")+
  ylab("Displacement rate (%)")+
  stat_cor(method="kendall", aes(family="Calibri"), label.y.npc=1, label.x.npc=0.5)+
  geom_smooth(method='lm', formula= y~x, col="#6C0091")

#Save plots
```

```r
setwd("C:/Users/44755/OneDrive - University of Strathclyde/5. OWF design and displacement/Plots")
ggsave('Density_vs_displ_within.png', Density_vs_displ_within, height = 5, width = 7)
ggsave('Swept_vs_displ_within.png', Swept_vs_displ_within, height = 5, width = 7)
ggsave('Column_spacing_vs_displ_within.png', Column_spacing_vs_displ_within, height = 5, width = 7)
ggsave('Diameter_vs_displ_within.png', Diameter_vs_displ_within, height = 5, width = 7)
ggsave('Avg_spacing_vs_displ_within.png', Avg_spacing_vs_displ_within, height = 5, width = 7)
ggsave('Avg_spacing_tower_vs_displ_within.png', Avg_spacing_tower_vs_displ_within, height = 5, width = 7)
```

Partial correlations - Displacement rate within OWF

```r
#Partial correlation displ vs density, controlling for no turbines
Partial_displ_density_noturbines<-pcor.test(Displ_within_OWF_merge$`% displ`, Displ_within_OWF_merge$`Density (turbines/km2)`, Displ_within_OWF_merge$`No. turbines`,  method = "kendall")
#Partial correlation displ vs density, controlling for rotor diameter
Partial_displ_density_diameter<-pcor.test(Displ_within_OWF_merge$`% displ`, Displ_within_OWF_merge$`Density (turbines/km2)`, Displ_within_OWF_merge$`Diameter (m)`,  method = "kendall")
#Partial correlation displ vs rotor diameter, controlling for density
Partial_displ_diameter_density<-pcor.test(Displ_within_OWF_merge$`% displ`, Displ_within_OWF_merge$`Diameter (m)`, Displ_within_OWF_merge$`Density (turbines/km2)`,  method = "kendall")
#Partial correlation displ vs density, controlling for height
Partial_displ_density_height<-pcor.test(Displ_within_OWF_merge$`% displ`, Displ_within_OWF_merge$`Density (turbines/km2)`, Displ_within_OWF_merge$`Height (m)`,  method = "kendall")
```

Select values - Max displacement distance

```r
#Find max displ dist per OWF
Displ_distance<-aggregate(`Displ distance` ~ OWF, data = Displ_values, max)
#Select corresponding OWF info
Displ_dist_OWFs <- subset(OWF_values, OWF %in% Displ_distance$OWF)
#Merge tables
Displ_dist_merge <- merge(Displ_distance, Displ_dist_OWFs, by="OWF")
#Remove rows with NA
Displ_dist_merge <- Displ_dist_merge[complete.cases(Displ_dist_merge), ]
```

Kendall stats - Max displacement distance

```r
Displ_dist_No_turb <- cor.test(Displ_dist_merge$`Displ distance`, Displ_dist_merge$`No. turbines`,  method = "kendall")
Displ_dist_Height <- cor.test(Displ_dist_merge$`Displ distance`, Displ_dist_merge$`Height (m)`,  method = "kendall")
Displ_dist_Area <- cor.test(Displ_dist_merge$`Displ distance`, Displ_dist_merge$`Area (km2)`,  method = "kendall")
```

```
Displ_dist_Spac_row <- cor.test(Displ_dist_merge$`Displ distance`, Displ_dist_merge$`Spacing row (m)`,  method = "kendall")
Displ_dist_Spac_col <- cor.test(Displ_dist_merge$`Displ distance`, Displ_dist_merge$`Spacing column (m)`,  method = "kendall")
Displ_dist_Density <- cor.test(Displ_dist_merge$`Displ distance`, Displ_dist_merge$`Density (turbines/km2)`,  method = "kendall")
Displ_dist_Swept <- cor.test(Displ_dist_merge$`Displ distance`, Displ_dist_merge$`Swept area (m2)`,  method = "kendall")
Displ_dist_Coast <- cor.test(Displ_dist_merge$`Displ distance`, Displ_dist_merge$`Distance to coast (km)`,  method = "kendall")
Displ_dist_Capacity <- cor.test(Displ_dist_merge$`Displ distance`, Displ_dist_merge$`Capacity (MW)`,  method = "kendall")
Displ_dist_Air_gap <- cor.test(Displ_dist_merge$`Displ distance`, Displ_dist_merge$`Air gap (m)`,  method = "kendall")
Displ_dist_Diameter <- cor.test(Displ_dist_merge$`Displ distance`, Displ_dist_merge$`Diameter (m)`,  method = "kendall")
Displ_dist_Density_perc <- cor.test(Displ_dist_merge$`Displ distance`, Displ_dist_merge$`Density (%)`,  method = "kendall")
Displ_dist_Avg_spacing_d <- cor.test(Displ_dist_merge$`Displ distance`, Displ_dist_merge$`Avg spacing (diameters)`,  method = "kendall")
Displ_dist_Avg_spacing_m <- cor.test(Displ_dist_merge$`Displ distance`, Displ_dist_merge$`Avg spacing (m)`,  method = "kendall")
Displ_dist_Avg_spacing_tower <- cor.test(Displ_dist_merge$`Displ distance`, Displ_dist_merge$`Avg spacing to tower (m)`, method = "kendall")
```

Kendall stats - Turbine parameters with one another

```
#Test for correlations between turbine parameters
Diameter_height<-cor.test(OWF_values$`Diameter (m)`, OWF_values$`Height (m)`,  method = "kendall")
Diameter_spacingtower<-cor.test(OWF_values$`Diameter (m)`, OWF_values$`Avg spacing to tower (m)`,  method = "kendall")
Diameter_spacingm<-cor.test(OWF_values$`Diameter (m)`, OWF_values$`Avg spacing (m)`, method = "kendall")
Diameter_spacingdiameter<-cor.test(OWF_values$`Diameter (m)`, OWF_values$`Avg spacing (diameters)`,  method = "kendall")
Diameter_densitypercentage<-cor.test(OWF_values$`Diameter (m)`, OWF_values$`Density (%)`,  method = "kendall")
Diameter_densityturbines<-cor.test(OWF_values$`Diameter (m)`, OWF_values$`Density (turbines/km2)`,  method = "kendall")
Spacingcolumn_densityturbines<-cor.test(OWF_values$`Spacing column (m)`, OWF_values$`Density (turbines/km2)`,  method = "kendall")
Spacingcolumn_diameter<-cor.test(OWF_values$`Spacing column (m)`, OWF_values$`Diameter (m)`,  method = "kendall")
```

Appendix F – R markdown code used in the analysis of Chapter 5

Packages required

```
library(ggplot2)
library(pwr)
library(ggpubr)
library(extrafont)
```

Set initial information

```
setwd("C:/Users/44755/OneDrive - University of Strathclyde/5. OWF design and displaceme
nt/Plots")
#Set area of study
Area<- 1174
#Density of birds in each transect spacing (from GIS)
Transect0.5_density <- 4.5176
Transect1.0_density <- 4.5501
Transect1.5_density <- 4.5257
Transect2.0_density <- 4.5372
Transect2.5_density <- 4.6154
Transect3.0_density <- 4.5524
#Import density information in each transect spacing (from GIS)
Transect_0.5km_numbers <- read.csv("C:/Users/44755/OneDrive - University of Strathclyde
/Old/JNCC internship/Journal article/Transect 0.5km numbers SPA clipped.csv")
Transect_1.0km_numbers <- read.csv("C:/Users/44755/OneDrive - University of Strathclyde
/Old/JNCC internship/Journal article/Transect 1km numbers SPA clipped.csv")
Transect_1.5km_numbers <- read.csv("C:/Users/44755/OneDrive - University of Strathclyde
/Old/JNCC internship/Journal article/Transect 1.5km numbers SPA clipped.csv")
Transect_2.0km_numbers <- read.csv("C:/Users/44755/OneDrive - University of Strathclyde
/Old/JNCC internship/Journal article/Transect 2km numbers SPA clipped.csv")
Transect_2.5km_numbers <- read.csv("C:/Users/44755/OneDrive - University of Strathclyde
/Old/JNCC internship/Journal article/Transect 2.5km numbers SPA clipped.csv")
Transect_3.0km_numbers <- read.csv("C:/Users/44755/OneDrive - University of Strathclyde
/Old/JNCC internship/Journal article/Transect 3km numbers SPA clipped.csv")
#Plot distribution of data
#0.5km transect
ggplot(Transect_0.5km_numbers, aes(x=Predict_nu)) + geom_histogram(binwidth=.5)+geo
m_vline(aes(xintercept=mean(Predict_nu, na.rm=T)),color="red", linetype="dashed", size=1
)
#1.0km transect
ggplot(Transect_1.0km_numbers, aes(x=Predict_nu)) + geom_histogram(binwidth=.5)+geo
m_vline(aes(xintercept=mean(Predict_nu, na.rm=T)),color="red", linetype="dashed", size=1
)
```

```
#1.5km transect
ggplot(Transect_1.5km_numbers, aes(x=Predict_nu)) + geom_histogram(binwidth=.5)+geo
m_vline(aes(xintercept=mean(Predict_nu, na.rm=T)),color="red", linetype="dashed", size=1
)
#2.0km transect
ggplot(Transect_2.0km_numbers, aes(x=Predict_nu)) + geom_histogram(binwidth=.5)+geo
m_vline(aes(xintercept=mean(Predict_nu, na.rm=T)),color="red", linetype="dashed", size=1
)
#2.5km transect
ggplot(Transect_2.5km_numbers, aes(x=Predict_nu)) + geom_histogram(binwidth=.5)+geo
m_vline(aes(xintercept=mean(Predict_nu, na.rm=T)),color="red", linetype="dashed", size=1
)
#3.0km transect
ggplot(Transect_3.0km_numbers, aes(x=Predict_nu)) + geom_histogram(binwidth=.5)+geo
m_vline(aes(xintercept=mean(Predict_nu, na.rm=T)),color="red", linetype="dashed", size=1
)
```

Calculate and plot difference in mean density of birds and SD in transect spacing scenarios

```
#Make table of densities, # of birds, mean bird density in each transect spacing as percentag
e of mean bird density in 0.5km spacing, and SD of bird density in each transect spacing as p
ercentage of SD of bird density in 0.5km spacing
Transect_error <- data.frame(transectspacing = c(0.5, 1.0, 1.5, 2.0, 2.5, 3.0),
                             density = c(Transect0.5_density, Transect1.0_density, Transect1.5_density,
Transect2.0_density, Transect2.5_density, Transect3.0_density),
                             nobirds = c(Transect0.5_density*Area, Transect1.0_density*Area, Transect
1.5_density*Area,Transect2.0_density*Area, Transect2.5_density*Area, Transect3.0_densit
y*Area),
                             mean_diff_perc = c((mean(Transect_0.5km_numbers$Predict_nu)-mean(Tr
ansect_0.5km_numbers$Predict_nu))/mean(Transect_0.5km_numbers$Predict_nu)*100,(
mean(Transect_1.0km_numbers$Predict_nu)-mean(Transect_0.5km_numbers$Predict_nu)
)/mean(Transect_0.5km_numbers$Predict_nu)*100,(mean(Transect_1.5km_numbers$Pred
ict_nu)-mean(Transect_0.5km_numbers$Predict_nu))/mean(Transect_0.5km_numbers$Pr
edict_nu)*100,(mean(Transect_2.0km_numbers$Predict_nu)-mean(Transect_0.5km_numb
ers$Predict_nu))/mean(Transect_0.5km_numbers$Predict_nu)*100,(mean(Transect_2.5km
_numbers$Predict_nu)-mean(Transect_0.5km_numbers$Predict_nu))/mean(Transect_0.5k
m_numbers$Predict_nu)*100,(mean(Transect_3.0km_numbers$Predict_nu)-mean(Transec
t_0.5km_numbers$Predict_nu))/mean(Transect_0.5km_numbers$Predict_nu)*100),
                             sd_diff_perc = c((sd(Transect_0.5km_numbers$Predict_nu)-sd(Transect_0.
5km_numbers$Predict_nu))/sd(Transect_0.5km_numbers$Predict_nu)*100,(sd(Transect_1
.0km_numbers$Predict_nu)-sd(Transect_0.5km_numbers$Predict_nu))/sd(Transect_0.5km
_numbers$Predict_nu)*100,(sd(Transect_1.5km_numbers$Predict_nu)-sd(Transect_0.5km
_numbers$Predict_nu))/sd(Transect_0.5km_numbers$Predict_nu)*100,(sd(Transect_2.0k
m_numbers$Predict_nu)-sd(Transect_0.5km_numbers$Predict_nu))/sd(Transect_0.5km_n
umbers$Predict_nu)*100,(sd(Transect_2.5km_numbers$Predict_nu)-sd(Transect_0.5km_n
umbers$Predict_nu))/sd(Transect_0.5km_numbers$Predict_nu)*100,(sd(Transect_3.0km_
numbers$Predict_nu)-sd(Transect_0.5km_numbers$Predict_nu))/sd(Transect_0.5km_num
bers$Predict_nu)*100))
#Make transect spacing factor
```

```r
Transect_error$transectspacing <- as.character(Transect_error$transectspacing)
#Plot mean as percentage of 0.5km spacing
Mean_perc_of0.5km_spacing <-
ggplot(Transect_error, aes(transectspacing, mean_diff_perc, colour = transectspacing)) +geom_point(size=2)+scale_color_manual(name="Transect\nspacing (km)",labels=c("0.5","1.0","1.5","2.0","2.5","3.0"),values=c(c('#DF0058', '#F58906', '#E4C540', '#89B883', '#096BB6', '#6C0091')))+theme_bw()+theme(plot.title = element_text(size=12, family="Calibri"),panel.border = element_blank(), axis.line = element_line(colour = "black"),legend.position = "right", legend.direction = "vertical", legend.margin = margin(-1,0,0,0, unit="cm"),text=element_text(size=14,  family="Calibri"))+ylab("Percentage difference")+xlab("Mean bird density (birds/km2)")
#Save plot
setwd("C:/Users/44755/OneDrive - University of Strathclyde/5. OWF design and displacement/Plots")
ggsave('Mean_perc_of0.5km_spacing.png', Mean_perc_of0.5km_spacing, height = 5, width = 6)
#Plot sd as percentage of 0.5km spacing
SD_perc_of0.5km_spacing <-ggplot(Transect_error, aes(transectspacing, sd_diff_perc, colour = transectspacing)) +geom_point(size=2)+scale_color_manual(name="Transect\nspacing (km)",labels=c("0.5","1.0","1.5","2.0","2.5","3.0"),values=c(c('#DF0058', '#F58906', '#E4C540', '#89B883', '#096BB6', '#6C0091')))+theme_bw()+theme(plot.title = element_text(size=12, family="Calibri"),panel.border = element_blank(), axis.line = element_line(colour = "black"),legend.position = "right", legend.direction = "vertical", legend.margin = margin(-1,0,0,0, unit="cm"),text=element_text(size=14,  family="Calibri"))+ylab("Percentage difference")+xlab("Standard deviation of bird density (birds/km2)")
#Save plot
ggsave('SD_perc_of0.5km_spacing.png', SD_perc_of0.5km_spacing, height = 5, width = 6)
#Calculate mean bird density in each transect spacing as percentage of mean bird density in 0.5km spacing
mean_diff_perc = c((mean(Transect_0.5km_numbers$Predict_nu)-mean(Transect_0.5km_numbers$Predict_nu))/mean(Transect_0.5km_numbers$Predict_nu)*100,(mean(Transect_1.0km_numbers$Predict_nu)-mean(Transect_0.5km_numbers$Predict_nu))/mean(Transect_0.5km_numbers$Predict_nu)*100,(mean(Transect_1.5km_numbers$Predict_nu)-mean(Transect_0.5km_numbers$Predict_nu))/mean(Transect_0.5km_numbers$Predict_nu)*100,(mean(Transect_2.0km_numbers$Predict_nu)-mean(Transect_0.5km_numbers$Predict_nu))/mean(Transect_0.5km_numbers$Predict_nu)*100,(mean(Transect_2.5km_numbers$Predict_nu)-mean(Transect_0.5km_numbers$Predict_nu))/mean(Transect_0.5km_numbers$Predict_nu)*100,(mean(Transect_3.0km_numbers$Predict_nu)-mean(Transect_0.5km_numbers$Predict_nu))/mean(Transect_0.5km_numbers$Predict_nu)*100)
#Calculate SD of bird density in each transect spacing as percentage of SD of bird density in 0.5km spacing
sd_diff_perc = c((sd(Transect_0.5km_numbers$Predict_nu)-sd(Transect_0.5km_numbers$Predict_nu))/sd(Transect_0.5km_numbers$Predict_nu)*100,(sd(Transect_1.0km_numbers$Predict_nu)-sd(Transect_0.5km_numbers$Predict_nu))/sd(Transect_0.5km_numbers$Predict_nu)*100,(sd(Transect_1.5km_numbers$Predict_nu)-sd(Transect_0.5km_numbers$Predict_nu))/sd(Transect_0.5km_numbers$Predict_nu)*100,(sd(Transect_2.0km_numbers$Predict_nu)-sd(Transect_0.5km_numbers$Predict_nu))/sd(Transect_0.5km_numbers$Predict_nu)*100,(sd(Transect_2.5km_numbers$Predict_nu)-sd(Transect_0.5km_numbers$Predict_nu))/sd(Transect_0.5km_numbers$Predict_nu)*100,(sd(Transect_3.0km_numbers$Predict_
```

```
nu)-sd(Transect_0.5km_numbers$Predict_nu))/sd(Transect_0.5km_numbers$Predict_nu)*
100)
```

Change number of samples, calculate power, same number of samples pre & post OWF construction

```
#Set # birds pre-construction
PreNoBirdsBASE <- 5
#Generate range of number of birds based on transect spacing
PreNoBirds <- data.frame(transectspacing=c(0.5,1.0,1.5,2.0,2.5,3.0),
             value = c(PreNoBirdsBASE*(1+(mean_diff_perc[1]/100)),PreNoBirdsBASE*(1+(
mean_diff_perc[2]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[3]/100)),PreNoBirdsBASE*(
1+(mean_diff_perc[4]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[5]/100)),PreNoBirdsBAS
E*(1+(mean_diff_perc[6]/100))))
#Set range of displacement rates
Displacement <- seq(0,100,5)
#Set scenarios of number of samples pre-construction
PreNoSamples <- c(12,24)
#Set SD
standardDevBASIC <- 2
#Generate range of SD based on transect spacing
transect_choices_df = data.frame(transectspacing=c(0.5,1.0,1.5,2.0,2.5,3.0),
                  value=c(standardDevBASIC*(1+(sd_diff_perc[1]/100)),standardDevBASIC
*(1+(sd_diff_perc[2]/100)),standardDevBASIC*(1+(sd_diff_perc[3]/100)),standardDevBASIC
*(1+(sd_diff_perc[4]/100)),standardDevBASIC*(1+(sd_diff_perc[5]/100)),standardDevBASIC
*(1+(sd_diff_perc[6]/100))))
#Make transect spacing a factor
transect_choices_df$transectspacing <- as.character(transect_choices_df$transectspacing)
#Set alpha for power analysis
alpha <- 0.05
#Calculate power of surveys for a range of transect spacings, displacement rates, and numb
er of samples pre-construction
Change_NoSamples_Same_df <- data.frame(PreNoBirds=NA,PreNoSamples=NA,Displaceme
nt=NA,transect=NA,Power=NA)
k<-1
m<-1
n<-1
for (c in transect_choices_df[,2]) {
 m<-1
 for (b in Displacement) {
  n<-1
  for (a in PreNoSamples) {
   Change_NoSamples_Same_df[((k-1)*length(PreNoSamples)*length(Displacement))+((m-
1)*length(PreNoSamples))+n,1]<-PreNoBirds[k,2]
   Change_NoSamples_Same_df[((k-1)*length(PreNoSamples)*length(Displacement))+((m-
1)*length(PreNoSamples))+n,2]<-a
   Change_NoSamples_Same_df[((k-1)*length(PreNoSamples)*length(Displacement))+((m-
1)*length(PreNoSamples))+n,3]<-b
   Change_NoSamples_Same_df[((k-1)*length(PreNoSamples)*length(Displacement))+((m-
1)*length(PreNoSamples))+n,4]<-transect_choices_df[k,1]
```

```r
   Change_NoSamples_Same_df[((k-1)*length(PreNoSamples)*length(Displacement))+((m-1)*length(PreNoSamples))+n,5]<-pwr.t.test(n = PreNoSamples[n],d = (abs(PreNoBirds[k,2]-(PreNoBirds[k,2]*(1-(Displacement[m]/100)))))/sqrt(((transect_choices_df[k,2]^2)+((transect_choices_df[k,2]*(1-(Displacement[m]/100)))^2))/2),sig.level = alpha,power = NULL, type="paired")$power
   n<-n+1
  }
  m<-m+1
 }
 k<-k+1
}
#Plot results
Power_0.8 <- data.frame(yintercept=0.8, Power=factor(0.8))
#Using 12 samples pre-construction
Change_NoSamples12_Same_Plot <- ggplot(subset(Change_NoSamples_Same_df, PreNoSamples==12), aes(`Displacement`, y=`Power`,colour = transect)) +geom_point(size=1.5)+scale_color_manual(name="Transect\nspacing (km)",labels=c("0.5","1.0","1.5","2.0","2.5","3.0"),values=c(c('#DF0058', '#F58906', '#E4C540', '#89B883', '#096BB6', '#6C0091')))+theme_bw()+theme(panel.border = element_blank(), axis.line = element_line(colour = "black"),legend.position = "right", legend.direction = "vertical",legend.margin = margin(-1,2,0,0, unit="cm"),text=element_text(size=12,  family="Calibri"))+ylab("Power")+xlab("Displacement (%)")+ggtitle("12 survey days")+geom_hline(data=Power_0.8, aes(yintercept=yintercept, linetype="18"), colour='grey', size=0.5) +scale_linetype_manual(name = "",values = c(1,1), labels="Power = 0.8")+ylim(0,1)+scale_x_continuous(breaks = seq(0, 100, by = 10))
#Using 24 samples pre-construction
Change_NoSamples24_Same_Plot <- ggplot(subset(Change_NoSamples_Same_df, PreNoSamples==24), aes(`Displacement`, y=`Power`,colour = transect)) +geom_point(size=1.5)+scale_color_manual(name="Transect\nspacing (km)",labels=c("0.5","1.0","1.5","2.0","2.5","3.0"),values=c(c('#DF0058', '#F58906', '#E4C540', '#89B883', '#096BB6', '#6C0091')))+theme_bw()+theme(panel.border = element_blank(), axis.line = element_line(colour = "black"),legend.position = "right", legend.direction = "vertical",legend.margin = margin(-1,2,0,0, unit="cm"),text=element_text(size=12,  family="Calibri"))+ylab("Power")+xlab("Displacement (%)")+ggtitle("24 survey days")+geom_hline(data=Power_0.8, aes(yintercept=yintercept, linetype="18"), colour='grey', size=0.5) +scale_linetype_manual(name = "",values = c(1,1), labels="Power = 0.8")+ylim(0,1)+scale_x_continuous(breaks = seq(0, 100, by = 10))
#Arrange both plots together
Change_NoSamples_Same_Plot <- ggarrange(Change_NoSamples12_Same_Plot, Change_NoSamples24_Same_Plot, common.legend = TRUE, legend="right")
#Save plots
setwd("C:/Users/44755/OneDrive - University of Strathclyde/Old/JNCC internship/Plots/All new plots")
ggsave('Change_NoSamples_Same_Plot_paired.png', Change_NoSamples_Same_Plot, height = 5, width = 10, dpi=600)
#Zoom in on 0.8 power where some transect spacings are under 0.8 and some are over 0.8 power
Zoom_NoSamples12__Same_Plot <- ggplot(subset(Change_NoSamples_Same_df, PreNoSamples==12), aes(`Displacement`, y=`Power`,colour = transect)) +geom_point(size=1.5)+scale_color_manual(name="Transect\nspacing (km)",labels=c("0.5","1.0","1.5","2.0","2.5","3.0"),values=c(c('#DF0058', '#F58906', '#E4C540', '#89B883', '#096BB6', '#6C0091')))+theme_bw()+theme(panel.border = element_blank(), axis.line = element_line(colour = "black"),legen
```

```
d.position = "right", legend.direction = "vertical",legend.margin = margin(-1,2,0,0, unit="cm
"),text=element_text(size=12,  family="Calibri"))+ylab("Power")+xlab("Displacement (%)")+
ggtitle("12 survey days")+geom_hline(data=Power_0.8, aes(yintercept=yintercept, linetype
="18"), colour='grey', size=0.5) +scale_linetype_manual(name = "",values = c(1,1), labels="P
ower = 0.8")+scale_y_continuous(limits=c(0.77, 0.81), breaks=seq(0.77, 0.81, 0.01))+scale_x
_continuous(limits=c(29, 31), breaks=seq(29, 31, 1))
#Save
ggsave('Zoom_NoSamples12__Same_Plot_paired.png', Zoom_NoSamples12__Same_Plot, h
eight = 5, width = 7)
```

Change number of samples, calculate power, same number of samples pre & post OWF construction, higher bird density

```
#Set # birds pre-construction
PreNoBirdsBASE <- 10
#Generate range of number of birds based on transect spacing
PreNoBirds <- data.frame(transectspacing=c(0.5,1.0,1.5,2.0,2.5,3.0),
                         value = c(PreNoBirdsBASE*(1+(mean_diff_perc[1]/100)),PreNoBirdsBASE*(1+(
mean_diff_perc[2]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[3]/100)),PreNoBirdsBASE*(
1+(mean_diff_perc[4]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[5]/100)),PreNoBirdsBAS
E*(1+(mean_diff_perc[6]/100))))
#Set range of displacement rates
Displacement <- seq(0,100,5)
#Set scenarios of number of samples pre-construction
PreNoSamples <- c(12,24)
#Set SD
standardDevBASIC <- 2
#Generate range of SD based on transect spacing
transect_choices_df = data.frame(transectspacing=c(0.5,1.0,1.5,2.0,2.5,3.0),
                                 value=c(standardDevBASIC*(1+(sd_diff_perc[1]/100)),standardDevBASIC
*(1+(sd_diff_perc[2]/100)),standardDevBASIC*(1+(sd_diff_perc[3]/100)),standardDevBASIC
*(1+(sd_diff_perc[4]/100)),standardDevBASIC*(1+(sd_diff_perc[5]/100)),standardDevBASIC
*(1+(sd_diff_perc[6]/100))))
#Make transect spacing a factor
transect_choices_df$transectspacing <- as.character(transect_choices_df$transectspacing)
#Set alpha for power analysis
alpha <- 0.05
#Calculate power of surveys for a range of transect spacings, displacement rates, and numb
er of samples pre-construction
Change_NoSamples_Same_Highden_df <- data.frame(PreNoBirds=NA,PreNoSamples=NA,D
isplacement=NA,transect=NA,Power=NA)
k<-1
m<-1
n<-1
for (c in transect_choices_df[,2]) {
  m<-1
  for (b in Displacement) {
    n<-1
    for (a in PreNoSamples) {
      Change_NoSamples_Same_Highden_df[((k-1)*length(PreNoSamples)*length(Displacem
```

```
ent))+((m-1)*length(PreNoSamples))+n,1]<-PreNoBirds[k,2]
   Change_NoSamples_Same_Highden_df[((k-1)*length(PreNoSamples)*length(Displacem
ent))+((m-1)*length(PreNoSamples))+n,2]<-a
   Change_NoSamples_Same_Highden_df[((k-1)*length(PreNoSamples)*length(Displacem
ent))+((m-1)*length(PreNoSamples))+n,3]<-b
   Change_NoSamples_Same_Highden_df[((k-1)*length(PreNoSamples)*length(Displacem
ent))+((m-1)*length(PreNoSamples))+n,4]<-transect_choices_df[k,1]
   Change_NoSamples_Same_Highden_df[((k-1)*length(PreNoSamples)*length(Displacem
ent))+((m-1)*length(PreNoSamples))+n,5]<-pwr.t.test(n = PreNoSamples[n],d = (abs(PreNo
Birds[k,2]-(PreNoBirds[k,2]*(1-(Displacement[m]/100)))))/sqrt(((transect_choices_df[k,2]^2
)+((transect_choices_df[k,2]*(1-(Displacement[m]/100)))^2))/2),sig.level = alpha,power = N
ULL, type="paired")$power
   n<-n+1
  }
  m<-m+1
 }
 k<-k+1
}
#Plot results
Power_0.8 <- data.frame(yintercept=0.8, Power=factor(0.8))
#Using 12 samples pre-construction
Change_NoSamples12_Same_HighDen_Plot <- ggplot(subset(Change_NoSamples_Same_Hi
ghden_df, PreNoSamples==12), aes(`Displacement`, y=`Power`,colour = transect)) +geom_p
oint(size=1.5)+scale_color_manual(name="Transect\nspacing (km)",labels=c("0.5","1.0","1.
5","2.0","2.5","3.0"),values=c(c('#DF0058', '#F58906', '#E4C540', '#89B883', '#096BB6', '#6C
0091')))+theme_bw()+theme(panel.border = element_blank(), axis.line = element_line(colo
ur = "black"),legend.position = "right", legend.direction = "vertical",legend.margin = margin(
-1,2,0,0, unit="cm"),text=element_text(size=12,  family="Calibri"))+ylab("Power")+xlab("Dis
placement (%)")+ggtitle("12 survey days")+geom_hline(data=Power_0.8, aes(yintercept=yin
tercept, linetype="18"), colour='grey', size=0.5) +scale_linetype_manual(name = "",values =
c(1,1), labels="Power = 0.8")+ylim(0,1)+scale_x_continuous(breaks = seq(0, 100, by = 10))
#Using 24 samples pre-construction
Change_NoSamples24_Same_HighDen_Plot <- ggplot(subset(Change_NoSamples_Same_Hi
ghden_df, PreNoSamples==24), aes(`Displacement`, y=`Power`,colour = transect)) +geom_p
oint(size=1.5)+scale_color_manual(name="Transect\nspacing (km)",labels=c("0.5","1.0","1.
5","2.0","2.5","3.0"),values=c(c('#DF0058', '#F58906', '#E4C540', '#89B883', '#096BB6', '#6C
0091')))+theme_bw()+theme(panel.border = element_blank(), axis.line = element_line(colo
ur = "black"),legend.position = "right", legend.direction = "vertical",legend.margin = margin(
-1,2,0,0, unit="cm"),text=element_text(size=12,  family="Calibri"))+ylab("Power")+xlab("Dis
placement (%)")+ggtitle("24 survey days")+geom_hline(data=Power_0.8, aes(yintercept=yin
tercept, linetype="18"), colour='grey', size=0.5) +scale_linetype_manual(name = "",values =
c(1,1), labels="Power = 0.8")+ylim(0,1)+scale_x_continuous(breaks = seq(0, 100, by = 10))
#Arrange both plots together
Change_NoSamples_Same_HighDen_Plot <- ggarrange(Change_NoSamples12_Same_HighD
en_Plot, Change_NoSamples24_Same_HighDen_Plot, common.legend = TRUE, legend="rig
ht")
#Save
ggsave('Change_NoSamples_Same_HighDen_Plot_paired.png', Change_NoSamples_Same_
HighDen_Plot, height = 5, width = 10, dpi=600)
#Zoom in on 0.8 power where some transect spacings are under 0.8 and some are over 0.8 p
```

```
ower
Change_NoSamples24_Same_HighDen_ZoomPlot <- ggplot(subset(Change_NoSamples_Same_Highden_df, PreNoSamples==24), aes(`Displacement`, y=`Power`,colour = transect)) +geom_point(size=2)+scale_color_manual(name="Transect\nspacing (km)",labels=c("0.5","1.0","1.5","2.0","2.5","3.0"),values=c(c('#DF0058', '#F58906', '#E4C540', '#89B883', '#096BB6', '#6C0091')))+theme_bw()+theme(plot.title = element_text(size=12, family="Calibri"),panel.border = element_blank(), axis.line = element_line(colour = "black"),legend.position = "right", legend.direction = "vertical", legend.margin = margin(-1,0,0,0, unit="cm"),text=element_text(size=14,  family="Calibri"))+ylab("Power")+xlab("Displacement (%)")+ggtitle("24 survey days")+geom_hline(data=Power_0.8, aes(yintercept=yintercept, linetype="18"), colour='grey', size=0.5) +scale_linetype_manual(name = "",values = c(1,1), labels="Power = 0.8")+ylim(0.75,0.85)+scale_x_continuous(breaks = seq(0, 100, by = 10))
#Save
ggsave('Change_NoSamples24_Same_HighDen_ZoomPlot.png', Change_NoSamples24_Same_HighDen_ZoomPlot, height = 5, width = 10, dpi=600)
```

Change SD, calculate power, same number of samples pre & post OWF construction

```
#Set SD at 2
#Set # birds pre-construction
PreNoBirdsBASE <- 5
#Generate range of number of birds based on transect spacing
PreNoBirds <- data.frame(transectspacing=c(0.5,1.0,1.5,2.0,2.5,3.0),
                         value = c(PreNoBirdsBASE*(1+(mean_diff_perc[1]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[2]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[3]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[4]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[5]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[6]/100))))
#Set range of displacement rates
Displacement <- seq(0,100,5)
#Set scenarios of number of samples pre-construction
PreNoSamples <- c(24)
#Set SD
standardDevBASIC <- 2
#Generate range of SD based on transect spacing
transect_choices_df = data.frame(transectspacing=c(0.5,1.0,1.5,2.0,2.5,3.0),
                               value=c(standardDevBASIC*(1+(sd_diff_perc[1]/100)),standardDevBASIC*(1+(sd_diff_perc[2]/100)),standardDevBASIC*(1+(sd_diff_perc[3]/100)),standardDevBASIC*(1+(sd_diff_perc[4]/100)),standardDevBASIC*(1+(sd_diff_perc[5]/100)),standardDevBASIC*(1+(sd_diff_perc[6]/100))))
#Make transect spacing a factor
transect_choices_df$transectspacing <- as.character(transect_choices_df$transectspacing)
#Set alpha for power analysis
alpha <- 0.05
#Calculate power of surveys for a range of transect spacings, and displacement rates for SD of 2
Change_SD_2_Same_df <- data.frame(PreNoBirds=NA,PreNoSamples=NA,Displacement=NA,transect=NA,Power=NA)
k<-1
m<-1
for (c in transect_choices_df[,2]) {
```

```
  m<-1
  for (b in Displacement) {
    Change_SD_2_Same_df[((k-1)*length(Displacement))+m,1]<-PreNoBirds[k,2]
    Change_SD_2_Same_df[((k-1)*length(Displacement))+m,2]<-a
    Change_SD_2_Same_df[((k-1)*length(Displacement))+m,3]<-b
    Change_SD_2_Same_df[((k-1)*length(Displacement))+m,4]<-transect_choices_df[k,1]
    Change_SD_2_Same_df[((k-1)*length(Displacement))+m,5]<-pwr.t.test(n = PreNoSamples,d = (abs(PreNoBirds[k,2]-(PreNoBirds[k,2]*(1-(Displacement[m]/100)))))/sqrt(((transect_choices_df[k,2]^2)+((transect_choices_df[k,2]*(1-(Displacement[m]/100)))^2))/2),sig.level = alpha,power = NULL, type="paired")$power
    m<-m+1
  }
  k<-k+1
}
#Set SD at 2
#Set # birds pre-construction
PreNoBirdsBASE <- 5
#Generate range of number of birds based on transect spacing
PreNoBirds <- data.frame(transectspacing=c(0.5,1.0,1.5,2.0,2.5,3.0),
                         value = c(PreNoBirdsBASE*(1+(mean_diff_perc[1]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[2]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[3]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[4]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[5]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[6]/100))))
#Set range of displacement rates
Displacement <- seq(0,100,5)
#Set scenarios of number of samples pre-construction
PreNoSamples <- c(24)
#Set SD
standardDevBASIC <- 4
#Generate range of SD based on transect spacing
transect_choices_df = data.frame(transectspacing=c(0.5,1.0,1.5,2.0,2.5,3.0),
                                 value=c(standardDevBASIC*(1+(sd_diff_perc[1]/100)),standardDevBASIC*(1+(sd_diff_perc[2]/100)),standardDevBASIC*(1+(sd_diff_perc[3]/100)),standardDevBASIC*(1+(sd_diff_perc[4]/100)),standardDevBASIC*(1+(sd_diff_perc[5]/100)),standardDevBASIC*(1+(sd_diff_perc[6]/100))))
#Make transect spacing a factor
transect_choices_df$transectspacing <- as.character(transect_choices_df$transectspacing)
#Set alpha for power analysis
alpha <- 0.05
#Calculate power of surveys for a range of transect spacings, and displacement rates for SD of 4
Change_SD_4_Same_df <- data.frame(PreNoBirds=NA,PreNoSamples=NA,Displacement=NA,transect=NA,Power=NA)
k<-1
m<-1
for (c in transect_choices_df[,2]) {
  m<-1
  for (b in Displacement) {
    Change_SD_4_Same_df[((k-1)*length(Displacement))+m,1]<-PreNoBirds[k,2]
    Change_SD_4_Same_df[((k-1)*length(Displacement))+m,2]<-a
```

```
  Change_SD_4_Same_df[((k-1)*length(Displacement))+m,3]<-b
  Change_SD_4_Same_df[((k-1)*length(Displacement))+m,4]<-transect_choices_df[k,1]
  Change_SD_4_Same_df[((k-1)*length(Displacement))+m,5]<-pwr.t.test(n = PreNoSamples,d = (abs(PreNoBirds[k,2]-(PreNoBirds[k,2]*(1-(Displacement[m]/100)))))/sqrt(((transect_choices_df[k,2]^2)+((transect_choices_df[k,2]*(1-(Displacement[m]/100)))^2))/2),sig.level = alpha,power = NULL, type="paired")$power
  m<-m+1
 }
 k<-k+1
}
#Plot results
Power_0.8 <- data.frame(yintercept=0.8, Power=factor(0.8))
#Using SD of 2
Change_SD_2_Same_df_Plot <- ggplot(Change_SD_2_Same_df, aes(`Displacement`, y=`Power`,colour = transect)) +geom_point(size=1.5)+scale_color_manual(name="Transect\nspacing (km)",labels=c("0.5","1.0","1.5","2.0","2.5","3.0"),values=c(c('#DF0058', '#F58906', '#E4C540', '#89B883', '#096BB6', '#6C0091')))+theme_bw()+theme(panel.border = element_blank(), axis.line = element_line(colour = "black"),legend.position = "right", legend.direction = "vertical",legend.margin = margin(-1,2,0,0, unit="cm"),text=element_text(size=12,  family="Calibri"))+ylab("Power")+xlab("Displacement (%)")+ggtitle(bquote("Standard deviation = 2 birds/km"^2))+geom_hline(data=Power_0.8, aes(yintercept=yintercept, linetype="18"), colour='grey', size=0.5) +scale_linetype_manual(name = "",values = c(1,1), labels="Power = 0.8")+ylim(0,1)+scale_x_continuous(breaks = seq(0, 100, by = 10))
#Using SD of 4
Change_SD_4_Same_df_Plot <- ggplot(Change_SD_4_Same_df, aes(`Displacement`, y=`Power`,colour = transect)) +geom_point(size=1.5)+scale_color_manual(name="Transect\nspacing (km)",labels=c("0.5","1.0","1.5","2.0","2.5","3.0"),values=c(c('#DF0058', '#F58906', '#E4C540', '#89B883', '#096BB6', '#6C0091')))+theme_bw()+theme(panel.border = element_blank(), axis.line = element_line(colour = "black"),legend.position = "right", legend.direction = "vertical",legend.margin = margin(-1,2,0,0, unit="cm"),text=element_text(size=12,  family="Calibri"))+ylab("Power")+xlab("Displacement (%)")+ggtitle(bquote("Standard deviation = 4 birds/km"^2))+geom_hline(data=Power_0.8, aes(yintercept=yintercept, linetype="18"), colour='grey', size=0.5) +scale_linetype_manual(name = "",values = c(1,1), labels="Power = 0.8")+ylim(0,1)+scale_x_continuous(breaks = seq(0, 100, by = 10))
#Arrange both plots together
Change_SD_Same_Plot <- ggarrange(Change_SD_2_Same_df_Plot, Change_SD_4_Same_df_Plot, common.legend = TRUE, legend="right")
#Save
ggsave('Change_SD_Same_Plot_paired.png', Change_SD_Same_Plot, height = 5, width = 10, dpi=600)
```

Different number of samples pre & post OWF construction, calculate number of samples post-construction

```
#Set # birds pre-construction
PreNoBirdsBASE <- 10
#Generate range of number of birds based on transect spacing
PreNoBirds <- data.frame(transectspacing=c(0.5,1.0,1.5,2.0,2.5,3.0),
                        value = c(PreNoBirdsBASE*(1+(mean_diff_perc[1]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[2]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[3]/100)),PreNoBirdsBASE*(
```

```
1+(mean_diff_perc[4]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[5]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[6]/100))))
#Set range of displacement rates
Displacement <- seq(0,100,5)
#Set scenarios of number of samples pre-construction
PreNoSamples <- c(6,12,24)
#Set SD
standardDevBASIC <- 2
#Generate range of SD based on transect spacing
transect_choices_df = data.frame(transectspacing=c(0.5,1.0,1.5,2.0,2.5,3.0),
                                 value=c(standardDevBASIC*(1+(sd_diff_perc[1]/100)),standardDevBASIC*(1+(sd_diff_perc[2]/100)),standardDevBASIC*(1+(sd_diff_perc[3]/100)),standardDevBASIC*(1+(sd_diff_perc[4]/100)),standardDevBASIC*(1+(sd_diff_perc[5]/100)),standardDevBASIC*(1+(sd_diff_perc[6]/100))))
#Make transect spacing a factor
transect_choices_df$transectspacing <- as.character(transect_choices_df$transectspacing)
#Set alpha for power analysis
alpha <- 0.05
#Set required power for power analysis
Power <- 0.8
#Calculate number of samples post-construction for a range of transect spacings, displacement rates, and number of samples pre-construction
Change_NoSamples_Diff_df <- data.frame(PreNoBirds=NA,PreNoSamples=NA,Displacement=NA,transect=NA,PostNoSamples=NA)
k<-1
m<-1
n<-1
for (c in transect_choices_df[,2]) {
 m<-1
 for (b in Displacement) {
  n<-1
  for (a in PreNoSamples) {
   Change_NoSamples_Diff_df[((k-1)*length(PreNoSamples)*length(Displacement))+((m-1)*length(PreNoSamples))+n,1]<-PreNoBirds[k,2]
   Change_NoSamples_Diff_df[((k-1)*length(PreNoSamples)*length(Displacement))+((m-1)*length(PreNoSamples))+n,2]<-a
   Change_NoSamples_Diff_df[((k-1)*length(PreNoSamples)*length(Displacement))+((m-1)*length(PreNoSamples))+n,3]<-b
   Change_NoSamples_Diff_df[((k-1)*length(PreNoSamples)*length(Displacement))+((m-1)*length(PreNoSamples))+n,4]<-transect_choices_df[k,1]
   Change_NoSamples_Diff_df[((k-1)*length(PreNoSamples)*length(Displacement))+((m-1)*length(PreNoSamples))+n,5]<-try(pwr.t2n.test(n1 = PreNoSamples[n],d = (abs(PreNoBirds[k,2]-(PreNoBirds[k,2]*(1-(Displacement[m]/100)))))/sqrt(((transect_choices_df[k,2]^2)+((transect_choices_df[k,2]*(1-(Displacement[m]/100)))^2))/2),sig.level = alpha,power = Power, n2 = NULL)$n2)
   n<-n+1
  }
  m<-m+1
 }
 k<-k+1
```

```
}
#Convert characters to numbers
Change_NoSamples_Diff_df$PostNoSamples <- as.numeric(Change_NoSamples_Diff_df$Po
stNoSamples)
#Round no. surveys
Change_NoSamples_Diff_df$PostNoSamples <- round(Change_NoSamples_Diff_df$PostNo
Samples, digits=1)
#Get values for table of results
subset(Change_NoSamples_Diff_df, PreNoSamples==6 & Displacement == 15)
subset(Change_NoSamples_Diff_df, PreNoSamples==6 & Displacement == 20)
subset(Change_NoSamples_Diff_df, PreNoSamples==6 & Displacement == 25)
subset(Change_NoSamples_Diff_df, PreNoSamples==6 & Displacement == 30)
subset(Change_NoSamples_Diff_df, PreNoSamples==12 & Displacement == 15)
subset(Change_NoSamples_Diff_df, PreNoSamples==12 & Displacement == 20)
subset(Change_NoSamples_Diff_df, PreNoSamples==12 & Displacement == 25)
subset(Change_NoSamples_Diff_df, PreNoSamples==12 & Displacement == 30)
subset(Change_NoSamples_Diff_df, PreNoSamples==24 & Displacement == 15)
subset(Change_NoSamples_Diff_df, PreNoSamples==24 & Displacement == 20)
subset(Change_NoSamples_Diff_df, PreNoSamples==24 & Displacement == 25)
subset(Change_NoSamples_Diff_df, PreNoSamples==24 & Displacement == 30)
```

Case study, same number of samples pre & post OWF construction, calculate number of samples

```
#Set # birds pre-construction
PreNoBirdsBASE <- 4.6
#Generate range of number of birds based on transect spacing
PreNoBirds <- data.frame(transectspacing=c(0.5,1.0,1.5,2.0,2.5,3.0),
                    value = c(PreNoBirdsBASE*(1+(mean_diff_perc[1]/100)),PreNoBirdsBASE*(1+(
mean_diff_perc[2]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[3]/100)),PreNoBirdsBASE*(
1+(mean_diff_perc[4]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[5]/100)),PreNoBirdsBAS
E*(1+(mean_diff_perc[6]/100))))
#Set range of displacement rates
Displacement <- seq(0,100,5)
#Set SD
standardDevBASIC <- 2
#Generate range of SD based on transect spacing
transect_choices_df = data.frame(transectspacing=c(0.5,1.0,1.5,2.0,2.5,3.0),
                    value=c(standardDevBASIC*(1+(sd_diff_perc[1]/100)),standardDevBASIC
*(1+(sd_diff_perc[2]/100)),standardDevBASIC*(1+(sd_diff_perc[3]/100)),standardDevBASIC
*(1+(sd_diff_perc[4]/100)),standardDevBASIC*(1+(sd_diff_perc[5]/100)),standardDevBASIC
*(1+(sd_diff_perc[6]/100))))
#Make transect spacing a factor
transect_choices_df$transectspacing <- as.character(transect_choices_df$transectspacing)
#Set alpha for power analysis
alpha <- 0.05
#Set required power for power analysis
Power <- 0.8
#Calculate number of samples for a range of transect spacings and displacement rates
Case_Change_NoSamples_Same_df <- data.frame(PreNoBirds=NA,na=NA,Displacement=N
```

```
A,transect=NA,NoSamples=NA)
k<-1
m<-1
n<-1
for (c in transect_choices_df[,2]) {
  m<-1
  for (b in Displacement) {
      Case_Change_NoSamples_Same_df[((k-1)*length(Displacement))+m,1]<-PreNoBirds[k,2
]
      Case_Change_NoSamples_Same_df[((k-1)*length(Displacement))+m,2]<-NA
      Case_Change_NoSamples_Same_df[((k-1)*length(Displacement))+m,3]<-b
      Case_Change_NoSamples_Same_df[((k-1)*length(Displacement))+m,4]<-transect_choic
es_df[k,1]
      Case_Change_NoSamples_Same_df[((k-1)*length(Displacement))+m,5]<-try(pwr.t.test(n
= NULL,d = (abs(PreNoBirds[k,2]-(PreNoBirds[k,2]*(1-(Displacement[m]/100)))))/sqrt(((trans
ect_choices_df[k,2]^2)+((transect_choices_df[k,2]*(1-(Displacement[m]/100)))^2))/2),sig.le
vel = alpha,Power, type="paired")$n)
    m<-m+1
  }
  k<-k+1
}
#Convert characters to numbers
Case_Change_NoSamples_Same_df$NoSamples <- as.numeric(Case_Change_NoSamples_S
ame_df$NoSamples)
#Round no. surveys
Case_Change_NoSamples_Same_df$NoSamples <- round(Case_Change_NoSamples_Same_
df$NoSamples, digits=0)
#Get values for table of results
subset(Case_Change_NoSamples_Same_df, Displacement == 5)
subset(Case_Change_NoSamples_Same_df, Displacement == 10)
subset(Case_Change_NoSamples_Same_df, Displacement == 15)
subset(Case_Change_NoSamples_Same_df, Displacement == 20)
subset(Case_Change_NoSamples_Same_df, Displacement == 25)
subset(Case_Change_NoSamples_Same_df, Displacement == 30)
subset(Case_Change_NoSamples_Same_df, Displacement == 35)
subset(Case_Change_NoSamples_Same_df, Displacement == 40)
subset(Case_Change_NoSamples_Same_df, Displacement == 45)
subset(Case_Change_NoSamples_Same_df, Displacement == 50)
```

Case study, different number of samples pre & post OWF construction, calculate number of samples post-construction

```
#Set # birds pre-construction
PreNoBirdsBASE <- 4.6
#Generate range of number of birds based on transect spacing
PreNoBirds <- data.frame(transectspacing=c(0.5,1.0,1.5,2.0,2.5,3.0),
                    value = c(PreNoBirdsBASE*(1+(mean_diff_perc[1]/100)),PreNoBirdsBASE*(1+(
mean_diff_perc[2]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[3]/100)),PreNoBirdsBASE*(
1+(mean_diff_perc[4]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[5]/100)),PreNoBirdsBAS
E*(1+(mean_diff_perc[6]/100))))
```

```
#Set range of displacement rates
Displacement <- seq(0,100,5)
#Set range of number of samples pre-construction
PreNoSamples <- c(6,12)
#Set SD
standardDevBASIC <- 2
#Generate range of SD based on transect spacing
transect_choices_df = data.frame(transectspacing=c(0.5,1.0,1.5,2.0,2.5,3.0),
                                 value=c(standardDevBASIC*(1+(sd_diff_perc[1]/100)),standardDevBASIC*(1+(sd_diff_perc[2]/100)),standardDevBASIC*(1+(sd_diff_perc[3]/100)),standardDevBASIC*(1+(sd_diff_perc[4]/100)),standardDevBASIC*(1+(sd_diff_perc[5]/100)),standardDevBASIC*(1+(sd_diff_perc[6]/100))))
#Make transect spacing a factor
transect_choices_df$transectspacing <- as.character(transect_choices_df$transectspacing)
#Set alpha for power analysis
alpha <- 0.05
#Set required power for power analysis
Power <- 0.8
#Calculate number of samples post-construction for a range of transect spacings, displacement rates, and number of samples pre-construction
Case_Change_NoSamples_Diff_df <- data.frame(PreNoBirds=NA,PreNoSamples=NA,Displacement=NA,transect=NA,PostNoSamples=NA)
k<-1
m<-1
n<-1
for (c in transect_choices_df[,2]) {
  m<-1
  for (b in Displacement) {
    n<-1
    for (a in PreNoSamples) {
      Case_Change_NoSamples_Diff_df[((k-1)*length(PreNoSamples)*length(Displacement))+((m-1)*length(PreNoSamples))+n,1]<-PreNoBirds[k,2]
      Case_Change_NoSamples_Diff_df[((k-1)*length(PreNoSamples)*length(Displacement))+((m-1)*length(PreNoSamples))+n,2]<-a
      Case_Change_NoSamples_Diff_df[((k-1)*length(PreNoSamples)*length(Displacement))+((m-1)*length(PreNoSamples))+n,3]<-b
      Case_Change_NoSamples_Diff_df[((k-1)*length(PreNoSamples)*length(Displacement))+((m-1)*length(PreNoSamples))+n,4]<-transect_choices_df[k,1]
      Case_Change_NoSamples_Diff_df[((k-1)*length(PreNoSamples)*length(Displacement))+((m-1)*length(PreNoSamples))+n,5]<-try(pwr.t2n.test(n1 = PreNoSamples[n],d = (abs(PreNoBirds[k,2]-(PreNoBirds[k,2]*(1-(Displacement[m]/100)))))/sqrt(((transect_choices_df[k,2]^2)+((transect_choices_df[k,2]*(1-(Displacement[m]/100)))^2))/2),sig.level = alpha,power = Power,n2 = NULL)$n2)
      n<-n+1
    }
    m<-m+1
  }
  k<-k+1
}
#Convert characters to numbers
```

```
Case_Change_NoSamples_Diff_df$PostNoSamples <- as.numeric(Case_Change_NoSamples_Diff_df$PostNoSamples)
#Round no. surveys
Case_Change_NoSamples_Diff_df$PostNoSamples <- round(Case_Change_NoSamples_Diff_df$PostNoSamples, digits=1)
#Get values for table of results
subset(Case_Change_NoSamples_Diff_df, PreNoSamples==6 & Displacement == 30)
subset(Case_Change_NoSamples_Diff_df, PreNoSamples==6 & Displacement == 35)
subset(Case_Change_NoSamples_Diff_df, PreNoSamples==6 & Displacement == 40)
subset(Case_Change_NoSamples_Diff_df, PreNoSamples==6 & Displacement == 45)
subset(Case_Change_NoSamples_Diff_df, PreNoSamples==6 & Displacement == 50)
subset(Case_Change_NoSamples_Diff_df, PreNoSamples==12 & Displacement == 30)
subset(Case_Change_NoSamples_Diff_df, PreNoSamples==12 & Displacement == 35)
subset(Case_Change_NoSamples_Diff_df, PreNoSamples==12 & Displacement == 40)
subset(Case_Change_NoSamples_Diff_df, PreNoSamples==12 & Displacement == 45)
subset(Case_Change_NoSamples_Diff_df, PreNoSamples==12 & Displacement == 50)
```

Compare number of samples required for a set power, when number of samples are the same pre- and post- and when they are different pre- and post-construction

```
#Select case of different number of sample pre- and post-construction, when pre-samples are 12, transect spacing is 3km, displacement rate is between 30% and 70%
Case_Change_NoSamples_Pre_df <- subset(Case_Change_NoSamples_Diff_df, PreNoSamples==12 & transect==3 & Displacement>=30 & Displacement<=70)
#Give column value "pre-impact"
Case_Change_NoSamples_Pre_df$Status <- c("Pre-impact")
#Remove post-number of samples column
Case_Change_NoSamples_Pre_df <- subset(Case_Change_NoSamples_Pre_df, select=-c(PostNoSamples))
#Select case of different number of sample pre- and post-construction, when pre-samples are 12, transect spacing is 3km, displacement rate is between 30% and 70%
Case_Change_NoSamples_Post_df <- subset(Case_Change_NoSamples_Diff_df, PreNoSamples==12 & transect==3 & Displacement>=30 & Displacement<=70)
#Give column value "pre-impact"
Case_Change_NoSamples_Post_df$Status <- c("Post-impact")
#Remove pre-number of samples column
Case_Change_NoSamples_Post_df <- subset(Case_Change_NoSamples_Post_df, select=-c(PreNoSamples))
#Rename columns
names(Case_Change_NoSamples_Pre_df)[names(Case_Change_NoSamples_Pre_df) == "PreNoSamples"] <- "NoSamples"
names(Case_Change_NoSamples_Post_df)[names(Case_Change_NoSamples_Post_df) == "PostNoSamples"] <- "NoSamples"
#Put all into dataframe
Case_Change_NoSamples_PrePost_df <- rbind(Case_Change_NoSamples_Pre_df,Case_Change_NoSamples_Post_df)
#Plot
Pre_Post_survey_days_plot <- ggplot(Case_Change_NoSamples_PrePost_df) +geom_point(aes(`Displacement`, y=`NoSamples`, colour=`Status`), size=1.5)+geom_line(aes(`Displacement`, y=`NoSamples`, colour=`Status`), size=0.5)+scale_color_manual(name=NULL, values=c(c
```

```
('#DF0058', '#6C0091')))+theme_bw()+theme(plot.title = element_text(size=12, family="Calibri"),panel.border = element_blank(), axis.line = element_line(colour = "black"),legend.position = "right", legend.direction = "vertical", legend.margin = margin(-1,0,0,0, unit="cm"),text=element_text(size=14,  family="Calibri"))+ylab("Number of survey days")+xlab("Displacement (%)")
#Save
ggsave('Pre_Post_survey_days_plot.png', Pre_Post_survey_days_plot, height = 5, width = 10, dpi=600)
```

Compare how much changing the displacement rate versus number of survey days impacts survey power

```
#Set # birds pre-construction
PreNoBirdsBASE <- 4.6
#Generate range of number of birds based on transect spacing
PreNoBirds <- data.frame(transectspacing=c(0.5,1.0,1.5,2.0,2.5,3.0),
                         value = c(PreNoBirdsBASE*(1+(mean_diff_perc[1]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[2]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[3]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[4]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[5]/100)),PreNoBirdsBASE*(1+(mean_diff_perc[6]/100))))
#Set range of displacement rates
Displacement <- seq(0,100,5)
#Set SD
standardDevBASIC <- 2
#Generate range of SD based on transect spacing
transect_choices_df = data.frame(transectspacing=c(0.5,1.0,1.5,2.0,2.5,3.0),
                                 value=c(standardDevBASIC*(1+(sd_diff_perc[1]/100)),standardDevBASIC*(1+(sd_diff_perc[2]/100)),standardDevBASIC*(1+(sd_diff_perc[3]/100)),standardDevBASIC*(1+(sd_diff_perc[4]/100)),standardDevBASIC*(1+(sd_diff_perc[5]/100)),standardDevBASIC*(1+(sd_diff_perc[6]/100))))
#Make transect spacing a factor
transect_choices_df$transectspacing <- as.character(transect_choices_df$transectspacing)
#Set alpha for power analysis
alpha <- 0.05
#Generate results for table
#Example of number of samples = 12, displacement = 15%. Change "n=x" to desired number of samples, and "Displacement[x]" to desired displacement rate
pwr.t.test(n = 12,d = (abs(PreNoBirds[2,2]-(PreNoBirds[2,2]*(1-(Displacement[4]/100)))))/sqrt(((transect_choices_df[2,2]^2)+((transect_choices_df[2,2]*(1-(Displacement[4]/100)))^2))/2),sig.level = alpha,power = NULL, type="paired")$power
```

Area that transect spacings cover

```
AreaOfTransects <- data.frame(transectspacing=c(0.5, 1.0, 1.5, 2.0, 2.5, 3.0),transectareas=c(1174, 585, 391, 293, 234, 193),AreaProportion=NA,NumberOfTransect=c(87, 43, 29, 21, 18, 15))
AreaOfTransects$AreaProportion <- round(c(AreaOfTransects[,2]/AreaOfTransects[1,2]), digits=2)
```

Appendix G – R markdown code used in the analysis of Chapter 6

Packages required

```
library("ggpubr")
library("readxl")
library("dgof")
library(dplyr)
library(extrafont)
library(ggpmisc)
library(ggtext)
library(forcats)
library(ggplot2)
```

Raw displacement gradients

```
#Set working directory
setwd("C:/Users/44755/OneDrive - University of Strathclyde/5. OWF d
esign and displacement/")
Gunfleet_Sands_raw <- data.frame(Distance=c(0,1,2), DisplRate=c(91.
29, 65.80, 20.95))
Kentish_Flats_raw <- data.frame(Distance=c(0,0.5,1,2,3), DisplRate=
c(94, 77, 69, 53, 56))
Lincs_raw <- data.frame(Distance=c(0, 1, 2, 3, 4, 5, 6, 7, 8), Disp
lRate=c(83.3, 77.4, 71.4, 62.5, 55.2, 50.8, 44.8, 42.3, 33.6))
London_Array_raw <- data.frame(Distance=seq(0, 11.5, 0.5), DisplRat
e=c(54.68,47.91,44.92,41,38.91,40.38,41.18,39.5,36.07,33.02,31.55,3
2.96,35,36.08,35.58,40.07,41.29,44.88,45.13,44.19,39.61,34.44,23.88
,12.62))
```

Extrapolate Gunfleet_Sands

```
#Correlation stats
Gunfleet_Sands_kendall <- cor.test(Gunfleet_Sands_raw$Distance,Gunf
leet_Sands_raw$DisplRate, method="kendall")
Gunfleet_Sands_regr <- lm(Gunfleet_Sands_raw$DisplRate~Gunfleet_San
ds_raw$Distance)
#Correlation equation
Gunfleet_Sands_eq <- paste0('y = ', round(coefficients(Gunfleet_San
ds_regr)[2], 4), 'x + ', round(coefficients(Gunfleet_Sands_regr)[1]
, 4))
Gunfleet_Sands_cor <- 0.98
Gunfleet_Sands_kendall_cor <- round(summary(Gunfleet_Sands_regr)$r.
squared,2)
#Make and save plot
Gunfleet_Sands_raw_plot<-
```

```
ggplot(data = Gunfleet_Sands_raw, aes(x = `Distance`, y=`DisplRate`)) +
  geom_point(col="#DF0059")+
  geom_smooth(method = "lm", col="#6C0091")+
  theme_bw()+
  theme(panel.border = element_blank(), axis.line = element_line(colour = "black"),
        legend.position = "bottom", legend.direction = "vertical",
        text=element_text(size=12,  family="Calibri"))+
  xlab("Maximum of distance band (km)")+
  ylab("Displacement rate (%)")+
  geom_label(aes(x = 1.1, y = 145, label = Gunfleet_Sands_eq), label.size = 0, family="Calibri")+
  annotate("text", x=1.1, y=135, label = deparse(bquote(R^2 ~ "=" ~ .(as.character(Gunfleet_Sands_kendall_cor)))),  check_overlap = TRUE , family="Calibri", size=4,parse=T)
ggsave('Gunfleet_Sands_raw_plot.png', Gunfleet_Sands_raw_plot, height = 5, width = 5)

#Use equation to extrapolate displacement rate values further spatially down to 0%

#y = -35.17x + 94.5167

#Extrapolate gradient
Gunfleet_Sands_extra <- data.frame(Distance=NA, DisplRate=NA)
Gunfleet_Sands_extr_distance <- c(3)
a<-1
for(d in Gunfleet_Sands_extr_distance){
  Gunfleet_Sands_extra[a,1] <- Gunfleet_Sands_extr_distance[a]
  Gunfleet_Sands_extra[a,2] <- (-35.17*Gunfleet_Sands_extr_distance[a])+94.5167
  a<-a+1
}
Gunfleet_Sands_extrapolated<-rbind(Gunfleet_Sands_raw,Gunfleet_Sands_extra)
#Make and save plot
Gunfleet_Sands_extrapolated_plot<-
ggplot(data = Gunfleet_Sands_extrapolated, aes(x = `Distance`, y=`DisplRate`)) +
  geom_point(col="#DF0059")+
  geom_smooth(method = "lm", col="#6C0091")+
  theme_bw()+
  theme(panel.border = element_blank(), axis.line = element_line(colour = "black"),
        legend.position = "bottom", legend.direction = "vertical",
        text=element_text(size=12,  family="Calibri"))+
  xlab("Maximum of distance band (km)")+
  ylab("Displacement rate (%)")
ggsave('Gunfleet_Sands_extrapolated_plot.png', Gunfleet_Sands_extrapolated_plot, height = 5, width = 5)
```

```
#Keep only displacement rates over zero
Gunfleet_Sands_final <- Gunfleet_Sands_extrapolated[Gunfleet_Sands_
extrapolated$DisplRate >= 0, ]
```

Extrapolate Kentish_Flats

```
#Correlation stats
Kentish_Flats_kendall <- cor.test(Kentish_Flats_raw$Distance,Kentis
h_Flats_raw$DisplRate, method="kendall")
Kentish_Flats_regr <- lm(Kentish_Flats_raw$DisplRate~Kentish_Flats_
raw$Distance)
#Correlation equation
Kentish_Flats_eq <- paste0('y = ', round(coefficients(Kentish_Flats
_regr)[2], 4), 'x + ', round(coefficients(Kentish_Flats_regr)[1], 4
))
Kentish_Flats_kendall_cor <- round(summary(Kentish_Flats_regr)$r.sq
uared,2)
#Make and save plot
Kentish_Flats_raw_plot<-
ggplot(data = Kentish_Flats_raw, aes(x = `Distance`, y=`DisplRate`)
) +
  geom_point(col="#DF0059")+
  geom_smooth(method = "lm", col="#6C0091")+
  theme_bw()+
  theme(panel.border = element_blank(), axis.line = element_line(co
lour = "black"),
        legend.position = "bottom", legend.direction = "vertical",
        text=element_text(size=12,  family="Calibri"))+
  xlab("Maximum of distance band (km)")+
  ylab("Displacement rate (%)")+
  scale_y_continuous(limits=c(0, 110), breaks=seq(0, 110, 10))+
  scale_x_continuous(limits=c(0, 3), breaks=seq(0, 3, 1))+
  geom_label(aes(x = 1.5, y = 95, label = Kentish_Flats_eq), label.
size = 0, family="Calibri")+
  annotate("text", x=1.5, y=90, label = deparse(bquote(R^2 ~ "=" ~
.(as.character(Kentish_Flats_kendall_cor)))),  check_overlap = TRUE
, family="Calibri", size=4,parse=T)
ggsave('Kentish_Flats_raw_plot.png', Kentish_Flats_raw_plot, height
= 5, width = 5)

#Use equation to extrapolate displacement rate values further spati
ally down to 0%

#y = -12.4483x + 85.9828

#Extrapolate gradient
Kentish_Flats_extra <- data.frame(Distance=NA, DisplRate=NA)
Kentish_Flats_extr_distance <- c(4,5,6,7)
a<-1
for(d in Kentish_Flats_extr_distance){
  Kentish_Flats_extra[a,1] <- Kentish_Flats_extr_distance[a]
  Kentish_Flats_extra[a,2] <- (-12.4483*Kentish_Flats_extr_distance
```

```
[a])+85.9828
  a<-a+1
}
Kentish_Flats_extrapolated<-rbind(Kentish_Flats_raw,Kentish_Flats_e
xtra)
#Make and save plot
Kentish_Flats_extrapolated_plot<-
ggplot(data = Kentish_Flats_extrapolated, aes(x = `Distance`, y=`Di
splRate`)) +
  geom_point(col="#DF0059")+
  geom_smooth(method = "lm", col="#6C0091")+
  theme_bw()+
  theme(panel.border = element_blank(), axis.line = element_line(co
lour = "black"),
        legend.position = "bottom", legend.direction = "vertical",
        text=element_text(size=12,  family="Calibri"))+
  xlab("Maximum of distance band (km)")+
  ylab("Displacement rate (%)")+
  scale_y_continuous(limits=c(-10, 100), breaks=seq(-10, 100, 10))+
  scale_x_continuous(limits=c(0, 7), breaks=seq(0, 7, 1))
ggsave('Kentish_Flats_extrapolated_plot.png', Kentish_Flats_extrapo
lated_plot, height = 5, width = 5)

#Keep only displacement rates over zero
Kentish_Flats_final <- Kentish_Flats_extrapolated[Kentish_Flats_ext
rapolated$DisplRate >= 0, ]
```

Extrapolate Lincs

```
#Correlation stats
Lincs_kendall <- cor.test(Lincs_raw$Distance,Lincs_raw$DisplRate, m
ethod="kendall")
Lincs_regr <- lm(Lincs_raw$DisplRate~Lincs_raw$Distance)
#Correlation equation
Lincs_eq <- paste0('y = ', round(coefficients(Lincs_regr)[2], 4), '
x + ', round(coefficients(Lincs_regr)[1], 4))
Lincs_kendall_cor <- round(summary(Lincs_regr)$r.squared,2)
#Make and save plot
Lincs_raw_plot<-
ggplot(data = Lincs_raw, aes(x = `Distance`, y=`DisplRate`)) +
  geom_point(col="#DF0059")+
  geom_smooth(method = "lm", col="#6C0091")+
  theme_bw()+
  theme(panel.border = element_blank(), axis.line = element_line(co
lour = "black"),
        legend.position = "bottom", legend.direction = "vertical",
        text=element_text(size=12,  family="Calibri"))+
  xlab("Maximum of distance band (km)")+
  ylab("Displacement rate (%)")+
  scale_y_continuous(limits=c(0, 100), breaks=seq(0, 100, 10))+
  scale_x_continuous(limits=c(0, 8), breaks=seq(0, 8, 1))+
  geom_label(aes(family="Calibri", x = mean(Distance), y = max(Disp
```

```
lRate), label = paste0('y = ', round(coefficients(Lincs_regr)[2], 4
), 'x + ', round(coefficients(Lincs_regr)[1], 4))),label.size = 0)+
  annotate("text",y = 80, x = 4, label = deparse(bquote(R^2 ~ "=" ~
.(as.character(Lincs_kendall_cor)))),  check_overlap = TRUE , famil
y="Calibri", size=4,parse=T)
ggsave('Lincs_raw_plot.png', Lincs_raw_plot, height = 5, width = 5)

#Use equation to extrapolate displacement rate values further spati
ally down to 0%

#y = -6.15x + 82.5222

#Extrapolate gradient
Lincs_extra <- data.frame(Distance=NA, DisplRate=NA)
Lincs_extr_distance <- c(9,10,11,12,13,14)
a<-1
for(d in Lincs_extr_distance){
  Lincs_extra[a,1] <- Lincs_extr_distance[a]
  Lincs_extra[a,2] <- (-6.15*Lincs_extr_distance[a])+82.5222
  a<-a+1
}
Lincs_extrapolated<-rbind(Lincs_raw,Lincs_extra)
#Make and save plot
Lincs_extrapolated_plot<-
ggplot(data = Lincs_extrapolated, aes(x = `Distance`, y=`DisplRate`
)) +
  geom_point(col="#DF0059")+
  geom_smooth(method = "lm", col="#6C0091")+
  theme_bw()+
  theme(panel.border = element_blank(), axis.line = element_line(co
lour = "black"),
        legend.position = "bottom", legend.direction = "vertical",
        text=element_text(size=12,  family="Calibri"))+
  xlab("Maximum of distance band (km)")+
  ylab("Displacement rate (%)")+
  scale_y_continuous(limits=c(-10, 100), breaks=seq(-10, 100, 10))+
  scale_x_continuous(limits=c(0, 14), breaks=seq(0, 14, 1))
ggsave('Lincs_extrapolated_plot.png', Lincs_extrapolated_plot, heig
ht = 5, width = 5)

#Keep only displacement rates over zero
Lincs_final <- Lincs_extrapolated[Lincs_extrapolated$DisplRate >= 0
, ]
```

Extrapolate London Array

```
#London Array survey extends beyond 0% displacement, therefore no n
eed for extrapolation
London_Array_final<-London_Array_raw
#Make and save plot
London_Array_extrapolated_plot<-
  ggplot(data = London_Array_extrapolated, aes(x = `Distance`, y=`D
```

```
isplRate`)) +
  geom_point(col="#DF0059")+
  theme_bw()+
  theme(panel.border = element_blank(), axis.line = element_line(co
lour = "black"),
        legend.position = "bottom", legend.direction = "vertical",
        text=element_text(size=12,  family="Calibri"))+
  xlab("Maximum of distance band (km)")+
  ylab("Displacement rate (%)")+
  scale_y_continuous(limits=c(0, 100), breaks=seq(0, 100, 10))+
  scale_x_continuous(limits=c(0, 12), breaks=seq(0, 12, 1))
```

All OWFs relative plot

```
#Gunfleet Sands
#Make new columns for relative values
Gunfleet_Sands_final$Perc_of_max_distance <- NA
Gunfleet_Sands_final$Perc_of_OWF_displ <- NA
#Loop through to make relative values
a<-1
for(e in Gunfleet_Sands_final[,1]){
  Gunfleet_Sands_final[a,3] <- (Gunfleet_Sands_final[a,1]/Gunfleet_
Sands_final[nrow(Gunfleet_Sands_final),1])*100
  Gunfleet_Sands_final[a,4] <- (Gunfleet_Sands_final[a,2]/Gunfleet_
Sands_final[1,2])*100
  a<-a+1
}

#Kentish Flats
#Make new columns for relative values
Kentish_Flats_final$Perc_of_max_distance <- NA
Kentish_Flats_final$Perc_of_OWF_displ <- NA
#Loop through to make relative values
a<-1
for(e in Kentish_Flats_final[,1]){
  Kentish_Flats_final[a,3] <- (Kentish_Flats_final[a,1]/Kentish_Fla
ts_final[nrow(Kentish_Flats_final),1])*100
  Kentish_Flats_final[a,4] <- (Kentish_Flats_final[a,2]/Kentish_Fla
ts_final[1,2])*100
  a<-a+1
}

#Lincs
#Make new columns for relative values
Lincs_final$Perc_of_max_distance <- NA
Lincs_final$Perc_of_OWF_displ <- NA
#Loop through to make relative values
a<-1
for(e in Lincs_final[,1]){
  Lincs_final[a,3] <- (Lincs_final[a,1]/Lincs_final[nrow(Lincs_fina
l),1])*100
  Lincs_final[a,4] <- (Lincs_final[a,2]/Lincs_final[1,2])*100
```

```
  a<-a+1
}

#London Array
#Make new columns for relative values
London_Array_final$Perc_of_max_distance <- NA
London_Array_final$Perc_of_OWF_displ <- NA
#Loop through to make relative values
a<-1
for(e in London_Array_final[,1]){
  London_Array_final[a,3] <- (London_Array_final[a,1]/London_Array_final[nrow(London_Array_final),1])*100
  London_Array_final[a,4] <- (London_Array_final[a,2]/London_Array_final[1,2])*100
  a<-a+1
}

#Bind OWFs into one dataframe
#Put OWF name into column first
Gunfleet_Sands_final$OWF <- "Gunfleet Sands"
Kentish_Flats_final$OWF <- "Kentish Flats"
Lincs_final$OWF <- "Lincs, L & ID"
London_Array_final$OWF <- "London Array"
#Bind
Relative_OWFs <- rbind(Gunfleet_Sands_final, Kentish_Flats_final, Lincs_final, London_Array_final)
#Make and save plot
Relative_OWFs_plot<-
ggplot(data = Relative_OWFs, aes(x = `Perc_of_max_distance`, y=`Perc_of_OWF_displ`, colour=`OWF`)) +
  geom_point()+
  geom_line()+
  scale_color_manual(values = c("#DF0059","#EDAD21","#47989D","#6C0091"))+
  theme_bw()+
  theme(panel.border = element_blank(), axis.line = element_line(colour = "black"),
        legend.position = "bottom", legend.direction = "horizontal",
        text=element_text(size=12,  family="Calibri"))+
  xlab("Distance from wind farm (% of maximum displacement distance)")+
  ylab("Displacement rate (% of within-OWF displacement rate)")+
  scale_y_continuous(limits=c(0, 100), breaks=seq(0, 100, 10))+
  scale_x_continuous(limits=c(0, 100), breaks=seq(0, 100, 25))
#Save plot
ggsave('Relative_OWFs_plot.png', Relative_OWFs_plot, height = 5, width = 7)
```

New full set of displacement gradients

```
#Individual OWFs
HornsRevI<-data.frame(OWF="Horns Rev I",Displ_distance=0,P_displ=10
0)
Nysted<-data.frame(OWF="Nysted",Displ_distance=0,P_displ=100)
AlphaVentus<-data.frame(OWF="Alpha Ventus",Displ_distance=0,P_displ
=90)
EgmondaanZee<-data.frame(OWF="Egmond aan Zee",Displ_distance=0,P_di
spl=68)
Thanet<-data.frame(OWF="Thanet",Displ_distance=0,P_displ=73)
GunfleetSands<-data.frame(OWF=c("Gunfleet Sands","Gunfleet Sands","
Gunfleet Sands"),Displ_distance=c(0,1,2),P_displ=c(91.29,65.8,20.95
))
KentishFlats<-data.frame(OWF=c("Kentish Flats","Kentish Flats","Ken
tish Flats","Kentish Flats","Kentish Flats","Kentish Flats","Kentis
h Flats","Kentish Flats"),Displ_distance=c(0,0.5,1,2,3,4,5,6),P_dis
pl=c(94,77,69,53,56,36,24,11))
LincsLID<-data.frame(OWF=c("Lincs, L & ID","Lincs, L & ID","Lincs,
L & ID","Lincs, L & ID","Lincs, L & ID","Lincs, L & ID","Lincs, L &
ID","Lincs, L & ID","Lincs, L & ID","Lincs, L & ID","Lincs, L & ID"
,"Lincs, L & ID","Lincs, L & ID","Lincs, L & ID"),Displ_distance=c(
0,1,2,3,4,5,6,7,8,9,10,11,12,13),P_displ=c(83.3,77.4,71.4,62.5,55.2
,50.8,44.8,42.3,33.6,27.2,21,14.9,8.7,2.6))
LondonArray<-data.frame(OWF=c("London Array","London Array","London
Array","London Array","London Array","London Array","London Array",
"London Array","London Array","London Array","London Array","London
Array","London Array","London Array","London Array","London Array",
"London Array","London Array","London Array","London Array","London
Array","London Array","London Array","London Array"),Displ_distance
=c(0,0.5,1,1.5,2,2.5,3,3.5,4,4.5,5,5.5,6,6.5,7,7.5,8,8.5,9,9.5,10,1
0.5,11,11.5),P_displ=c(54.68,47.91,44.92,41.0,38.91,40.38,41.18,39.
5,36.07,33.02,31.55,32.96,35.0,36.08,35.58,40.07,41.29,44.88,45.13,
44.19,39.61,34.44,23.88,12.62))

#Generate table of all data
All_data<-rbind(HornsRevI,Nysted,AlphaVentus,EgmondaanZee,Thanet,Gu
nfleetSands,KentishFlats,LincsLID,LondonArray)
```

Summary stats

```
#All OWFs
Mean_max_dist_all <- mean(tapply(All_data$Displ_distance, All_data$
OWF, max))
Median_max_dist_all <- median(tapply(All_data$Displ_distance, All_d
ata$OWF, max))

#Only OWFs with displ outside OWF
Displ_outside_OWF <- subset(All_data, Displ_distance>0)
Mean_max_dist_outside <- mean(tapply(Displ_outside_OWF$Displ_distan
ce, Displ_outside_OWF$OWF, max))
Median_max_dist_outside <- median(tapply(Displ_outside_OWF$Displ_di
stance, Displ_outside_OWF$OWF, max))
```

```
#Only OWFs with displ inside OWF
Displ_inside_OWF <- subset(All_data, Displ_distance==0)
Mean_displ_inside <- mean(Displ_inside_OWF$P_displ)
Median_displ_inside <- median(Displ_inside_OWF$P_displ)
```

Generate averages, maximums and non-dimensional values

```
#Generate averages in 1km distance bands
Average_1km_data <- data.frame(Displ_distance=NA,P_displ=NA)
a<-1
for (b in 0:max(All_data$Displ_distance)){
  Average_1km_data[a,1]<-b
  Average_1km_data[a,2]<-colMeans(subset(All_data,Displ_distance<a
& Displ_distance>=a-1,select=P_displ))
  a<-a+1
}

#Generate maximums in 1km distance bands
Max_1km_data <- data.frame(Displ_distance=NA,P_displ=NA)
a<-1
for (b in 0:max(All_data$Displ_distance)){
  Max_1km_data[a,1]<-b
  Max_1km_data[a,2]<-max(subset(All_data,Displ_distance<a & Displ_d
istance>=a-1,select=P_displ))
  a<-a+1
}

#Generate non-dimensional values
#Non-dim Gunfleet Sands
Non_dim_GunfleetSands <- data.frame(Displ_distance=NA,Non_dim_dista
nce=NA,P_displ=NA,Non_dim_displ=NA)
a<-1
for (b in GunfleetSands$Displ_distance){
  Non_dim_GunfleetSands[a,1]<-GunfleetSands[a,2]
  Non_dim_GunfleetSands[a,2]<-(GunfleetSands[a,2]/max(GunfleetSands
$Displ_distance))*100
  Non_dim_GunfleetSands[a,3]<-GunfleetSands[a,3]
  Non_dim_GunfleetSands[a,4]<-(GunfleetSands[a,3]/GunfleetSands[1,3
])*100
  a<-a+1
}
#Non-dim Kentish Flats
Non_dim_KentishFlats <- data.frame(Displ_distance=NA,Non_dim_distan
ce=NA,P_displ=NA,Non_dim_displ=NA)
a<-1
for (b in KentishFlats$Displ_distance){
  Non_dim_KentishFlats[a,1]<-KentishFlats[a,2]
  Non_dim_KentishFlats[a,2]<-(KentishFlats[a,2]/max(KentishFlats$Di
spl_distance))*100
  Non_dim_KentishFlats[a,3]<-KentishFlats[a,3]
  Non_dim_KentishFlats[a,4]<-(KentishFlats[a,3]/KentishFlats[1,3])*
100
```

```
  a<-a+1
}
#Non-dim LincsLLID
Non_dim_LincsLID <- data.frame(Displ_distance=NA,Non_dim_distance=N
A,P_displ=NA,Non_dim_displ=NA)
a<-1
for (b in LincsLID$Displ_distance){
  Non_dim_LincsLID[a,1]<-LincsLID[a,2]
  Non_dim_LincsLID[a,2]<-(LincsLID[a,2]/max(LincsLID$Displ_distance
))*100
  Non_dim_LincsLID[a,3]<-LincsLID[a,3]
  Non_dim_LincsLID[a,4]<-(LincsLID[a,3]/LincsLID[1,3])*100
  a<-a+1
}
#Non-dim London Array
Non_dim_LondonArray <- data.frame(Displ_distance=NA,Non_dim_distanc
e=NA,P_displ=NA,Non_dim_displ=NA)
a<-1
for (b in LondonArray$Displ_distance){
  Non_dim_LondonArray[a,1]<-LondonArray[a,2]
  Non_dim_LondonArray[a,2]<-(LondonArray[a,2]/max(LondonArray$Displ
_distance))*100
  Non_dim_LondonArray[a,3]<-LondonArray[a,3]
  Non_dim_LondonArray[a,4]<-(LondonArray[a,3]/LondonArray[1,3])*100
  a<-a+1
}
Non_dim_data <- rbind(Non_dim_GunfleetSands,Non_dim_KentishFlats,No
n_dim_LincsLID,Non_dim_LondonArray)
```

Generate trend from all data

```
#Correlation stats
All_data_trend <- lm(P_displ~Displ_distance, data = All_data)
#Correlation equation
All_data_trend_eq <- paste0("y = ",sprintf(" %+.2f%s ",coefficients
(All_data_trend)[-1],"x")," + ",as.numeric(round(coefficients(All_d
ata_trend)[1],2)))
All_data_trend_R2 <- round(summary(All_data_trend)$r.squared,2)
#Make and save plot
All_data_plot <- ggplot(data = All_data, aes(x = Displ_distance, y=
P_displ)) +
  geom_point(col="#DF0059")+
  geom_smooth(method = "lm", col="#6C0091")+
  theme_bw()+
  theme(panel.border = element_blank(), axis.line = element_line(co
lour = "black"),
        legend.position = "bottom", legend.direction = "vertical",
        text=element_text(size=12,  family="Calibri"))+
  xlab("Maximum of distance band (km)")+
  ylab("Displacement rate (%)")+
  scale_y_continuous(limits=c(-10, 100), breaks=seq(-10, 100, 10))+
  scale_x_continuous(limits=c(0, 13), breaks=seq(0, 13, 1))+
```

```
  geom_text(y = 80, x = 9, label = All_data_trend_eq,  check_overlap = TRUE , family="Calibri", size=4)+
  annotate("text",y = 75, x = 9, label = deparse(bquote(R^2 ~ "=" ~ .(All_data_trend_R2))),  check_overlap = TRUE , family="Calibri", size=4,parse=T)
```

Generate trend from average 1km

```
#Correlation stats
Average_1km_data_trend <- lm(P_displ~Displ_distance, data = Average_1km_data)
#Correlation equation
Average_1km_data_trend_eq <- paste0("y = ",sprintf(" %+.2f%s ",coefficients(Average_1km_data_trend)[-1],"x")," + ",as.numeric(round(coefficients(Average_1km_data_trend)[1],2)))
Average_1km_data_trend_R2 <- round(summary(Average_1km_data_trend)$r.squared,2)
#Make and save plot
Average_1km_data_plot <- ggplot(data = Average_1km_data, aes(x =Displ_distance, y=P_displ)) +
  geom_point(col="#DF0059")+
  geom_smooth(method = "lm", col="#6C0091")+
  theme_bw()+
  theme(panel.border = element_blank(), axis.line = element_line(colour = "black"),
        legend.position = "bottom", legend.direction = "vertical",
        text=element_text(size=12,  family="Calibri"))+
  xlab("Maximum of distance band (km)")+
  ylab("Displacement rate (%)")+
  scale_y_continuous(limits=c(-10, 100), breaks=seq(-10, 100, 10))+
  scale_x_continuous(limits=c(0, 13), breaks=seq(0, 13, 1))+
  geom_text(y = 80, x = 9, label = Average_1km_data_trend_eq,  check_overlap = TRUE , family="Calibri", size=4)+
  annotate("text",y = 75, x = 9, label = deparse(bquote(R^2 ~ "=" ~ .(Average_1km_data_trend_R2))),  check_overlap = TRUE , family="Calibri", size=4,parse=T)
```

Generate trend from Max 1km

```
#Correlation stats
Max_1km_data_trend <- lm(P_displ~Displ_distance, data = Max_1km_data)
#Correlation equation
Max_1km_data_trend_eq <- paste0("y = ",sprintf(" %+.2f%s ",coefficients(Max_1km_data_trend)[-1],"x")," + ",as.numeric(round(coefficients(Max_1km_data_trend)[1],2)))
Max_1km_data_trend_R2 <- round(summary(Max_1km_data_trend)$r.squared,2)
#Make and save plot
Max_1km_data_plot <- ggplot(data = Max_1km_data, aes(x = Displ_distance, y=P_displ)) +
  geom_point(col="#DF0059")+
```

```
  geom_smooth(method = "lm", col="#6C0091")+
  theme_bw()+
  theme(panel.border = element_blank(), axis.line = element_line(co
lour = "black"),
        legend.position = "bottom", legend.direction = "vertical",
        text=element_text(size=12,  family="Calibri"))+
  xlab("Maximum of distance band (km)")+
  ylab("Displacement rate (%)")+
  scale_y_continuous(limits=c(-10, 100), breaks=seq(-10, 100, 10))+
  scale_x_continuous(limits=c(0, 13), breaks=seq(0, 13, 1))+
  geom_text(y = 80, x = 9, label = Max_1km_data_trend_eq,  check_ov
erlap = TRUE , family="Calibri", size=4)+
  annotate("text",y = 75, x = 9, label = deparse(bquote(R^2 ~ "=" ~
.(Max_1km_data_trend_R2))),  check_overlap = TRUE , family="Calibri
", size=4,parse=T)
```

Non-dimensional

```
#Correlation stats
Non_dim_data_trend <- lm(Non_dim_displ~Non_dim_distance, data = Non
_dim_data)
#Correlation equation
Non_dim_data_trend_eq <- paste0("y = ",sprintf(" %+.2f%s ",coeffici
ents(Non_dim_data_trend)[-1],"x")," + ",as.numeric(round(coefficien
ts(Non_dim_data_trend)[1],2)))
Non_dim_data_trend_R2 <- round(summary(Non_dim_data_trend)$r.square
d,2)
#Make and save plot
Non_dim_data_plot <- ggplot(data = Non_dim_data, aes(x = Non_dim_di
stance, y=Non_dim_displ)) +
  geom_point(col="#DF0059")+
  geom_smooth(method = "lm", col="#6C0091")+
  theme_bw()+
  theme(panel.border = element_blank(), axis.line = element_line(co
lour = "black"),
        legend.position = "bottom", legend.direction = "vertical",
        text=element_text(size=12,  family="Calibri"))+
  xlab("Percentage of maximum displacement distance (%)")+
  ylab("Percentage of within-wind farm displacement rate (%)")+
  scale_y_continuous(limits=c(0, 100), breaks=seq(0, 100, 10))+
  scale_x_continuous(limits=c(0, 100), breaks=seq(0, 100, 10))+
  geom_text(y = 100, x = 90, label = Non_dim_data_trend_eq,  check_
overlap = TRUE , family="Calibri", size=4)+
  annotate("text",y = 95, x = 90, label = deparse(bquote(R^2 ~ "="
~ .(Non_dim_data_trend_R2))),  check_overlap = TRUE , family="Calib
ri", size=4,parse=T)
```

Save plots

```
setwd("C:/Users/44755/OneDrive - University of Strathclyde/1. Thesi
s/12. Thesis V2")
ggsave('All_data_plot.png', All_data_plot, height = 5, width = 7)
```

```
ggsave('Average_1km_data_plot.png', Average_1km_data_plot, height = 5, width = 7)
ggsave('Max_1km_data_plot.png', Max_1km_data_plot, height = 5, width = 7)
ggsave('Non_dim_data_plot.png', Non_dim_data_plot, height = 5, width = 7)
```

Convert to values

```
#Find coefficients x and c of final gradient
All_data_x <- as.numeric(round(coefficients(All_data_trend)[-1],2))
All_data_c <- as.numeric(round(coefficients(All_data_trend)[1],2))
Average_1km_data_x <- as.numeric(round(coefficients(Average_1km_data_trend)[-1],2))
Average_1km_data_c <- as.numeric(round(coefficients(Average_1km_data_trend)[1],2))
Max_1km_data_x <- as.numeric(round(coefficients(Max_1km_data_trend)[-1],2))
Max_1km_data_c <- as.numeric(round(coefficients(Max_1km_data_trend)[1],2))
Non_dim_data_x <- as.numeric(round(coefficients(Non_dim_data_trend)[-1],2))
Non_dim_data_c <- as.numeric(round(coefficients(Non_dim_data_trend)[1],2))
#Put into table
Rep_gradient_values <- data.frame(Displ_distance=NA,All_data=NA,Average_1km=NA,Max_1km=NA,Non_dim=NA)
Range<-0:13
Within_OWF_displ<-100
a<-1
for(b in Range){
  Rep_gradient_values[a,1]<-b
  Rep_gradient_values[a,2]<-round((All_data_x*b)+All_data_c,0)
  Rep_gradient_values[a,3]<-round((Average_1km_data_x*b)+Average_1km_data_c,0)
  Rep_gradient_values[a,4]<-round((Max_1km_data_x*b)+Max_1km_data_c,0)
  if(a==1){Rep_gradient_values[a,5]<-Within_OWF_displ}else if(a>1){Rep_gradient_values[a,5]<-round((((Non_dim_data_x*((b/max(Range))*100))+Non_dim_data_c)/100)*Within_OWF_displ,0)}
  a<-a+1
}
```

Within-OWF displ rate vs. max displ distance

```
#Generate table of maximum values
Displ_vs_distance <- data.frame(MaxDist=c(max(GunfleetSands$Displ_distance),max(KentishFlats$Displ_distance),max(LincsLID$Displ_distance),max(LondonArray$Displ_distance)),
                                DisplRate=c(max(GunfleetSands$P_displ),max(KentishFlats$P_displ),max(LincsLID$P_displ),max(LondonArray$P_displ)))
```

```
#Correlation stats & equation
Displ_vs_distance_regr <- lm(Displ_vs_distance$DisplRate~Displ_vs_distance$MaxDist)
Displ_vs_distance_eq <- paste0('y = ', round(coefficients(Displ_vs_distance_regr)[2], 4), 'x + ', round(coefficients(Displ_vs_distance_regr)[1], 4))
Displ_vs_distance_R2 <- round(summary(Displ_vs_distance_regr)$r.squared,2)
#Make and save plot
Displ_vs_distance_plot <-
ggplot(data = Displ_vs_distance, aes(x = `MaxDist`, y=`DisplRate`))+
  geom_point(col="#DF0059")+
  geom_smooth(method = "lm", col="#6C0091")+
  theme_bw()+
  theme(panel.border = element_blank(), axis.line = element_line(colour = "black"),
        legend.position = "bottom", legend.direction = "vertical",
        text=element_text(size=12,  family="Calibri"))+
  xlab("Maximum displacement distance (km)")+
  ylab("Displacement rate within the wind farm (%)")+
  scale_y_continuous(limits=c(0, 160), breaks=seq(0, 160, 10))+
  scale_x_continuous(limits=c(2, 13), breaks=seq(2, 13, 1))+
  geom_text(y = 40, x = 7, label = Displ_vs_distance_eq,  check_overlap = TRUE , family="Calibri", size=4)+
  annotate("text",y = 35, x = 7, label = deparse(bquote(R^2 ~ "=" ~ .(Displ_vs_distance_R2))),  check_overlap = TRUE , family="Calibri", size=4,parse=T)
ggsave('Displ_vs_distance_plot.png', Displ_vs_distance_plot, height = 5, width = 7)
```

Table of gradients for each scenario of max displ distance

```
#Linear regression equation
Non_dim_data_x <- as.numeric(round(coefficients(Non_dim_data_trend)[-1],2))
Non_dim_data_c <- as.numeric(round(coefficients(Non_dim_data_trend)[1],2))

#Within-OWF displ rate vs. max displ distance equation
Within_vs_dist_x <- as.numeric(round(coefficients(Displ_vs_distance_regr)[-1],2))
Within_vs_dist_c <- as.numeric(round(coefficients(Displ_vs_distance_regr)[1],2))

#Make sequence of max displ distance
Max_dist <- seq(0,16,1)

#Set within-OWF displ when it's fixed
Within_OWF_displ<-100

#Make blank data frame
```

```
Displ_gradients_change_max_dist <- data.frame(Max_displ_dist=NA, Ring=NA, Displ_rate_100=NA, Displ_rate_change=NA)

#Loop through different max displ distances
a<-1
for(m in Max_dist){
  for(n in Max_dist){
    Displ_gradients_change_max_dist[a,1]<-m
    Displ_gradients_change_max_dist[a,2]<-n
    if(n==0){Displ_gradients_change_max_dist[a,3]<-Within_OWF_displ}else if(n!=0){Displ_gradients_change_max_dist[a,3]<-0}
    if(n!=0 & n<=m){Displ_gradients_change_max_dist[a,3]<-round((((Non_dim_data_x*((n/m)*100))+Non_dim_data_c)/100)*Within_OWF_displ,0)}
    if(n==0 & m==0){Displ_gradients_change_max_dist[a,3]<-Within_OWF_displ}
    if(n==0){Displ_gradients_change_max_dist[a,4]<-(m*Within_vs_dist_x)+Within_vs_dist_c}
    if(n!=0 & n<=m){Displ_gradients_change_max_dist[a,4]<-Displ_gradients_change_max_dist[(length(Max_dist)*m)+1,4]*(Displ_gradients_change_max_dist[(length(Max_dist)*m)+n+1,3]/100)}
    if(n>m){Displ_gradients_change_max_dist[a,4]<-0}
    a<-a+1
  }
}

#Plot up to 13km max displ distance
Displ_gradients_to_apply_under13km <- subset(Displ_gradients_change_max_dist, Max_displ_dist<=13)
Displ_gradients_to_apply_under13km <- subset(Displ_gradients_to_apply_under13km, Ring<=13)
Displ_gradients_to_apply_under13km_no0 <- subset(Displ_gradients_to_apply_under13km, Displ_rate_change!=0)
Displ_gradients_to_apply_under13km_no0$`Max_displ_dist` <- as.character(Displ_gradients_to_apply_under13km_no0$`Max_displ_dist`)
#Make and save plot
Displ_gradients_to_apply_under13km_plot<-ggplot(data = Displ_gradients_to_apply_under13km_no0, aes(x = `Ring`, y=`Displ_rate_change`, colour=fct_inorder(`Max_displ_dist`))) +
  geom_point(size=2)+
  geom_line(linewidth=1)+
  scale_color_manual(values = c("#E00457","#E93F33","#F0691A","#F69201","#EEAB1E","#E6BF39","#DDD556",
                                "#B4CD71","#73AD8B","#3690A3","#066FB7","#254CAB","#47289F", "#6C0091"))+
  theme_bw()+
  theme(panel.border = element_blank(), axis.line = element_line(colour = "black"),
        legend.position = "right", legend.direction = "vertical",
        text=element_text(size=12,  family="Calibri"))+
  xlab("Maximum of distance band (km))")+
  ylab("Displacement rate (%)")+
```

```
  scale_y_continuous(limits=c(0, 100), breaks=seq(0, 100, 10))+
  scale_x_continuous(limits=c(0, 13), breaks=seq(0, 13, 1))+
  labs(color="Maximum displacement\ndistance (km)")
ggsave('Displ_gradients_to_apply_under13km_plot.png', Displ_gradients_to_apply_under13km_plot, height = 5, width = 7)
#Save table
write.csv(Displ_gradients_change_max_dist, "Displ_gradients_change_max_dist.csv")
```

Calculate displacement-affected area for each scenario of max displ distance

```
#Set displacement distances
Max_dist_13 <- seq(0,13,1)

#Set OWF area as 28km2
oWF_area <- 28

#Set baseline density at 4.6birds/km2
Baseline_density <- 4.6

#Make new columns for area, number of birds
Displ_gradients_to_apply_under13km$Area <- NA
Displ_gradients_to_apply_under13km$Baseline_number <- NA
Displ_gradients_to_apply_under13km$Post_density <- NA

#Loop through to calculate displ-affected area
a<-1
for(m in Max_dist_13){
  for(n in Max_dist_13){
    if(n==0){Displ_gradients_to_apply_under13km[a,5]<-oWF_area}
    if(n!=0 & n<=m){Displ_gradients_to_apply_under13km[a,5]<-(((sqrt(oWF_area/pi)+n)^2)*pi)-sum(subset(Displ_gradients_to_apply_under13km, Max_displ_dist==m & Ring<=n)[,"Area"],na.rm=TRUE)}
    Displ_gradients_to_apply_under13km[a,6] <- Displ_gradients_to_apply_under13km[a,5] * Baseline_density
    Displ_gradients_to_apply_under13km[a,7] <-  ((100-Displ_gradients_to_apply_under13km[a,4])/100)*Displ_gradients_to_apply_under13km[a,6]
    a<-a+1
  }
}

#Summarise into table of max displ distance
#Make basic data frame
Displ_affected_area_13km <- data.frame(Max_displ_dist=NA, Post_birds=NA, Post_density=NA, Displ_rate=NA, Area=NA, Birds_lost=NA)
#Loop through to summarise for each max displ distance
a<-1
for(m in Max_dist_13){
  Displ_affected_area_13km[a,1] <- Max_dist_13[a]
  Displ_affected_area_13km[a,2] <- sum(subset(Displ_gradients_to_apply_under13km,Max_displ_dist==m)[,"Post_density"],na.rm=TRUE)
```

```
  Displ_affected_area_13km[a,3] <- Displ_affected_area_13km[a,2]/su
m(subset(Displ_gradients_to_apply_under13km,Max_displ_dist==m)[,"Ar
ea"],na.rm=TRUE)
  Displ_affected_area_13km[a,4] <- round((Baseline_density-Displ_af
fected_area_13km[a,3])/Baseline_density*100,2)
  Displ_affected_area_13km[a,5] <- round(sum(subset(Displ_gradients
_to_apply_under13km,Max_displ_dist==m)[,"Area"],na.rm=TRUE),0)
  Displ_affected_area_13km[a,6] <- round(sum(subset(Displ_gradients
_to_apply_under13km,Max_displ_dist==m)[,"Baseline_number"],na.rm=TR
UE)-sum(subset(Displ_gradients_to_apply_under13km,Max_displ_dist==m
)[,"Post_density"],na.rm=TRUE),0)
  a<-a+1
}
#Make and save plot
Displ_affected_area_13km$`Max_displ_dist_char` <- as.character(Disp
l_affected_area_13km$`Max_displ_dist`)
ggplot(data = Displ_affected_area_13km, aes(x = `Max_displ_dist`, y
=`Birds_lost`, colour=fct_inorder(`Max_displ_dist_char`))) +
  geom_point(size=2)+
  scale_color_manual(values = c("#E00457","#E93F33","#F0691A","#F69
201","#EEAB1E","#E6BF39","#DDD556",
                                "#B4CD71","#73AD8B","#3690A3","#066
FB7","#254CAB","#47289F", "#6C0091"))+
  theme_bw()+
  theme(panel.border = element_blank(), axis.line = element_line(co
lour = "black"),
        legend.position = "right", legend.direction = "vertical",
        text=element_text(size=12,  family="Calibri"))+
  xlab("Maximum displacement distance (km))")+
  ylab("Number of birds displaced")+
  scale_y_continuous(limits=c(0, 1500), breaks=seq(0, 1500, 100))+
  scale_x_continuous(limits=c(0, 13), breaks=seq(0, 13, 1))+
  labs(color="Maximum displacement\ndistance (km)")
```

Apply to OWFs in OTE SPA

```
#Set baseline density at 4.6birds/km2
Baseline_density <- 4.6

#Gunfleet Sands affected area displ stats
Gunfleet_Sands_affected <- data.frame()

#Enter distance, displacement rate, & name of OWF into new data fra
me
Gunfleet_Sands_Distance <- subset(Relative_OWFs,OWF=='Gunfleet Sand
s', select='Distance')
Gunfleet_Sands_DisplRate <- subset(Relative_OWFs,OWF=='Gunfleet San
ds', select='DisplRate')
Gunfleet_Sands_affected <- cbind(Gunfleet_Sands_Distance,Gunfleet_S
ands_DisplRate)
Gunfleet_Sands_affected$OWF <- 'Gunfleet Sands'
Gunfleet_Sands_affected$Area <- NA
```

```
Gunfleet_Sands_affected$Baseline_number <- NA
Gunfleet_Sands_affected$Post_density <- NA
Gunfleet_Sands_Area <- 17.5

#Calculate area, baseline number of birds, and post-density of bird
s
a<-1
for(n in unlist(Gunfleet_Sands_Distance)){
  if(n==0){Gunfleet_Sands_affected[a,4]<-Gunfleet_Sands_Area}
  if(n!=0){Gunfleet_Sands_affected[a,4]<-(((sqrt(Gunfleet_Sands_Are
a/pi)+n)^2)*pi)-sum(subset(Gunfleet_Sands_affected, Distance<=n)[,"
Area"],na.rm=TRUE)}
  Gunfleet_Sands_affected[a,5] <- Gunfleet_Sands_affected[a,4] * Ba
seline_density
  Gunfleet_Sands_affected[a,6] <- ((100-Gunfleet_Sands_affected[a,2
])/100)*Gunfleet_Sands_affected[a,5]
  a<-a+1
}

#Summarise into table of max displ distance
#Make basic data fram
Gunfleet_Sands_affected_total <- data.frame(Post_birds=NA, Post_den
sity=NA, Displ_rate=NA, Area=NA, Birds_lost=NA)

#Loop through to summarse for each max displ distance
Gunfleet_Sands_affected_total[,1] <- sum(subset(Gunfleet_Sands_affe
cted)[,"Post_density"],na.rm=TRUE)
Gunfleet_Sands_affected_total[,2] <- Gunfleet_Sands_affected_total[
,1]/sum(subset(Gunfleet_Sands_affected)[,"Area"],na.rm=TRUE)
Gunfleet_Sands_affected_total[,3] <- (Baseline_density-Gunfleet_San
ds_affected_total[,2])/Baseline_density*100
Gunfleet_Sands_affected_total[,4] <- sum(subset(Gunfleet_Sands_affe
cted)[,"Area"],na.rm=TRUE)
Gunfleet_Sands_affected_total[,5] <- sum(subset(Gunfleet_Sands_affe
cted)[,"Baseline_number"],na.rm=TRUE)-sum(subset(Gunfleet_Sands_aff
ected)[,"Post_density"],na.rm=TRUE)

#Kentish Flats affected area displ stats
#Enter distance, displacement rate, & name of OWF into new data fra
me
Kentish_Flats_Distance <- subset(Relative_OWFs,OWF=='Kentish Flats'
, select='Distance')
Kentish_Flats_DisplRate <- subset(Relative_OWFs,OWF=='Kentish Flats
', select='DisplRate')
Kentish_Flats_affected <- cbind(Kentish_Flats_Distance,Kentish_Flat
s_DisplRate)
Kentish_Flats_affected$OWF <- 'Kentish Flats'
Kentish_Flats_affected$Area <- NA
Kentish_Flats_affected$Baseline_number <- NA
Kentish_Flats_affected$Post_density <- NA
Kentish_Flats_Area <- 10
```

```
#Calculate area, baseline number of birds, and post-density of bird
s
a<-1
for(n in unlist(Kentish_Flats_Distance)){
  if(n==0){Kentish_Flats_affected[a,4]<-Kentish_Flats_Area}
  if(n!=0){Kentish_Flats_affected[a,4]<-(((sqrt(Kentish_Flats_Area/
pi)+n)^2)*pi)-sum(subset(Kentish_Flats_affected, Distance<=n)[,"Are
a"],na.rm=TRUE)}
  Kentish_Flats_affected[a,5] <- Kentish_Flats_affected[a,4] * Base
line_density
  Kentish_Flats_affected[a,6] <- ((100-Kentish_Flats_affected[a,2])
/100)*Kentish_Flats_affected[a,5]
  a<-a+1
}

#Summarise into table of max displ distance
#Make basic data fram
Kentish_Flats_affected_total <- data.frame(Post_birds=NA, Post_dens
ity=NA, Displ_rate=NA, Area=NA, Birds_lost=NA)

#Loop through to summarse for each max displ distance
Kentish_Flats_affected_total[,1] <- sum(subset(Kentish_Flats_affect
ed)[,"Post_density"],na.rm=TRUE)
Kentish_Flats_affected_total[,2] <- Kentish_Flats_affected_total[,1
]/sum(subset(Kentish_Flats_affected)[,"Area"],na.rm=TRUE)
Kentish_Flats_affected_total[,3] <- (Baseline_density-Kentish_Flats
_affected_total[,2])/Baseline_density*100
Kentish_Flats_affected_total[,4] <- sum(subset(Kentish_Flats_affect
ed)[,"Area"],na.rm=TRUE)
Kentish_Flats_affected_total[,5] <- sum(subset(Kentish_Flats_affect
ed)[,"Baseline_number"],na.rm=TRUE)-sum(subset(Kentish_Flats_affect
ed)[,"Post_density"],na.rm=TRUE)

#Lincs, L & ID affected area displ stats
#Enter distance, displacement rate, & name of OWF into new data fra
me
LLID_Distance <- subset(Relative_OWFs,OWF=='Lincs, L & ID', select=
'Distance')
LLID_DisplRate <- subset(Relative_OWFs,OWF=='Lincs, L & ID', select
='DisplRate')
LLID_affected <- cbind(LLID_Distance,LLID_DisplRate)
LLID_affected$OWF <- 'Lincs, L & ID'
LLID_affected$Area <- NA
LLID_affected$Baseline_number <- NA
LLID_affected$Post_density <- NA
LLID_Area <- 55

#Calculate area, baseline number of birds, and post-density of bird
s
a<-1
for(n in unlist(LLID_Distance)){
  if(n==0){LLID_affected[a,4]<-LLID_Area}
```

```
  if(n!=0){LLID_affected[a,4]<-(((sqrt(LLID_Area/pi)+n)^2)*pi)-sum(
subset(LLID_affected, Distance<=n)[,"Area"],na.rm=TRUE)}
  LLID_affected[a,5] <- LLID_affected[a,4] * Baseline_density
  LLID_affected[a,6] <- ((100-LLID_affected[a,2])/100)*LLID_affecte
d[a,5]
  a<-a+1
}

#Summarise into table of max displ distance
#Make basic data fram
LLID_affected_total <- data.frame(Post_birds=NA, Post_density=NA, D
ispl_rate=NA, Area=NA, Birds_lost=NA)

#Loop through to summarse for each max displ distance
LLID_affected_total[,1] <- sum(subset(LLID_affected)[,"Post_density
"],na.rm=TRUE)
LLID_affected_total[,2] <- LLID_affected_total[,1]/sum(subset(LLID_
affected)[,"Area"],na.rm=TRUE)
LLID_affected_total[,3] <- (Baseline_density-LLID_affected_total[,2
])/Baseline_density*100
LLID_affected_total[,4] <- sum(subset(LLID_affected)[,"Area"],na.rm
=TRUE)
LLID_affected_total[,5] <- sum(subset(LLID_affected)[,"Baseline_num
ber"],na.rm=TRUE)-sum(subset(LLID_affected)[,"Post_density"],na.rm=
TRUE)

#London Array affected area displ stats
#Enter distance, displacement rate, & name of OWF into new data fra
me
London_Array_Distance <- subset(Relative_OWFs,OWF=='London Array',
select='Distance')
London_Array_DisplRate <- subset(Relative_OWFs,OWF=='London Array',
select='DisplRate')
London_Array_affected <- cbind(London_Array_Distance,London_Array_D
isplRate)
London_Array_affected$OWF <- 'London Array'
London_Array_affected$Area <- NA
London_Array_affected$Baseline_number <- NA
London_Array_affected$Post_density <- NA
London_Array_Area <- 100

#Calculate area, baseline number of birds, and post-density of bird
s
a<-1
for(n in unlist(London_Array_Distance)){
  if(n==0){London_Array_affected[a,4]<-London_Array_Area}
  if(n!=0){London_Array_affected[a,4]<-(((sqrt(London_Array_Area/pi
)+n)^2)*pi)-sum(subset(London_Array_affected, Distance<=n)[,"Area"]
,na.rm=TRUE)}
  London_Array_affected[a,5] <- London_Array_affected[a,4] * Baseli
ne_density
  London_Array_affected[a,6] <- ((100-London_Array_affected[a,2])/1
```

```
00)*London_Array_affected[a,5]
  a<-a+1
}

#Summarise into table of max displ distance
#Make basic data fram
London_Array_affected_total <- data.frame(Post_birds=NA, Post_densi
ty=NA, Displ_rate=NA, Area=NA, Birds_lost=NA)

#Loop through to summarse for each max displ distance
London_Array_affected_total[,1] <- sum(subset(London_Array_affected
)[,"Post_density"],na.rm=TRUE)
London_Array_affected_total[,2] <- London_Array_affected_total[,1]/
sum(subset(London_Array_affected)[,"Area"],na.rm=TRUE)
London_Array_affected_total[,3] <- (Baseline_density-London_Array_a
ffected_total[,2])/Baseline_density*100
London_Array_affected_total[,4] <- sum(subset(London_Array_affected
)[,"Area"],na.rm=TRUE)
London_Array_affected_total[,5] <- sum(subset(London_Array_affected
)[,"Baseline_number"],na.rm=TRUE)-sum(subset(London_Array_affected)
[,"Post_density"],na.rm=TRUE)

#Give names
Gunfleet_Sands_affected_total$OWF <- 'Gunfleet Sands'
Kentish_Flats_affected_total$OWF <- 'Kentish Flats'
LLID_affected_total$OWF <- 'LLID'
London_Array_affected_total$OWF <- 'London Array'

#Bind tables
OTESPA_affected <- rbind(Gunfleet_Sands_affected_total,Kentish_Flat
s_affected_total,LLID_affected_total,London_Array_affected_total)

#Plot gradients with horizontal lines to show buffer region of whic
h displ rate is calculated
Displ_rate_buffers_width <- data.frame(OWF=c("Horns Rev I","Horns R
ev I","Nysted","Nysted","Alpha Ventus","Alpha Ventus","Egmond aan Z
ee","Egmond aan Zee","Thanet","Thanet","Butendiek & Helgoland Clust
er (a)","Butendiek & Helgoland Cluster (a)","Butendiek & Helgoland 
Cluster (b)","Butendiek & Helgoland Cluster (b)","German Bight","Ge
rman Bight","Gunfleet Sands","Gunfleet Sands","Gunfleet Sands","Gun
fleet Sands","Gunfleet Sands","Gunfleet Sands","Kentish Flats","Ken
tish Flats","Kentish Flats","Kentish Flats","Kentish Flats","Kentis
h Flats","Kentish Flats","Kentish Flats","Kentish Flats","Kentish F
lats","Kentish Flats","Kentish Flats","Kentish Flats","Kentish Flat
s","Kentish Flats","Kentish Flats","Lincs, L & ID","Lincs, L & ID",
"Lincs, L & ID","Lincs, L & ID","Lincs, L & ID","Lincs, L & ID","Li
ncs, L & ID","Lincs, L & ID","Lincs, L & ID","Lincs, L & ID","Lincs
, L & ID","Lincs, L & ID","Lincs, L & ID","Lincs, L & ID","Lincs, L
& ID","Lincs, L & ID","Lincs, L & ID","Lincs, L & ID","Lincs, L & I
D","Lincs, L & ID","Lincs, L & ID","Lincs, L & ID","Lincs, L & ID",
"Lincs, L & ID","Lincs, L & ID","Lincs, L & ID","Lincs, L & ID","Li
ncs, L & ID","London Array","London Array","London Array","London A
```

```
rray","London Array","London Array","London Array","London Array","
London Array","London Array","London Array","London Array","London
Array","London Array","London Array","London Array","London Array",
"London Array","London Array","London Array","London Array","London
Array","London Array","London Array","London Array","London Array",
"London Array","London Array","London Array","London Array","London
Array","London Array","London Array","London Array","London Array",
"London Array","London Array","London Array","London Array","London
Array","London Array","London Array","London Array","London Array",
"London Array","London Array","London Array","London Array"),Displ_
dist=c(-1,0,-1,0,-1,0,-1,0,-1,0,-1,3,-1,10,-1,5,-1,0,0,1,1,2,-1,0,0
,0.5,0.5,1,1,2,2,3,3,4,4,5,5,6,-1,0,0,1,1,2,2,3,3,4,4,5,5,6,6,7,7,8
,8,9,9,10,10,11,11,12,12,13,-1,0,0,0.5,0.5,1.0,1.0,1.5,1.5,2.0,2.0,
2.5,2.5,3.0,3.0,3.5,3.5,4.0,4.0,4.5,4.5,5.0,5.0,5.5,5.5,6.0,6.0,6.5
,6.5,7.0,7.0,7.5,7.5,8.0,8.0,8.5,8.5,9.0,9.0,9.5,9.5,10.0,10.0,10.5
,10.5,11.0,11.0,11.5),P_Displ=c(100,100,100,100,90,90,68,68,73,73,7
0.8,70.8,44.5,44.5,90,90,91.29,91.29,65.8,65.8,20.95,20.95,94,94,77
,77,69,69,53,53,56,56,36,36,24,24,11,11,83.3,83.3,77.4,77.4,71.4,71
.4,62.5,62.5,55.2,55.2,50.8,50.8,44.8,44.8,42.3,42.3,33.6,33.6,27.2
,27.2,21.0,21.0,14.9,14.9,8.7,8.7,2.6,2.6,54.68,54.68,47.91,47.91,4
4.92,44.92,41.00,41.00,38.91,38.91,40.38,40.38,41.18,41.18,39.50,39
.50,36.07,36.07,33.02,33.02,31.55,31.55,32.96,32.96,35.00,35.00,36.
08,36.08,35.58,35.58,40.07,40.07,41.29,41.29,44.88,44.88,45.13,45.1
3,44.19,44.19,39.61,39.61,34.44,34.44,23.88,23.88,12.62,12.62))
#Make and save plot
Displ_gradient_width_plot <- ggplot(Displ_rate_buffers_width , aes(
x=Displ_dist, y=P_Displ, colour=OWF, group=OWF))+
  geom_point(size=2, aes(shape=OWF))+
  geom_line()+
  theme_bw()+
  theme(panel.border = element_blank(), axis.line = element_line(co
lour = "black"),
        legend.position = "bottom", legend.direction = "horizontal"
,
        text=element_text(size=12,  family="Calibri"))+
  xlab("Distance from wind farm (km)")+
  ylab("Displacement rate (%)")+
  scale_y_continuous(limits=c(0, 100), breaks=seq(0, 100, 10))+
  scale_x_continuous(limits=c(-1, 13), breaks=seq(-1, 13, 1), label
s = c("within-\nOWF","0","1","2","3","4","5","6","7","8","9","10","
11","12","13"))+
  scale_shape_manual(values=c(17, 8, 16, 17, 8, 16, 17, 8, 16, 17,
8, 16))+
  scale_color_manual(values = c("#DF0059","#EB4A2D","#F47D0E","#F2A
112","#E8BB33","#DED252","#B5CD72","#6DAA8D","#2788AA","#1261B2","#
363AA5","#6C0091"))
ggsave('Displ_gradient_width_plot.png', Displ_gradient_width_plot,
height = 6, width = 8)
```

Appendix H – Displacement rates used to simulate future scenarios of seabird displacement at offshore wind farms

Table H1. Example displacement rates used within each distance band in different maximum displacement distance scenarios, with a within wind farm displacement rate of ("100% within").

	Displacement rate (%) for each maximum displacement scenario																
Distance band	**0km**	**1km**	**2km**	**3km**	**4km**	**5km**	**6km**	**7km**	**8km**	**9km**	**10km**	**11km**	**12km**	**13km**	**14km**	**15km**	**16km**
Within OWF	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
0 - 1 km		31	61	71	76	79	81	83	84	85	85	86	86	87	87	87	87
1 - 2 km			31	51	61	67	71	74	76	78	79	80	81	82	83	83	84
2 - 3 km				31	46	55	61	65	69	71	73	75	76	77	78	79	80
3 - 4 km					31	43	51	57	61	65	67	69	71	73	74	75	76
4 - 5 km						31	41	48	54	58	61	64	66	68	40	71	72
5 - 6 km							31	40	46	51	55	58	61	63	65	67	69
6 - 7 km								31	39	45	49	53	56	59	61	63	65
7 - 8 km									31	38	43	48	51	54	57	59	61
8 - 9 km										31	37	42	46	50	53	55	57
9 - 10 km											31	37	41	45	48	51	54
10 - 11 km												31	36	40	44	47	50
11 - 12 km													31	36	40	43	46
12 - 13 km														31	35	39	42
13 - 14 km															31	35	39
14 - 15 km																31	35
15 - 16 km																	31

Table H2. Example displacement rates used within each distance band in different maximum displacement distance scenarios, with a within wind farm displacement rate based on the maximum displacement distance ("Basic gradient").

Distance band	**0km**	**1km**	**2km**	**3km**	**4km**	**5km**	**6km**	**7km**	**8km**	**9km**	**10km**	**11km**	**12km**	**13km**	**14km**	**15km**	**16km**
Within OWF	98.53	96.35	94.17	91.99	89.81	87.63	85.45	83.27	81.09	78.91	76.73	74.55	72.37	70.19	68.01	65.83	63.65
0 - 1 km		29.87	57.44	65.31	68.26	69.23	69.21	69.11	68.12	67.07	65.22	64.11	62.24	61.07	59.17	57.27	55.38
1 - 2 km			29.19	46.91	54.78	58.71	60.67	61.62	61.63	61.55	60.62	59.64	58.62	57.56	56.45	54.64	53.47
2 - 3 km				28.52	41.31	48.20	52.12	54.13	55.95	56.03	56.01	55.91	55.00	54.05	53.05	52.01	50.92
3 - 4 km					27.84	37.68	43.58	47.46	49.46	51.29	51.41	51.44	51.38	51.24	50.33	49.37	48.37
4 - 5 km						27.17	35.03	39.97	43.79	45.77	46.81	47.71	47.76	47.73	47.61	46.74	45.83
5 - 6 km							26.49	33.31	37.30	40.24	42.20	43.24	44.15	44.22	44.21	44.11	43.92
6 - 7 km								25.81	31.63	35.51	37.60	39.51	40.53	41.41	41.49	41.47	41.37
7 - 8 km									25.14	29.99	32.99	35.78	36.91	37.90	38.77	38.84	38.83
8 - 9 km										24.46	28.39	31.31	33.29	35.10	36.05	36.21	36.28
9 - 10 km											23.79	27.58	29.67	31.59	32.64	33.57	34.37
10 - 11 km												23.11	26.05	28.08	29.92	30.94	31.83
11 - 12 km													22.43	25.27	27.20	28.31	29.28
12 - 13 km														21.76	23.80	25.67	26.73
13 - 14 km															21.08	23.04	24.82
14 - 15 km																20.41	22.28
15 - 16 km																	19.73

Appendix I – R markdown code used in the analysis of Chapter 7

Packages required

```
library(sf)
library(sp)
library(maptools)
library(spatstat)
library(tmap)
library(raster)
library(rgdal)
library(rgeos)
library(NLP)
library(ggplot2)
library(forcats)
library(ggpubr)
library("readxl")
library(extrafont)
loadfonts(device = "win")
```

OWF data

```
setwd("C:/Users/44755/OneDrive - University of Strathclyde/7. Futur
e cumulative displacement/Maps/Background maps/Crown Estate Offshor
e Wind Sites 22.02.2023")
#Import shapefile
OWF.sf <- st_read("WindSiteAgreements_EnglandWalesAndNI_TheCrownEst
ate.shp")
#Convert to spatial data
OWF.sp <- as(OWF.sf, "Spatial")
#Transform to EPSG 27700
OWF.sprepro <- spTransform(OWF.sp, CRS("+init=epsg:27700"))
#Replace status of those incorrect
OWF.sprepro@data$Inf_Status <- as.character(OWF.sprepro@data$Inf_St
atus)
#Load merged Gunfleet Sands
GunfleetSands.sf <- st_read("Gunfleet Sands.shp")
#Convert to spatial data
GunfleetSands.sp <- as(GunfleetSands.sf, "Spatial")
#Transform to EPSG 27700
GunfleetSands.sprepro <- spTransform(GunfleetSands.sp, CRS("+init=e
psg:27700"))
#Replace status of those incorrect
GunfleetSands.sprepro@data$Inf_Status <- as.character(GunfleetSands
.sprepro@data$Inf_Status)
#Plot
tm_shape(OWF.sprepro) + tm_polygons(col="Inf_Status", palette='Spec
```

```
tral', border.col = NULL)+ tm_legend
#Calculate area in km^2
OWF.sprepro$Area <- area(OWF.sprepro)/1000000
```

Import and set displacement gradients

```
setwd("C:/Users/44755/OneDrive - University of Strathclyde/1. Thesi
s/12. Thesis V2")
Displ_together <- read.csv("Displ_gradients_change_max_dist.csv")
#Set which displacement gradient to use
#Within hundred = 4
#Gradient = 5
Displ_grad <- 4
```

Import non-breeding aerial sitting + flying red-throated diver data

```
setwd("C:/Users/44755/OneDrive - University of Strathclyde/7. Futur
e cumulative displacement/Maps/Seabird_Sensitivity_Mapping_SeaMaST_
England/Seabird_Sensitivity_Mapping_SeaMaST_England/Data")
#Import shapefile
RTD_density.sf <- st_read("BDMPS_Non_Breeding_Aerial_Sitting_Plus_F
lying_DSM_D.shp")
#Convert to spatial data
RTD_density.sp <- as(RTD_density.sf, "Spatial")
#Transform to EPSG 27700
RTD_density.sprepro <- spTransform(RTD_density.sp, CRS("+init=epsg:
27700"))
#Plot
tm_shape(RTD_density.sprepro) + tm_polygons(col="RH_D", border.col
= NULL)+tm_legend(outside = TRUE)
```

Import SPA data

```
setwd("C:/Users/44755/OneDrive - University of Strathclyde/7. Futur
e cumulative displacement/Maps/Background maps/SPAs")
#Import shapefile
SPA.sf <- st_read("c20220316_UKSPAswithMarineComponents_WGS84.shp")
#Convert to spatial data
SPA.sp <- as(SPA.sf, "Spatial")
#Transform to EPSG 27700
SPA.sprepro <- spTransform(SPA.sp, CRS("+init=epsg:27700"))
#Remove duplicates
SPA.sprepro <- SPA.sprepro[!duplicated(data.frame(SPA.sprepro)),]
```

Outer Thames Estuary SPA & RTD data

```
#Select Outer Thames Estuary SPA
Outer_Thames_Estuary_SPA <- SPA.sprepro[SPA.sprepro@data$SITE_NAME
== "Outer Thames Estuary",]
#plot SPA
tm_shape(Outer_Thames_Estuary_SPA) + tm_borders()

#Crop RTD density to Outer_Thames_Estuary_SPA
RTD_density_Outer_Thames_Estuary_SPA <- intersect(RTD_density.sprep
ro, Outer_Thames_Estuary_SPA)
```

```
#Plot map
#Create colour palette
RTD_density_col <- c('#DF0059','#EB4B2C','#F68D04','#ECAF24','#DFD050','#A6C677','#4F9C9A','#066FB7','#3839A5','#6C0091')
setwd("Y:/Marine Species/Rebecca Hall/Laptop files/PhD work/Future cumulative displ/UK Coastline")
#Load Uk coastline
UK.sf <- st_read("UKIreland_Coastline.shp")
#Convert to spatial data
UK.sp <- as(UK.sf, "Spatial")
#Transform to EPSG 27700
UK.seprepro <- spTransform(UK.sp, CRS("+init=epsg:27700"))
#Plot
OTE_SPA_RTD_density_map <-tm_shape(Outer_Thames_Estuary_SPA)+tm_borders()+tm_shape(UK.sprepro)+tm_fill(col='#89B883')+tm_borders(col='black')+tm_shape(RTD_density_Outer_Thames_Estuary_SPA) + tm_polygons(col="RH_D", border.col = NULL, style = "fixed",breaks = c(0,2.5,5,7.5,10,12.5,15,17.5,20,22.5,25),palette=RTD_density_col)+tm_legend(show=FALSE) +tm_shape(Outer_Thames_Estuary_SPA)+tm_borders(col='white',lwd=5)+tm_shape(Outer_Thames_Estuary_SPA)+tm_borders(col='black',lwd=3)+tm_compass(north = 0,type='4star',position=c("LEFT","TOP"),size=3,show.labels=0)+tm_scale_bar(text.size=1)
#Save plot
setwd("Y:/Marine Species/Rebecca Hall/Laptop files/PhD work/Future cumulative displ/Maps")
tmap_save(OTE_SPA_RTD_density_map, "OTE_SPA_RTD_density_map.png")

#Plot OTE SPA relative to UK
Outer_Thames_Estuary_SPA_20km_buf <- gBuffer(Outer_Thames_Estuary_SPA, width = 20000, byid=TRUE)
Region_of_UK <- bind(Outer_Thames_Estuary_SPA_20km_buf,UK.sprepro)
OTE_SPA_UK_map <-tm_shape(Region_of_UK)+tm_borders(col='white')+tm_shape(UK.sprepro)+tm_fill(col='#89B883')+tm_borders(col='black')+tm_shape(Outer_Thames_Estuary_SPA)+tm_borders(col='black',lwd=2)+tm_legend(show=FALSE) +tm_compass(north = 0,type='4star',position=c("LEFT","TOP"),size=3,show.labels=0)
#Save plot
setwd("Y:/Marine Species/Rebecca Hall/Laptop files/PhD work/Future cumulative displ/Maps")
tmap_save(OTE_SPA_UK_map, "OTE_SPA_UK_map.png")

#Calculate number of birds within OTE SPA
OTE_SPA_num_RTD <- sum(RTD_density_Outer_Thames_Estuary_SPA@data$RH_D * 9)
```

~~~~~ Impacted once from closest ~~~~~

OPERATIONAL Impacted once from closest

```
#Select operational OWFs
OWF_plusoperational <-OWF.sprepro[OWF.sprepro@data$Name_Prop == "Scroby Sands" | OWF.sprepro@data$Name_Prop == "Kentish Flats" | OWF.s
```

```
prepro@data$Name_Prop == "Thanet" | OWF.sprepro@data$Name_Prop == "
Greater Gabbard" | OWF.sprepro@data$Name_Prop == "London Array" | O
WF.sprepro@data$Name_Prop == "Gunfleet Sands Demo" | OWF.sprepro@da
ta$Name_Prop == "Kentish Flats Extension" | OWF.sprepro@data$Name_P
rop == "East Anglia ONE",]
#Remove extra column from Gunfleet Sands data
GunfleetSands.sprepro@data <- GunfleetSands.sprepro@data[,1:11]
#Bind other OWF data and GUnfleet Sands dats
OWF_plusoperational<-rbind(OWF_plusoperational,GunfleetSands.sprepr
o)

#Make buffers
buffer <- 1:16
for (bf in buffer) {
  eval(parse(text = paste0("OWF_", bf, "km_buf_plusoperational <- g
Buffer(OWF_plusoperational, width = bf*1000, byid=TRUE)")))
}
#Create rings from buffers
OWF_0km_ring_plusoperational <- OWF_plusoperational
OWF_1km_ring_plusoperational <- erase(OWF_1km_buf_plusoperational,
OWF_plusoperational)
buffer <- 1:16
for (bf in buffer[2:16]) {
  eval(parse(text = paste0("OWF_", bf, "km_ring_plusoperational <-
erase(OWF_", bf, "km_buf_plusoperational, OWF_", bf - 1, "km_buf_pl
usoperational)")))
}
#merge overlapping rings
buffer <- 0:16
for (bf in buffer) {
  eval(parse(text = paste0("OWF_", bf, "km_ring_plusoperational <-g
UnaryUnion(OWF_", bf, "km_ring_plusoperational)")))
}
```

Plot map of Impacted once from closest buffers

```
#Load Uk coastline
setwd("C:/Users/44755/OneDrive - University of Strathclyde/7. Futur
e cumulative displacement/Maps/Background maps/UK Coastline")
UK.sf <- st_read("UKIreland_Coastline.shp")
#Convert to spatial data
UK.sp <- as(UK.sf, "Spatial")
#Transform to EPSG 27700
UK.sprepro <- spTransform(UK.sp, CRS("+init=epsg:27700"))
#Plot
Plus_operational_map<-tm_shape(Outer_Thames_Estuary_SPA)+tm_borders
()+tm_shape(UK.sprepro)+tm_fill(col='#89B883')+tm_borders(col='blac
k')+tm_shape(OWF_0km_ring_plusoperational)+tm_fill(col='#AFABAB')+t
m_borders(col='black')+tm_shape(OWF_1km_ring_plusoperational)+tm_fi
ll(col='#E2134E')+tm_borders(col='black')+tm_shape(OWF_2km_ring_plu
soperational)+tm_fill(col='#E83639')+tm_borders(col='black')+tm_sha
pe(OWF_3km_ring_plusoperational)+tm_fill(col='#EE5D21')+tm_borders(
```

```
col='black')+tm_shape(OWF_4km_ring_plusoperational)+tm_fill(col='#F
58509')+tm_borders(col='black')+tm_shape(OWF_5km_ring_plusoperation
al)+tm_fill(col='#F29F0F')+tm_borders(col='black')+tm_shape(OWF_6km
_ring_plusoperational)+tm_fill(col='#EBB127')+tm_borders(col='black
')+tm_shape(OWF_7km_ring_plusoperational)+tm_fill(col='#E4C33E')+tm
_borders(col='black')+tm_shape(OWF_8km_ring_plusoperational)+tm_fil
l(col='#DDD657')+tm_borders(col='black')+tm_shape(OWF_9km_ring_plus
operational)+tm_fill(col='#BDD16E')+tm_borders(col='black')+tm_shap
e(OWF_10km_ring_plusoperational)+tm_fill(col='#87B783')+tm_borders(
col='black')+tm_shape(OWF_11km_ring_plusoperational)+tm_fill(col='#
509C99')+tm_borders(col='black')+tm_shape(OWF_12km_ring_plusoperati
onal)+tm_fill(col='#1D83AE')+tm_borders(col='black')+tm_shape(OWF_1
3km_ring_plusoperational)+tm_fill(col='#1064B3')+tm_borders(col='bl
ack')+tm_shape(OWF_14km_ring_plusoperational)+tm_fill(col='#2949AA'
)+tm_borders(col='black')+tm_shape(OWF_15km_ring_plusoperational)+t
m_fill(col='#432BA0')+tm_borders(col='black')+tm_shape(OWF_16km_rin
g_plusoperational)+tm_fill(col='#5E0E96')+tm_borders(col='black')+t
m_shape(Outer_Thames_Estuary_SPA)+tm_borders(col='white',lwd=6)+tm_
shape(Outer_Thames_Estuary_SPA)+tm_borders(col='black',lwd=3)
setwd("Y:/Marine Species/Rebecca Hall/Laptop files/PhD work/Future
cumulative displ/Maps")
tmap_save(Plus_operational_map, "Plus_operational_map.png")
```

Crop RTD density to Impacted once from closest and buffers

```
#Set range of buffer sizes
buffer <- 0:16
for (bf in buffer) {
  eval(parse(text = paste0("RTD_density_Outer_Thames_Estuary_SPA_OW
F_", bf, "km_ring_plusoperational <-raster::intersect(RTD_density_O
uter_Thames_Estuary_SPA, OWF_", bf, "km_ring_plusoperational)")))
}
```

Calculate area

```
#Crop rings to SPA
buffer <- 0:16
for (bf in buffer) {
  eval(parse(text = paste0("OWF_", bf, "km_ring_plusoperational_OTE
_SPA <-intersect(OWF_", bf, "km_ring_plusoperational, Outer_Thames_
Estuary_SPA)")))
}
#Make empty data frame
Plus_operational_area_OTE_SPA <- data.frame(Ring=NA, Area=NA)
#Calculate area
a<-1
for(bf in buffer){
  try(
    eval(parse(text = paste0("Plus_operational_area_OTE_SPA[a,1] <-
bf
      Plus_operational_area_OTE_SPA[a,2] <- area(OWF_", bf, "km_rin
g_plusoperational_OTE_SPA)/1000000")))
  )
```

```
  a<-a+1
}
#Save
setwd("C:/Users/44755/OneDrive - University of Strathclyde/1. Thesi
s/12. Thesis V2")
write.csv(Plus_operational_area_OTE_SPA,"Plus_operational_area_OTE_
SPA.csv")
```

Displace birds in buffers & rings

```
#Displace birds using displacement gradient
for (fb in buffer){
  for(bf in buffer){
    eval(parse(text = paste0("RTD_density_Outer_Thames_Estuary_SPA_
OWF_",fb,"km_ring_plusoperational@data$RH_D_MaxDispl",bf," <- as.nu
meric(sapply((1-(Displ_together[(bf*17)+(fb+1),Displ_grad])/100),'*
',RTD_density_Outer_Thames_Estuary_SPA_OWF_",fb,"km_ring_plusoperat
ional@data$RH_D))")))
  }
}
```

Calculate numbers of birds displaced and mortality and as proportion of SPA

```
#No. birds in SPA
RTD_density_Outer_Thames_Estuary_SPA_sum <- sum((area(RTD_density_O
uter_Thames_Estuary_SPA)/1000000)*RTD_density_Outer_Thames_Estuary_
SPA@data$RH_D)
#Set range of displacement rings
ring <- 0:16
#Calculate percentage loss
for (rg in ring) {
  eval(parse(text = paste0("RTD_density_Outer_Thames_Estuary_SPA_OW
F_", rg, "km_ring_plusoperational_sum <-sum((area(RTD_density_Outer
_Thames_Estuary_SPA_OWF_", rg, "km_ring_plusoperational)/1000000)*R
TD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_plusoperati
onal@data$RH_D)")))
  for (bf in ring) {
    eval(parse(text = paste0("RTD_density_Outer_Thames_Estuary_SPA_
OWF_", rg, "km_ring_plusoperational_sum_", bf, " <-sum((area(RTD_de
nsity_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_plusoperational)
/1000000)*RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_
plusoperational@data$RH_D_MaxDispl", bf, ")RTD_percloss_Outer_Thame
s_Estuary_SPA_OWF_", rg, "km_ring_plusoperational_", bf, " <- ((RTD
_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_plusoperation
al_sum - RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_p
lusoperational_sum_", bf, ")/RTD_density_Outer_Thames_Estuary_SPA_s
um)*100")))
  }
}
#Set range of mortality rates
Mortality_rate <- 1:10
#Calculate numbers of bird casualties and as proportion of SPA
RTD_percloss_Outer_Thames_Estuary_SPA_plusoperational <- data.frame
```

```
(Max_displ_km=NA, Ring=NA, MortalityRate=NA, NoBirds=NA, RingArea=N
A, NoBirdLoss=NA, SPAPercLoss=NA, NoBirdMortality=NA, SPAPercMortal
ity=NA)
a<-1
for (bf in ring) {
  b<-1
  for (rg in ring) {
    c<-1
    for (mt in Mortality_rate) {
      RTD_percloss_Outer_Thames_Estuary_SPA_plusoperational[((a-1)*
length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))
+c,1] <- bf
      RTD_percloss_Outer_Thames_Estuary_SPA_plusoperational[((a-1)*
length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))
+c,2] <- rg
      RTD_percloss_Outer_Thames_Estuary_SPA_plusoperational[((a-1)*
length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))
+c,3] <- mt
      eval(parse(text = paste0("RTD_percloss_Outer_Thames_Estuary_S
PA_plusoperational[((a-1)*length(Mortality_rate)*length(ring))+((b-
1)*length(Mortality_rate))+c,4] <- RTD_density_Outer_Thames_Estuary
_SPA_OWF_", rg, "km_ring_plusoperational_sum
      RTD_percloss_Outer_Thames_Estuary_SPA_plusoperational[((a-1)*
length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))
+c,5] <- sum(area(RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "
km_ring_plusoperational)/1000000)
      RTD_percloss_Outer_Thames_Estuary_SPA_plusoperational[((a-1)*
length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))
+c,6] <- RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_p
lusoperational_sum - RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg
, "km_ring_plusoperational_sum_", bf, "
      RTD_percloss_Outer_Thames_Estuary_SPA_plusoperational[((a-1)*
length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))
+c,7] <- RTD_percloss_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_
plusoperational_", bf, "
      RTD_percloss_Outer_Thames_Estuary_SPA_plusoperational[((a-1)*
length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))
+c,8] <- (RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_
plusoperational_sum - RTD_density_Outer_Thames_Estuary_SPA_OWF_", r
g, "km_ring_plusoperational_sum_", bf, ")/100*mt
      RTD_percloss_Outer_Thames_Estuary_SPA_plusoperational[((a-1)*
length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))
+c,9] <- RTD_percloss_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_
plusoperational_", bf, "/100*mt")))
      c<-c+1
    }
    b<-b+1
  }
  a<-a+1
}
#Sum % birds for each scenario
RTD_percloss_total_Outer_Thames_Estuary_SPA_plusoperational <- data
```

```
.frame(Max_displ_km=NA, MortalityRate=NA, NoBirdLoss=NA, SPAPercLoss=NA, NoBirdMortality=NA, SPAPercMortality=NA)
a<-1
for (bf in ring) {
  b<-1
  for (mt in Mortality_rate) {
    RTD_percloss_total_Outer_Thames_Estuary_SPA_plusoperational[((a-1)*length(Mortality_rate))+b,1] <- bf
    RTD_percloss_total_Outer_Thames_Estuary_SPA_plusoperational[((a-1)*length(Mortality_rate))+b,2] <- mt
    eval(parse(text = paste0("RTD_percloss_total_Outer_Thames_Estuary_SPA_plusoperational[((a-1)*length(Mortality_rate))+b,3] <- sum(subset(RTD_percloss_Outer_Thames_Estuary_SPA_plusoperational, Max_displ_km==bf & MortalityRate==mt, select=NoBirdLoss))
      RTD_percloss_total_Outer_Thames_Estuary_SPA_plusoperational[((a-1)*length(Mortality_rate))+b,4] <- sum(subset(RTD_percloss_Outer_Thames_Estuary_SPA_plusoperational, Max_displ_km==bf & MortalityRate==mt, select=SPAPercLoss))
      RTD_percloss_total_Outer_Thames_Estuary_SPA_plusoperational[((a-1)*length(Mortality_rate))+b,5] <- sum(subset(RTD_percloss_Outer_Thames_Estuary_SPA_plusoperational, Max_displ_km==bf & MortalityRate==mt, select=NoBirdMortality))
      RTD_percloss_total_Outer_Thames_Estuary_SPA_plusoperational[((a-1)*length(Mortality_rate))+b,6] <- sum(subset(RTD_percloss_Outer_Thames_Estuary_SPA_plusoperational, Max_displ_km==bf & MortalityRate==mt, select=SPAPercMortality))")))
    b<-b+1
  }
  a<-a+1
}

setwd("C:/Users/44755/OneDrive - University of Strathclyde/1. Thesis/12. Thesis V2")
#If using hundred within gradient save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_plusoperational,"RTD_percloss_total_Outer_Thames_Estuary_SPA_plusoperational_Hundred_Within.csv")
#If using basic gradient save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_plusoperational,"RTD_percloss_total_Outer_Thames_Estuary_SPA_plusoperational_Gradient.csv")
```

CONSENTED Impacted once from closest

```
#Select operational and consented OWFs
OWF_plusconsented <-OWF.sprepro[OWF.sprepro@data$Name_Prop == "Scroby Sands" | OWF.sprepro@data$Name_Prop == "Kentish Flats" | OWF.sprepro@data$Name_Prop == "Thanet"| OWF.sprepro@data$Name_Prop == "Greater Gabbard" | OWF.sprepro@data$Name_Prop == "London Array" | OWF.sprepro@data$Name_Prop == "Gunfleet Sands Demo" | OWF.sprepro@data$Name_Prop == "Kentish Flats Extension" | OWF.sprepro@data$Name_Prop == "East Anglia ONE" | OWF.sprepro@data$Name_Prop == "East Anglia O
```

```
NE NORTH" | OWF.sprepro@data$Name_Prop == "East Anglia TWO",]
#Add in Gunfleet Sands
OWF_plusconsented<-rbind(OWF_plusconsented,GunfleetSands.sprepro)
#Make buffers
buffer <- 1:16
for (bf in buffer) {
  eval(parse(text = paste0("OWF_", bf, "km_buf_plusconsented <- gBu
ffer(OWF_plusconsented, width = bf*1000, byid=TRUE)")))
}
#Create rings from buffers
OWF_0km_ring_plusconsented <- OWF_plusconsented
OWF_1km_ring_plusconsented <- erase(OWF_1km_buf_plusconsented, OWF_
plusconsented)
buffer <- 1:16
for (bf in buffer[2:16]) {
  eval(parse(text = paste0("OWF_", bf, "km_ring_plusconsented <- er
ase(OWF_", bf, "km_buf_plusconsented, OWF_", bf - 1, "km_buf_plusco
nsented)")))
}
#Merge overlapping rings
buffer <- 0:16
for (bf in buffer) {
  eval(parse(text = paste0("OWF_", bf, "km_ring_plusconsented <-gUn
aryUnion(OWF_", bf, "km_ring_plusconsented)")))
}
```

Plot map

```
setwd("C:/Users/44755/OneDrive - University of Strathclyde/7. Futur
e cumulative displacement/Maps/Background maps/UK Coastline")
#Load Uk coastline
UK.sf <- st_read("UKIreland_Coastline.shp")
#Convert to spatial data
UK.sp <- as(UK.sf, "Spatial")
#Transform to EPSG 27700
UK.sprepro <- spTransform(UK.sp, CRS("+init=epsg:27700"))
#Plot
Plus_consented_map<-tm_shape(Outer_Thames_Estuary_SPA)+tm_borders()
+tm_shape(UK.sprepro)+tm_fill(col='#89B883')+tm_borders(col='black'
)+tm_shape(OWF_0km_ring_plusconsented)+tm_fill(col='#AFABAB')+tm_bo
rders(col='black')+tm_shape(OWF_1km_ring_plusconsented)+tm_fill(col
='#E2134E')+tm_borders(col='black')+tm_shape(OWF_2km_ring_plusconse
nted)+tm_fill(col='#E83639')+tm_borders(col='black')+tm_shape(OWF_3
km_ring_plusconsented)+tm_fill(col='#EE5D21')+tm_borders(col='black
')+tm_shape(OWF_4km_ring_plusconsented)+tm_fill(col='#F58509')+tm_b
orders(col='black')+tm_shape(OWF_5km_ring_plusconsented)+tm_fill(co
l='#F29F0F')+tm_borders(col='black')+tm_shape(OWF_6km_ring_pluscons
ented)+tm_fill(col='#EBB127')+tm_borders(col='black')+tm_shape(OWF_
7km_ring_plusconsented)+tm_fill(col='#E4C33E')+tm_borders(col='blac
k')+tm_shape(OWF_8km_ring_plusconsented)+tm_fill(col='#DDD657')+tm_
borders(col='black')+tm_shape(OWF_9km_ring_plusconsented)+tm_fill(c
ol='#BDD16E')+tm_borders(col='black')+tm_shape(OWF_10km_ring_plusco
```

```
nsented)+tm_fill(col='#87B783')+tm_borders(col='black')+tm_shape(OW
F_11km_ring_plusconsented)+tm_fill(col='#509C99')+tm_borders(col='b
lack')+tm_shape(OWF_12km_ring_plusconsented)+tm_fill(col='#1D83AE')
+tm_borders(col='black')+tm_shape(OWF_13km_ring_plusconsented)+tm_f
ill(col='#1064B3')+tm_borders(col='black')+tm_shape(OWF_14km_ring_p
lusconsented)+tm_fill(col='#2949AA')+tm_borders(col='black')+tm_sha
pe(OWF_15km_ring_plusconsented)+tm_fill(col='#432BA0')+tm_borders(c
ol='black')+tm_shape(OWF_16km_ring_plusconsented)+tm_fill(col='#5E0
E96')+tm_borders(col='black')+tm_shape(Outer_Thames_Estuary_SPA)+tm
_borders(col='white',lwd=6)+tm_shape(Outer_Thames_Estuary_SPA)+tm_b
orders(col='black',lwd=3)
setwd("Y:/Marine Species/Rebecca Hall/Laptop files/PhD work/Future 
cumulative displ/Maps")
tmap_save(Plus_consented_map, "Plus_consented_map.png")
```

Crop density to consented OWF and buffers

```
#Set range of buffers
buffer <- 0:16
#Crop RTD density
for (bf in buffer) {
  eval(parse(text = paste0("RTD_density_Outer_Thames_Estuary_SPA_OW
F_", bf, "km_ring_plusconsented <-raster::intersect(RTD_density_Out
er_Thames_Estuary_SPA, OWF_", bf, "km_ring_plusconsented)")))
}
```

Calculate area

```
#Crop rings to SPA
buffer <- 0:16
for (bf in buffer) {
  eval(parse(text = paste0("OWF_", bf, "km_ring_plusconsented_OTE_S
PA <-intersect(OWF_", bf, "km_ring_plusconsented, Outer_Thames_Estu
ary_SPA)")))
}
#Calculate areas
Plus_consented_area_OTE_SPA <- data.frame(Ring=NA, Area=NA)
a<-1
for(bf in buffer){
  try(
    eval(parse(text = paste0("Plus_consented_area_OTE_SPA[a,1] <- b
f
                             Plus_consented_area_OTE_SPA[a,2] <- ar
ea(OWF_", bf, "km_ring_plusconsented_OTE_SPA)/1000000"))))
  a<-a+1
}
#Remove area of operational OWFs to get consented OWFs only area
Plus_consented_area_OTE_SPA_only <- as.data.frame(Plus_operational_
area_OTE_SPA[,1])
Plus_consented_area_OTE_SPA_only$Area <- Plus_consented_area_OTE_SP
A[,2] - Plus_operational_area_OTE_SPA[,2]
names(Plus_consented_area_OTE_SPA_only)[names(Plus_consented_area_O
TE_SPA_only) == "Plus_operational_area_OTE_SPA[, 1]"] <- "Ring"
```

```
#Save
setwd("C:/Users/44755/OneDrive - University of Strathclyde/1. Thesi
s/12. Thesis V2")
write.csv(Plus_consented_area_OTE_SPA,"Plus_consented_area_OTE_SPA.
csv")
write.csv(Plus_consented_area_OTE_SPA_only,"Plus_consented_area_OTE
_SPA_only.csv")
```

Displace birds in buffers & rings

```
#Displace birds using displacement gradient
for (fb in buffer){
  for(bf in buffer){
    try(
      eval(parse(text = paste0("RTD_density_Outer_Thames_Estuary_SP
A_OWF_",fb,"km_ring_plusconsented@data$RH_D_MaxDispl",bf," <- as.nu
meric(sapply((1-(Displ_together[(bf*17)+(fb+1),Displ_grad])/100),'*
',RTD_density_Outer_Thames_Estuary_SPA_OWF_",fb,"km_ring_plusconsen
ted@data$RH_D))"))))
  }
}
```

Calculate numbers of birds displaced and mortality and as proportion of SPA

```
#No. birds in SPA
RTD_density_Outer_Thames_Estuary_SPA_sum <- sum((area(RTD_density_O
uter_Thames_Estuary_SPA)/1000000)*RTD_density_Outer_Thames_Estuary_
SPA@data$RH_D)
#Percentage loss
for (rg in ring) {
  eval(parse(text = paste0("try(RTD_density_Outer_Thames_Estuary_SP
A_OWF_", rg, "km_ring_plusconsented_sum <-sum((area(RTD_density_Out
er_Thames_Estuary_SPA_OWF_", rg, "km_ring_plusconsented)/1000000)*R
TD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_plusconsent
ed@data$RH_D))")))
  for (bf in ring) {
    eval(parse(text = paste0("try({RTD_density_Outer_Thames_Estuary
_SPA_OWF_", rg, "km_ring_plusconsented_sum_", bf, " <-sum((area(RTD
_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_plusconsented
)/1000000)*RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring
_plusconsented@data$RH_D_MaxDispl", bf, ")RTD_percloss_Outer_Thames
_Estuary_SPA_OWF_", rg, "km_ring_plusconsented_", bf, " <- ((RTD_de
nsity_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_plusconsented_su
m - RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_plusco
nsented_sum_", bf, ")/RTD_density_Outer_Thames_Estuary_SPA_sum)*100
})")))
  }
}
#Calculate numbers of bird casualties and as proportion of SPA
Mortality_rate <- 1:10
#Put into table
RTD_percloss_Outer_Thames_Estuary_SPA_plusconsented <- data.frame(M
ax_displ_km=NA, Ring=NA, MortalityRate=NA, NoBirds=NA, RingArea=NA,
```

```
NoBirdLoss=NA, SPAPercLoss=NA, NoBirdMortality=NA, SPAPercMortality=NA)
a<-1
for (bf in ring) {
  b<-1
  for (rg in ring) {
    c<-1
    for (mt in Mortality_rate) {
      RTD_percloss_Outer_Thames_Estuary_SPA_plusconsented[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))+c,1] <- bf
      RTD_percloss_Outer_Thames_Estuary_SPA_plusconsented[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))+c,2] <- rg
      RTD_percloss_Outer_Thames_Estuary_SPA_plusconsented[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))+c,3] <- mt
      eval(parse(text = paste0("try({RTD_percloss_Outer_Thames_Estuary_SPA_plusconsented[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))+c,4] <- RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_plusconsented_sum
      RTD_percloss_Outer_Thames_Estuary_SPA_plusconsented[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))+c,5] <- sum(area(RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_plusconsented)/1000000)
      RTD_percloss_Outer_Thames_Estuary_SPA_plusconsented[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))+c,6] <- RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_plusconsented_sum - RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_plusconsented_sum_", bf, "
      RTD_percloss_Outer_Thames_Estuary_SPA_plusconsented[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))+c,7] <- RTD_percloss_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_plusconsented_", bf, "
      RTD_percloss_Outer_Thames_Estuary_SPA_plusconsented[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))+c,8] <- (RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_plusconsented_sum - RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_plusconsented_sum_", bf, ")/100*mt
      RTD_percloss_Outer_Thames_Estuary_SPA_plusconsented[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))+c,9] <- RTD_percloss_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_plusconsented_", bf, "/100*mt})")))
      c<-c+1
    }
    b<-b+1
  }
  a<-a+1
}

#Sum % birds for each scenario
RTD_percloss_total_Outer_Thames_Estuary_SPA_plusconsented <- data.f
```

```
rame(Max_displ_km=NA, MortalityRate=NA, NoBirdLoss=NA, SPAPercLoss=
NA, NoBirdMortality=NA, SPAPercMortality=NA)
a<-1
for (bf in ring) {
  b<-1
  for (mt in Mortality_rate) {
    RTD_percloss_total_Outer_Thames_Estuary_SPA_plusconsented[((a-1
)*length(Mortality_rate))+b,1] <- bf
    RTD_percloss_total_Outer_Thames_Estuary_SPA_plusconsented[((a-1
)*length(Mortality_rate))+b,2] <- mt
    eval(parse(text = paste0("try({RTD_percloss_total_Outer_Thames_
Estuary_SPA_plusconsented[((a-1)*length(Mortality_rate))+b,3] <- su
m(subset(RTD_percloss_Outer_Thames_Estuary_SPA_plusconsented, Max_d
ispl_km==bf & MortalityRate==mt, select=NoBirdLoss), na.rm=TRUE)
      RTD_percloss_total_Outer_Thames_Estuary_SPA_plusconsented[((a
-1)*length(Mortality_rate))+b,4] <- sum(subset(RTD_percloss_Outer_T
hames_Estuary_SPA_plusconsented, Max_displ_km==bf & MortalityRate==
mt, select=SPAPercLoss), na.rm=TRUE)
      RTD_percloss_total_Outer_Thames_Estuary_SPA_plusconsented[((a
-1)*length(Mortality_rate))+b,5] <- sum(subset(RTD_percloss_Outer_T
hames_Estuary_SPA_plusconsented, Max_displ_km==bf & MortalityRate==
mt, select=NoBirdMortality), na.rm=TRUE)
      RTD_percloss_total_Outer_Thames_Estuary_SPA_plusconsented[((a
-1)*length(Mortality_rate))+b,6] <- sum(subset(RTD_percloss_Outer_T
hames_Estuary_SPA_plusconsented, Max_displ_km==bf & MortalityRate==
mt, select=SPAPercMortality), na.rm=TRUE)}) ")))
    b<-b+1
  }
  a<-a+1
}

setwd("C:/Users/44755/OneDrive - University of Strathclyde/1. Thesi
s/12. Thesis V2")
#If using hundred within gradient save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_plusconsented
,"RTD_percloss_total_Outer_Thames_Estuary_SPA_plusconsented_Hundred
_Within.csv")
#If using basic gradient save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_plusconsented
,"RTD_percloss_total_Outer_Thames_Estuary_SPA_plusconsented_Gradien
t.csv")
```

PREPLANNING merged OWFs

```
#Select pluspreplanning OWFs only
OWF_pluspreplanning <-
  OWF.sprepro[OWF.sprepro@data$Name_Prop == "Scroby Sands" | OWF.sp
repro@data$Name_Prop == "Kentish Flats" | OWF.sprepro@data$Name_Pro
p == "Thanet"| OWF.sprepro@data$Name_Prop == "Greater Gabbard" | OW
F.sprepro@data$Name_Prop == "London Array" | OWF.sprepro@data$Name_
Prop == "Gunfleet Sands Demo" | OWF.sprepro@data$Name_Prop == "Kent
ish Flats Extension" | OWF.sprepro@data$Name_Prop == "East Anglia O
```

```
NE" | OWF.sprepro@data$Name_Prop == "East Anglia ONE NORTH" | OWF.s
prepro@data$Name_Prop == "East Anglia TWO"| OWF.sprepro@data$Name_P
rop == "North Falls",]
#Add in Gunfleet Sands
OWF_pluspreplanning<-rbind(OWF_pluspreplanning,GunfleetSands.sprepr
o)
#Make buffers
buffer <- 1:16
for (bf in buffer) {
  eval(parse(text = paste0("OWF_", bf, "km_buf_pluspreplanning <- g
Buffer(OWF_pluspreplanning, width = bf*1000, byid=TRUE)")))
}
#Create rings from buffers
OWF_0km_ring_pluspreplanning <- OWF_pluspreplanning
OWF_1km_ring_pluspreplanning <- erase(OWF_1km_buf_pluspreplanning,
OWF_pluspreplanning)
buffer <- 1:16
for (bf in buffer[2:16]) {
  eval(parse(text = paste0("OWF_", bf, "km_ring_pluspreplanning <-
erase(OWF_", bf, "km_buf_pluspreplanning, OWF_", bf - 1, "km_buf_pl
uspreplanning)")))
}
#merge overlapping rings
buffer <- 0:16
for (bf in buffer) {
  eval(parse(text = paste0("OWF_", bf, "km_ring_pluspreplanning <-g
UnaryUnion(OWF_", bf, "km_ring_pluspreplanning)")))
}
```

Plot map

```
setwd("C:/Users/44755/OneDrive - University of Strathclyde/7. Futur
e cumulative displacement/Maps/Background maps/UK Coastline")
#Load Uk coastline
UK.sf <- st_read("UKIreland_Coastline.shp")
#Convert to spatial data
UK.sp <- as(UK.sf, "Spatial")
#Transform to EPSG 27700
UK.sprepro <- spTransform(UK.sp, CRS("+init=epsg:27700"))
#Plot
Plus_preplanning_map<-tm_shape(Outer_Thames_Estuary_SPA)+tm_borders
()+tm_shape(UK.sprepro)+tm_fill(col='#89B883')+tm_borders(col='blac
k')+tm_shape(OWF_0km_ring_pluspreplanning)+tm_fill(col='#AFABAB')+t
m_borders(col='black')+tm_shape(OWF_1km_ring_pluspreplanning)+tm_fi
ll(col='#E2134E')+tm_borders(col='black')+tm_shape(OWF_2km_ring_plu
spreplanning)+tm_fill(col='#E83639')+tm_borders(col='black')+tm_sha
pe(OWF_3km_ring_pluspreplanning)+tm_fill(col='#EE5D21')+tm_borders(
col='black')+tm_shape(OWF_4km_ring_pluspreplanning)+tm_fill(col='#F
58509')+tm_borders(col='black')+tm_shape(OWF_5km_ring_pluspreplanni
ng)+tm_fill(col='#F29F0F')+tm_borders(col='black')+tm_shape(OWF_6km
_ring_pluspreplanning)+tm_fill(col='#EBB127')+tm_borders(col='black
')+tm_shape(OWF_7km_ring_pluspreplanning)+tm_fill(col='#E4C33E')+tm
```

```
_borders(col='black')+tm_shape(OWF_8km_ring_pluspreplanning)+tm_fil
l(col='#DDD657')+tm_borders(col='black')+tm_shape(OWF_9km_ring_plus
preplanning)+tm_fill(col='#BDD16E')+tm_borders(col='black')+tm_shap
e(OWF_10km_ring_pluspreplanning)+tm_fill(col='#87B783')+tm_borders(
col='black')+tm_shape(OWF_11km_ring_pluspreplanning)+tm_fill(col='#
509C99')+tm_borders(col='black')+tm_shape(OWF_12km_ring_pluspreplan
ning)+tm_fill(col='#1D83AE')+tm_borders(col='black')+tm_shape(OWF_1
3km_ring_pluspreplanning)+tm_fill(col='#1064B3')+tm_borders(col='bl
ack')+tm_shape(OWF_14km_ring_pluspreplanning)+tm_fill(col='#2949AA'
)+tm_borders(col='black')+tm_shape(OWF_15km_ring_pluspreplanning)+t
m_fill(col='#432BA0')+tm_borders(col='black')+tm_shape(OWF_16km_rin
g_pluspreplanning)+tm_fill(col='#5E0E96')+tm_borders(col='black')+t
m_shape(Outer_Thames_Estuary_SPA)+tm_borders(col='white',lwd=6)+tm_
shape(Outer_Thames_Estuary_SPA)+tm_borders(col='black',lwd=3)
setwd("Y:/Marine Species/Rebecca Hall/Laptop files/PhD work/Future
cumulative displ/Maps")
tmap_save(Plus_preplanning_map, "Plus_preplanning_map.png")
```

Crop density to preplanning OWF and buffers

```
#Set range of buffers
buffer <- 0:16
#Crop density
for (bf in buffer) {
  eval(parse(text = paste0("RTD_density_Outer_Thames_Estuary_SPA_OW
F_", bf, "km_ring_pluspreplanning <-raster::intersect(RTD_density_O
uter_Thames_Estuary_SPA, OWF_", bf, "km_ring_pluspreplanning)")))
}
```

Calculate area

```
#Crop to SPA
for(bf in buffer){
  try(eval(parse(text = paste0("OWF_", bf, "km_ring_pluspreplanning
_OTE_SPA <- intersect(OWF_", bf, "km_ring_pluspreplanning, Outer_Th
ames_Estuary_SPA)"))))
}
#Table
Plus_preplanning_area_OTE_SPA <- data.frame(Ring=NA, Area=NA)
a<-1
for(bf in buffer){
  try(eval(parse(text = paste0("Plus_preplanning_area_OTE_SPA[a,1]
<- bf
      Plus_preplanning_area_OTE_SPA[a,2] <- area(OWF_", bf, "km_rin
g_pluspreplanning_OTE_SPA)/1000000"))))
  a<-a+1
}
#Remove operational and consented to get solely pre-planning
Plus_preplanning_area_OTE_SPA_only<-as.data.frame(Plus_preplanning_
area_OTE_SPA[,1])
Plus_preplanning_area_OTE_SPA_only$Area<-Plus_preplanning_area_OTE_
SPA[,2]-Plus_consented_area_OTE_SPA_only[,2]
names(Plus_preplanning_area_OTE_SPA_only)[names(Plus_preplanning_ar
```

```
ea_OTE_SPA_only) == "Plus_preplanning_area_OTE_SPA[, 1]"] <- "Ring"
#Save
setwd("C:/Users/44755/OneDrive - University of Strathclyde/1. Thesi
s/12. Thesis V2")
write.csv(Plus_preplanning_area_OTE_SPA,"Plus_preplanning_area_OTE_
SPA.csv")
write.csv(Plus_preplanning_area_OTE_SPA_only,"Plus_preplanning_area
_OTE_SPA_only.csv")
```

Displace birds in buffers & rings

```
#Displace using displacement gradient
for (fb in buffer){
  for(bf in buffer){
    try(eval(parse(text = paste0("RTD_density_Outer_Thames_Estuary_
SPA_OWF_",fb,"km_ring_pluspreplanning@data$RH_D_MaxDispl",bf," <- a
s.numeric(sapply((1-(Displ_together[(bf*17)+(fb+1),Displ_grad])/100
),'*',RTD_density_Outer_Thames_Estuary_SPA_OWF_",fb,"km_ring_pluspr
eplanning@data$RH_D))"))))
  }
}
```

Calculate numbers of birds displaced and mortality and as proportion of SPA

```
#No. birds in SPA
RTD_density_Outer_Thames_Estuary_SPA_sum <- sum((area(RTD_density_O
uter_Thames_Estuary_SPA)/1000000)*RTD_density_Outer_Thames_Estuary_
SPA@data$RH_D)
#Percentage loss
for (rg in ring) {
  eval(parse(text = paste0("try(
  RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_plusprep
lanning_sum <-sum((area(RTD_density_Outer_Thames_Estuary_SPA_OWF_",
rg, "km_ring_pluspreplanning)/1000000)*RTD_density_Outer_Thames_Est
uary_SPA_OWF_", rg, "km_ring_pluspreplanning@data$RH_D))")))
  for (bf in ring) {
    eval(parse(text = paste0("try({
    RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_pluspr
eplanning_sum_", bf, " <-sum((area(RTD_density_Outer_Thames_Estuary
_SPA_OWF_", rg, "km_ring_pluspreplanning)/1000000)*RTD_density_Oute
r_Thames_Estuary_SPA_OWF_", rg, "km_ring_pluspreplanning@data$RH_D_
MaxDispl", bf, ")
    RTD_percloss_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_plusp
replanning_", bf, " <- ((RTD_density_Outer_Thames_Estuary_SPA_OWF_"
, rg, "km_ring_pluspreplanning_sum - RTD_density_Outer_Thames_Estua
ry_SPA_OWF_", rg, "km_ring_pluspreplanning_sum_", bf, ")/
                                                RTD_density_Outer_T
hames_Estuary_SPA_sum)*100})
")))
  }
}
#Calculate numbers of bird casualties and as proportion of SPA
Mortality_rate <- 1:10
```

```
#Put into table
RTD_percloss_Outer_Thames_Estuary_SPA_pluspreplanning <- data.frame
(Max_displ_km=NA, Ring=NA, MortalityRate=NA, NoBirds=NA, RingArea=N
A, NoBirdLoss=NA, SPAPercLoss=NA, NoBirdMortality=NA, SPAPercMortal
ity=NA)
a<-1
for (bf in ring) {
  b<-1
  for (rg in ring) {
    c<-1
    for (mt in Mortality_rate) {
      RTD_percloss_Outer_Thames_Estuary_SPA_pluspreplanning[((a-1)*
length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))
+c,1] <- bf
      RTD_percloss_Outer_Thames_Estuary_SPA_pluspreplanning[((a-1)*
length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))
+c,2] <- rg
      RTD_percloss_Outer_Thames_Estuary_SPA_pluspreplanning[((a-1)*
length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))
+c,3] <- mt
      eval(parse(text = paste0("try({RTD_percloss_Outer_Thames_Estu
ary_SPA_pluspreplanning[((a-1)*length(Mortality_rate)*length(ring))
+((b-1)*length(Mortality_rate))+c,4] <- RTD_density_Outer_Thames_Es
tuary_SPA_OWF_", rg, "km_ring_pluspreplanning_sum
      RTD_percloss_Outer_Thames_Estuary_SPA_pluspreplanning[((a-1)*
length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))
+c,5] <- sum(area(RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "
km_ring_pluspreplanning)/1000000)
      RTD_percloss_Outer_Thames_Estuary_SPA_pluspreplanning[((a-1)*
length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))
+c,6] <- RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_p
luspreplanning_sum - RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg
, "km_ring_pluspreplanning_sum_", bf, "
      RTD_percloss_Outer_Thames_Estuary_SPA_pluspreplanning[((a-1)*
length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))
+c,7] <- RTD_percloss_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_
pluspreplanning_", bf, "
      RTD_percloss_Outer_Thames_Estuary_SPA_pluspreplanning[((a-1)*
length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))
+c,8] <- (RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_
pluspreplanning_sum - RTD_density_Outer_Thames_Estuary_SPA_OWF_", r
g, "km_ring_pluspreplanning_sum_", bf, ")/100*mt
      RTD_percloss_Outer_Thames_Estuary_SPA_pluspreplanning[((a-1)*
length(Mortality_rate)*length(ring))+((b-1)*length(Mortality_rate))
+c,9] <- RTD_percloss_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_
pluspreplanning_", bf, "/100*mt}, silent=TRUE)")))
      c<-c+1
    }
    b<-b+1
  }
  a<-a+1
}
```

```
#Sum % birds for each scenario
RTD_percloss_total_Outer_Thames_Estuary_SPA_pluspreplanning <- data
.frame(Max_displ_km=NA, MortalityRate=NA, NoBirdLoss=NA, SPAPercLos
s=NA, NoBirdMortality=NA, SPAPercMortality=NA)
a<-1
for (bf in ring) {
  b<-1
  for (mt in Mortality_rate) {
    RTD_percloss_total_Outer_Thames_Estuary_SPA_pluspreplanning[((a
-1)*length(Mortality_rate))+b,1] <- bf
    RTD_percloss_total_Outer_Thames_Estuary_SPA_pluspreplanning[((a
-1)*length(Mortality_rate))+b,2] <- mt
    eval(parse(text = paste0("try({RTD_percloss_total_Outer_Thames_
Estuary_SPA_pluspreplanning[((a-1)*length(Mortality_rate))+b,3] <-
sum(subset(RTD_percloss_Outer_Thames_Estuary_SPA_pluspreplanning, M
ax_displ_km==bf & MortalityRate==mt, select=NoBirdLoss), na.rm=TRUE
)
      RTD_percloss_total_Outer_Thames_Estuary_SPA_pluspreplanning[(
(a-1)*length(Mortality_rate))+b,4] <- sum(subset(RTD_percloss_Outer
_Thames_Estuary_SPA_pluspreplanning, Max_displ_km==bf & MortalityRa
te==mt, select=SPAPercLoss), na.rm=TRUE)
      RTD_percloss_total_Outer_Thames_Estuary_SPA_pluspreplanning[(
(a-1)*length(Mortality_rate))+b,5] <- sum(subset(RTD_percloss_Outer
_Thames_Estuary_SPA_pluspreplanning, Max_displ_km==bf & MortalityRa
te==mt, select=NoBirdMortality), na.rm=TRUE)
      RTD_percloss_total_Outer_Thames_Estuary_SPA_pluspreplanning[(
(a-1)*length(Mortality_rate))+b,6] <- sum(subset(RTD_percloss_Outer
_Thames_Estuary_SPA_pluspreplanning, Max_displ_km==bf & MortalityRa
te==mt, select=SPAPercMortality), na.rm=TRUE)}, silent=TRUE)  ")))
    b<-b+1
  }
  a<-a+1
}
#Save tables
setwd("C:/Users/44755/OneDrive - University of Strathclyde/1. Thesi
s/12. Thesis V2")
#If using hundred within gradient save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_pluspreplanni
ng,"RTD_percloss_total_Outer_Thames_Estuary_SPA_pluspreplanning_Hun
dred_Within.csv")
#If using basic gradient save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_pluspreplanni
ng,"RTD_percloss_total_Outer_Thames_Estuary_SPA_pluspreplanning_Gra
dient.csv")
```

Put all stages into table

```
#Add stage colummn
RTD_percloss_total_Outer_Thames_Estuary_SPA_plusoperational$Stage <
- "operational"
#Reorder columns
RTD_percloss_total_Outer_Thames_Estuary_SPA_plusoperational<-RTD_pe
```

```
rcloss_total_Outer_Thames_Estuary_SPA_plusoperational[,c(7,1,2,3,4,5,6)]
#Take operational values away from consented values, to get consented only
RTD_percloss_total_Outer_Thames_Estuary_SPA_plusconsented_only <-cbind((RTD_percloss_total_Outer_Thames_Estuary_SPA_plusconsented[,3:6]-RTD_percloss_total_Outer_Thames_Estuary_SPA_plusoperational[,4:7]),RTD_percloss_total_Outer_Thames_Estuary_SPA_plusconsented[,1:2])
#Add stage column
RTD_percloss_total_Outer_Thames_Estuary_SPA_plusconsented_only$Stage <- "consented"
#Reorder columns
RTD_percloss_total_Outer_Thames_Estuary_SPA_plusconsented_only<-RTD_percloss_total_Outer_Thames_Estuary_SPA_plusconsented_only[,c(7,5,6,1,2,3,4)]
#Take operational and consented values away from pre-plannning values, to get pre-plannning only
RTD_percloss_total_Outer_Thames_Estuary_SPA_pluspreplanning_only <-cbind((RTD_percloss_total_Outer_Thames_Estuary_SPA_pluspreplanning[,3:6]-RTD_percloss_total_Outer_Thames_Estuary_SPA_plusconsented[,3:6]),RTD_percloss_total_Outer_Thames_Estuary_SPA_pluspreplanning[,1:2])
#Add stage column
RTD_percloss_total_Outer_Thames_Estuary_SPA_pluspreplanning_only$Stage <- "preplanning"
#Reorder columns
RTD_percloss_total_Outer_Thames_Estuary_SPA_pluspreplanning_only<-RTD_percloss_total_Outer_Thames_Estuary_SPA_pluspreplanning_only[,c(7,5,6,1,2,3,4)]
#Bind all values into one table
RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF <- rbind(RTD_percloss_total_Outer_Thames_Estuary_SPA_plusoperational,RTD_percloss_total_Outer_Thames_Estuary_SPA_plusconsented_only,RTD_percloss_total_Outer_Thames_Estuary_SPA_pluspreplanning_only)
#Save tables
setwd("C:/Users/44755/OneDrive - University of Strathclyde/1. Thesis/12. Thesis V2")
#If using hundred within displacement gradient, save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF,"RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF_Hundred_Within.csv")
#If using basic gradient displacement gradient, save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF,"RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF_Gradient.csv")
```

~~~~~ Impacted multiple times ~~~~~

OPERATIONAL Impacted multiple times

```
#Select operational OWFs only
OWF_operational_only <- OWF.sprepro[OWF.sprepro@data$Inf_Status == "Active/In Operation",]
```

```
#Split into individual OWFs
for (ip in 1:length(OWF_operational_only)) {
  eval(parse(text = paste0("OWF_operational_", ip, " <- OWF_operati
onal_only[ip,]")))
}
#Make rings around operational OWFs only
for (ip in 1:length(OWF_operational_only)) {
  #Make buffers
  eval(parse(text = paste0("OWF_0km_buf_operational_", ip, " <- OWF
_operational_", ip, "")))
  buffer <- 1:16
  for (bf in buffer) {
    eval(parse(text = paste0("OWF_", bf, "km_buf_operational_", ip,
" <- gBuffer(OWF_operational_", ip, ", width = bf*1000, byid=TRUE)"
)))
  }
  #Create rings from buffers
  eval(parse(text = paste0("
    OWF_0km_ring_operational_", ip, " <- OWF_operational_", ip, "
    OWF_1km_ring_operational_", ip, " <- erase(OWF_1km_buf_operatio
nal_", ip, ", OWF_operational_", ip, ")
  ")))
  buffer <- 1:16
  for (bf in buffer[2:16]) {
    eval(parse(text = paste0("OWF_", bf, "km_ring_operational_", ip
, " <- erase(OWF_", bf, "km_buf_operational_", ip, ", OWF_", bf - 1
, "km_buf_operational_", ip, ")")))
  }
}
```

Crop density

```
#Crop density to operational OWF and buffers
for (ip in 1:length(OWF_operational_only)) {
  buffer <- 0:16
  for (bf in buffer) {
    try(eval(parse(text = paste0("RTD_density_Outer_Thames_Estuary_
SPA_OWF_", bf, "km_ring_operational_", ip, " <-raster::intersect(RT
D_density_Outer_Thames_Estuary_SPA, OWF_", bf, "km_ring_operational
_", ip, ")"))))
  }
}
#Check which OWF intersect SPA
OWF_operational_SPA <- c()
for (ip in 1:length(OWF_operational_only)) {
  eval(parse(text = paste0("try(if(!is.null(RTD_density_Outer_Thame
s_Estuary_SPA_OWF_16km_ring_operational_", ip, ")){OWF_operational_
SPA <- append(OWF_operational_SPA,ip)})")))
}
```

Calculate area

```r
#Call number of operational OWFs
Individual_OWFs <- c(18,13,10,11,16,17,15,12,14,28,35)
#Table
Individual_operational_area <- data.frame(OWF=NA, Ring=NA, Area=NA)
a<-1
for(ip in Individual_OWFs){
  b<-1
  for(fb in buffer){
    try(eval(parse(text = paste0("Individual_operational_area[((a-1)*length(buffer))+b,1] <- ip
        Individual_operational_area[((a-1)*length(buffer))+b,2] <- fb
        Individual_operational_area[((a-1)*length(buffer))+b,3] <- area(OWF_", fb,"km_ring_operational_", ip,")/1000000"))))
    b<-b+1
  }
  a<-a+1
}
#Crop to SPA
a<-1
for(ip in Individual_OWFs){
  b<-1
  for(fb in buffer){
    try(eval(parse(text = paste0("OWF_", fb,"km_ring_operational_", ip,"_OTESPA <- raster::intersect(Outer_Thames_Estuary_SPA, OWF_", fb,"km_ring_operational_", ip,")"))))
    b<-b+1
  }
  a<-a+1
}
#Table
Individual_operational_area_OTE_SPA <- data.frame(OWF=NA, Ring=NA, Area=NA)
a<-1
for(ip in Individual_OWFs){
  b<-1
  for(fb in buffer){
    try(eval(parse(text = paste0("Individual_operational_area_OTE_SPA[((a-1)*length(buffer))+b,1] <- ip
        Individual_operational_area_OTE_SPA[((a-1)*length(buffer))+b,2] <- fb
        Individual_operational_area_OTE_SPA[((a-1)*length(buffer))+b,3] <- area(OWF_", fb,"km_ring_operational_", ip,"_OTESPA)/1000000"))))
    b<-b+1
  }
  a<-a+1
}
#Save
setwd("C:/Users/44755/OneDrive - University of Strathclyde/1. Thesis/12. Thesis V2")
```

```
write.csv(Individual_operational_area_OTE_SPA,"Individual_operational_area_OTE_SPA.csv")
```

Displace birds in buffers & rings

```
#Displace birds usin displacement gradient
for (ip in OWF_operational_SPA) {
  for (fb in buffer){
    for(bf in buffer){
      eval(parse(text = paste0("if(exists('RTD_density_Outer_Thames_Estuary_SPA_OWF_",fb,"km_ring_operational_", ip, "')){if(!is.null(RTD_density_Outer_Thames_Estuary_SPA_OWF_",fb,"km_ring_operational_", ip, ")){RTD_density_Outer_Thames_Estuary_SPA_OWF_",fb,"km_ring_operational_", ip, "@data$RH_D_MaxDispl",bf," <- as.numeric(sapply((1-(Displ_together[(bf*17)+(fb+1),Displ_grad])/100),'*',RTD_density_Outer_Thames_Estuary_SPA_OWF_",fb,"km_ring_operational_", ip, "@data$RH_D))}}")))
    }
  }
}
```

Calculate numbers of birds displaced and mortality and as proportion of SPA

```
#Set range of rings
ring <- 0:16
#No. birds in SPA
RTD_density_Outer_Thames_Estuary_SPA_sum <- sum((area(RTD_density_Outer_Thames_Estuary_SPA)/1000000)*RTD_density_Outer_Thames_Estuary_SPA@data$RH_D)
#Percentage loss
for (ip in OWF_operational_SPA) {
  for (rg in ring) {
    eval(parse(text = paste0("try(if(!is.null(RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_operational_", ip, ")){RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_operational_", ip, "_sum <-sum((area(RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_operational_", ip, ")/1000000)*RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_operational_", ip, "@data$RH_D)})")))
    for (bf in ring) {
      eval(parse(text = paste0("try(if(!is.null(RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_operational_", ip, ")){RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_operational_", ip, "_sum_", bf, " <-sum((area(RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_operational_", ip, ")/1000000)*RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_operational_", ip, "@data$RH_D_MaxDispl", bf, ")
      RTD_percloss_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_operational_", ip, "_", bf, " <- ((RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_operational_", ip, "_sum - RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_operational_", ip, "_sum_", bf, ")/RTD_density_Outer_Thames_Estuary_SPA_sum)*100})")))
    }
  }
```

```
}
#Calculate numbers of bird casualties and as proportion of SPA
Mortality_rate <- 1:10
#Put into table
for (ip in OWF_operational_SPA) {
  eval(parse(text = paste0("RTD_percloss_Outer_Thames_Estuary_SPA_o
perational_", ip, " <- data.frame(Max_displ_km=NA, Ring=NA, Mortali
tyRate=NA, RingArea=NA, NoBirds=NA, NoBirdLoss=NA, SPAPercLoss=NA,
NoBirdMortality=NA, SPAPercMortality=NA)")))
  a<-1
  for (bf in ring) {
    b<-1
    for (rg in ring) {
      c<-1
      for (mt in Mortality_rate) {
        eval(parse(text = paste0("try(if(!is.null(RTD_density_Outer
_Thames_Estuary_SPA_OWF_", rg, "km_ring_operational_", ip, ")){
          RTD_percloss_Outer_Thames_Estuary_SPA_operational_", ip,
"[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortali
ty_rate))+c,1] <- bf
          RTD_percloss_Outer_Thames_Estuary_SPA_operational_", ip,
"[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortali
ty_rate))+c,2] <- rg
          RTD_percloss_Outer_Thames_Estuary_SPA_operational_", ip,
"[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortali
ty_rate))+c,3] <- mt
          RTD_percloss_Outer_Thames_Estuary_SPA_operational_", ip,
"[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortali
ty_rate))+c,4] <-
            sum(area(RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg
, "km_ring_operational_", ip, ")/1000000)
          RTD_percloss_Outer_Thames_Estuary_SPA_operational_", ip,
"[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortali
ty_rate))+c,5] <-
            RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_rin
g_operational_", ip, "_sum
          RTD_percloss_Outer_Thames_Estuary_SPA_operational_", ip,
"[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortali
ty_rate))+c,6] <-
            RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_rin
g_operational_", ip, "_sum - RTD_density_Outer_Thames_Estuary_SPA_O
WF_", rg, "km_ring_operational_", ip, "_sum_", bf, "
          RTD_percloss_Outer_Thames_Estuary_SPA_operational_", ip,
"[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortali
ty_rate))+c,7] <-
            RTD_percloss_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ri
ng_operational_", ip, "_", bf, "
          RTD_percloss_Outer_Thames_Estuary_SPA_operational_", ip,
"[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortali
ty_rate))+c,8] <-
            (RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ri
ng_operational_", ip, "_sum - RTD_density_Outer_Thames_Estuary_SPA_
```

```
OWF_", rg, "km_ring_operational_", ip, "_sum_", bf, ")/100*mt
          RTD_percloss_Outer_Thames_Estuary_SPA_operational_", ip,
"[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortali
ty_rate))+c,9] <-
            (RTD_percloss_Outer_Thames_Estuary_SPA_OWF_", rg, "km_r
ing_operational_", ip, "_", bf, ")/100*mt})")))
        c<-c+1
      }
      b<-b+1
    }
    a<-a+1
  }
}
#Sum % birds for each scenario
for (ip in OWF_operational_SPA) {
  eval(parse(text = paste0("RTD_percloss_total_Outer_Thames_Estuary
_SPA_operational_", ip, " <- data.frame(OWF_num=NA, Max_displ_km=NA
, MortalityRate=NA, NoBirdLoss=NA, SPAPercLoss=NA, NoBirdMortality=
NA, SPAPercMortality=NA, Area=NA)")))
  a<-1
  for (bf in ring) {
    b<-1
    for (mt in Mortality_rate) {eval(parse(text = paste0("RTD_percl
oss_total_Outer_Thames_Estuary_SPA_operational_", ip, "[((a-1)*leng
th(Mortality_rate))+b,1] <- ip
        RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_",
ip, "[((a-1)*length(Mortality_rate))+b,2] <- bf
        RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_",
ip, "[((a-1)*length(Mortality_rate))+b,3] <- mt
        try({RTD_percloss_total_Outer_Thames_Estuary_SPA_operationa
l_", ip, "[((a-1)*length(Mortality_rate))+b,4] <-sum(subset(RTD_per
closs_Outer_Thames_Estuary_SPA_operational_", ip, ", Max_displ_km==
bf & MortalityRate==mt, select=NoBirdLoss), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_",
ip, "[((a-1)*length(Mortality_rate))+b,5] <-sum(subset(RTD_percloss
_Outer_Thames_Estuary_SPA_operational_", ip, ", Max_displ_km==bf &
MortalityRate==mt, select=SPAPercLoss), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_",
ip, "[((a-1)*length(Mortality_rate))+b,6] <-sum(subset(RTD_percloss
_Outer_Thames_Estuary_SPA_operational_", ip, ", Max_displ_km==bf &
MortalityRate==mt, select=NoBirdMortality), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_",
ip, "[((a-1)*length(Mortality_rate))+b,7] <-sum(subset(RTD_percloss
_Outer_Thames_Estuary_SPA_operational_", ip, ", Max_displ_km==bf &
MortalityRate==mt, select=SPAPercMortality), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_",
ip, "[((a-1)*length(Mortality_rate))+b,8] <-sum(subset(RTD_percloss
_Outer_Thames_Estuary_SPA_operational_", ip, ", Max_displ_km==bf &
SPAPercLoss>0, select=RingArea), na.rm=TRUE)}, silent=TRUE)")))
      b<-b+1
    }
    a<-a+1
```

```
  }
}
#Export as csv
setwd("C:/Users/44755/OneDrive - University of Strathclyde/1. Thesi
s/12. Thesis V2")
#If using hundred within gradient save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_3
,"RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_3_Hundred
_Within.csv")
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_5
,"RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_5_Hundred
_Within.csv")
#If using basic gradient save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_3
,"RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_3_Gradien
t.csv")
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_5
,"RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_5_Gradien
t.csv")

#Sum individual OWF impacts
#Individual OWFs summed
RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_sum <- data
.frame()
a<-1
for (ip in OWF_operational_SPA) {
  eval(parse(text = paste0("RTD_percloss_total_Outer_Thames_Estuary
_SPA_operational_sum <- rbind(RTD_percloss_total_Outer_Thames_Estua
ry_SPA_operational_sum, RTD_percloss_total_Outer_Thames_Estuary_SPA
_operational_", OWF_operational_SPA[a], ")")))
  a<-a+1
}
#Save
#If using hundred within gradient save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_s
um,"RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_allOWFs
_Hundred_Within.csv")
#If using basic gradient save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_s
um,"RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_allOWFs
_Gradient.csv")

#All OWFs summed
RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_sum_total <
- aggregate(RTD_percloss_total_Outer_Thames_Estuary_SPA_operational
_sum[,4:7],by=list(Max_displ_km = RTD_percloss_total_Outer_Thames_E
stuary_SPA_operational_sum$Max_displ_km,MortalityRate = RTD_perclos
s_total_Outer_Thames_Estuary_SPA_operational_sum$MortalityRate),sum
)
#Save
#If using hundred within gradient save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_s
```

```
um_total,"RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_s
um_total_Hundred_Within.csv")
#If using basic gradient save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_s
um_total,"RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_s
um_total_Gradient.csv")
```

CONSENTED Impacted multiple times

```
#Select consented OWFs only
OWF_consented_only <- OWF.sprepro[OWF.sprepro@data$Inf_Status == "C
onsented",]
#Split into individual OWFs
for (ip in 1:length(OWF_consented_only)) {
  eval(parse(text = paste0("OWF_consented_", ip, " <- OWF_consented
_only[ip,]")))
}
#Make rings around in planning OWFs only
for (ip in 1:length(OWF_consented_only)) {
  #Make buffers
  eval(parse(text = paste0("OWF_0km_buf_consented_", ip, " <- OWF_c
onsented_", ip, "")))
  buffer <- 1:16
  for (bf in buffer) {
    eval(parse(text = paste0("OWF_", bf, "km_buf_consented_", ip, "
<- gBuffer(OWF_consented_", ip, ", width = bf*1000, byid=TRUE)")))
  }
  #Create rings from buffers
  eval(parse(text = paste0("OWF_0km_ring_consented_", ip, " <- OWF_
consented_", ip, "
    OWF_1km_ring_consented_", ip, " <- erase(OWF_1km_buf_consented_
", ip, ", OWF_consented_", ip, ")")))
  buffer <- 1:16
  for (bf in buffer[2:16]) {
    eval(parse(text = paste0("OWF_", bf, "km_ring_consented_", ip,
" <- erase(OWF_", bf, "km_buf_consented_", ip, ", OWF_", bf - 1, "k
m_buf_consented_", ip, ")")))
  }
}
#Crop density to consented OWF and buffers
for (ip in 1:length(OWF_consented_only)) {
  buffer <- 0:16
  for (bf in buffer) {
    try(eval(parse(text = paste0("RTD_density_Outer_Thames_Estuary_
SPA_OWF_", bf, "km_ring_consented_", ip, " <-raster::intersect(RTD_
density_Outer_Thames_Estuary_SPA, OWF_", bf, "km_ring_consented_",
ip, ")"))))
  }
}
#Check which OWF intersect SPA
OWF_consented_SPA <- c()
for (ip in 1:length(OWF_consented_only)) {
```

```
  eval(parse(text = paste0("try(if(!is.null(RTD_density_Outer_Thame
s_Estuary_SPA_OWF_16km_ring_consented_", ip, ")){OWF_consented_SPA
<- append(OWF_consented_SPA,ip)})")))
}
```

Calculate area

```
#Calculate area
Individual_consented_OWFs <- c(1,2)
Individual_consented_area <- data.frame(OWF=NA, Ring=NA, Area=NA)
a<-1
for(ip in Individual_consented_OWFs){
 b<-1
 for(fb in buffer){
   try(eval(parse(text = paste0("Individual_consented_area[((a-1)*l
ength(buffer))+b,1] <- ip
       Individual_consented_area[((a-1)*length(buffer))+b,2] <- fb
       Individual_consented_area[((a-1)*length(buffer))+b,3] <- are
a(OWF_", fb,"km_ring_consented_", ip,")/1000000"))))
   b<-b+1
 }
 a<-a+1
}
#Save
setwd("Y:/Marine Species/Rebecca Hall/Laptop files/PhD work/Future
cumulative displ/Results tables")
write.csv(Individual_consented_area,"Individual_consented_area.csv"
)
#Crop to SPA
a<-1
for(ip in Individual_consented_OWFs){
 b<-1
 for(fb in buffer){
   try(eval(parse(text = paste0("OWF_", fb,"km_ring_consented_", ip
,"_OTESPA <- raster::intersect(Outer_Thames_Estuary_SPA, OWF_", fb,
"km_ring_consented_", ip,")"))))
   b<-b+1
 }
 a<-a+1
}
#Table
Individual_consented_area_OTESPA <- data.frame(OWF=NA, Ring=NA, Are
a=NA)
a<-1
for(ip in Individual_consented_OWFs){
 b<-1
 for(fb in buffer){
   try(eval(parse(text = paste0("Individual_consented_area_OTESPA[(
(a-1)*length(buffer))+b,1] <- ip
       Individual_consented_area_OTESPA[((a-1)*length(buffer))+b,2]
<- fb
       Individual_consented_area_OTESPA[((a-1)*length(buffer))+b,3]
```

```
<- area(OWF_", fb,"km_ring_consented_", ip,"_OTESPA)/1000000"))))
   b<-b+1
 }
 a<-a+1
}
#Save
setwd("Y:/Marine Species/Rebecca Hall/Laptop files/PhD work/Future
cumulative displ/Results tables")
write.csv(Individual_consented_area_OTESPA,"Individual_consented_ar
ea_OTESPA.csv")
```

Displace birds in buffers & rings

```
for (ip in OWF_consented_SPA) {
  for (fb in buffer){
    for(bf in buffer){
      eval(parse(text = paste0("if(exists('RTD_density_Outer_Thames
_Estuary_SPA_OWF_",fb,"km_ring_consented_", ip, "')){if(!is.null(RT
D_density_Outer_Thames_Estuary_SPA_OWF_",fb,"km_ring_consented_", i
p, ")){RTD_density_Outer_Thames_Estuary_SPA_OWF_",fb,"km_ring_conse
nted_", ip, "@data$RH_D_MaxDispl",bf," <- as.numeric(sapply((1-(Dis
pl_together[(bf*17)+(fb+1),Displ_grad])/100),'*',RTD_density_Outer_
Thames_Estuary_SPA_OWF_",fb,"km_ring_consented_", ip, "@data$RH_D))
}}")))
    }
  }
}
```

Calculate numbers of birds displaced and mortality and as proportion of SPA

```
#No. birds in SPA
RTD_density_Outer_Thames_Estuary_SPA_sum <- sum((area(RTD_density_O
uter_Thames_Estuary_SPA)/1000000)*RTD_density_Outer_Thames_Estuary_
SPA@data$RH_D)
#Percentage loss
for (ip in OWF_consented_SPA) {
  for (rg in ring) {
    eval(parse(text = paste0("try(if(!is.null(RTD_density_Outer_Tha
mes_Estuary_SPA_OWF_", rg, "km_ring_consented_", ip, ")){RTD_densit
y_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_consented_", ip, "_s
um <-sum((area(RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_
ring_consented_", ip, ")/1000000)*RTD_density_Outer_Thames_Estuary_
SPA_OWF_", rg, "km_ring_consented_", ip, "@data$RH_D)})")))
    for (bf in ring) {
      eval(parse(text = paste0("try(if(!is.null(RTD_density_Outer_T
hames_Estuary_SPA_OWF_", rg, "km_ring_consented_", ip, ")){RTD_dens
ity_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_consented_", ip, "
_sum_", bf, " <-sum((area(RTD_density_Outer_Thames_Estuary_SPA_OWF_
", rg, "km_ring_consented_", ip, ")/1000000)*RTD_density_Outer_Tham
es_Estuary_SPA_OWF_", rg, "km_ring_consented_", ip, "@data$RH_D_Max
Displ", bf, ")
      RTD_percloss_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_con
sented_", ip, "_", bf, " <- ((RTD_density_Outer_Thames_Estuary_SPA_
```

```
OWF_", rg, "km_ring_consented_", ip, "_sum - RTD_density_Outer_Tham
es_Estuary_SPA_OWF_", rg, "km_ring_consented_", ip, "_sum_", bf, ")
/
                                                  RTD_density_Outer
_Thames_Estuary_SPA_sum)*100})")))
    }
  }
}
#Calculate numbers of bird casualties and as proportion of SPA
Mortality_rate <- 1:10
#Put into table
for (ip in OWF_consented_SPA) {
  eval(parse(text = paste0("RTD_percloss_Outer_Thames_Estuary_SPA_c
onsented_", ip, " <- data.frame(Max_displ_km=NA, Ring=NA, Mortality
Rate=NA, RingArea=NA, NoBirds=NA, NoBirdLoss=NA, SPAPercLoss=NA, No
BirdMortality=NA, SPAPercMortality=NA)")))
  a<-1
  for (bf in ring) {
    b<-1
    for (rg in ring) {
      c<-1
      for (mt in Mortality_rate) {
        eval(parse(text = paste0("try(if(!is.null(RTD_density_Outer
_Thames_Estuary_SPA_OWF_", rg, "km_ring_consented_", ip, ")){
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_", ip, "[
((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortality
_rate))+c,1] <- bf
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_", ip, "[
((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortality
_rate))+c,2] <- rg
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_", ip, "[
((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortality
_rate))+c,3] <- mt
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_", ip, "[
((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortality
_rate))+c,4] <-sum(area(RTD_density_Outer_Thames_Estuary_SPA_OWF_",
rg, "km_ring_consented_", ip, ")/1000000)
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_", ip, "[
((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortality
_rate))+c,5] <-RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_
ring_consented_", ip, "_sum
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_", ip, "[
((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortality
_rate))+c,6] <-RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_
ring_consented_", ip, "_sum - RTD_density_Outer_Thames_Estuary_SPA_
OWF_", rg, "km_ring_consented_", ip, "_sum_", bf, "
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_", ip, "[
((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortality
_rate))+c,7] <-RTD_percloss_Outer_Thames_Estuary_SPA_OWF_", rg, "km
_ring_consented_", ip, "_", bf, "
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_", ip, "[
((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortality
```

```
_rate))+c,8] <-(RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km
_ring_consented_", ip, "_sum - RTD_density_Outer_Thames_Estuary_SPA
_OWF_", rg, "km_ring_consented_", ip, "_sum_", bf, ")/100*mt
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_", ip, "[
((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortality
_rate))+c,9] <-(RTD_percloss_Outer_Thames_Estuary_SPA_OWF_", rg, "k
m_ring_consented_", ip, "_", bf, ")/100*mt})")))
        c<-c+1
      }
      b<-b+1
    }
    a<-a+1
  }
}
#Sum % birds for each scenario
for (ip in OWF_consented_SPA) {
  eval(parse(text = paste0("RTD_percloss_total_Outer_Thames_Estuary
_SPA_consented_", ip, " <- data.frame(OWF_num=NA, Max_displ_km=NA,
MortalityRate=NA, NoBirdLoss=NA, SPAPercLoss=NA, NoBirdMortality=NA
, SPAPercMortality=NA, Area=NA)")))
  a<-1
  for (bf in ring) {
    b<-1
    for (mt in Mortality_rate) {
      eval(parse(text = paste0("RTD_percloss_total_Outer_Thames_Est
uary_SPA_consented_", ip, "[((a-1)*length(Mortality_rate))+b,1] <-
ip
        RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_", ip
, "[((a-1)*length(Mortality_rate))+b,2] <- bf
        RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_", ip
, "[((a-1)*length(Mortality_rate))+b,3] <- mt
        try({RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_
", ip, "[((a-1)*length(Mortality_rate))+b,4] <-sum(subset(RTD_percl
oss_Outer_Thames_Estuary_SPA_consented_", ip, ", Max_displ_km==bf &
MortalityRate==mt, select=NoBirdLoss), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_", ip
, "[((a-1)*length(Mortality_rate))+b,5] <-sum(subset(RTD_percloss_O
uter_Thames_Estuary_SPA_consented_", ip, ", Max_displ_km==bf & Mort
alityRate==mt, select=SPAPercLoss), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_", ip
, "[((a-1)*length(Mortality_rate))+b,6] <-sum(subset(RTD_percloss_O
uter_Thames_Estuary_SPA_consented_", ip, ", Max_displ_km==bf & Mort
alityRate==mt, select=NoBirdMortality), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_", ip
, "[((a-1)*length(Mortality_rate))+b,7] <-sum(subset(RTD_percloss_O
uter_Thames_Estuary_SPA_consented_", ip, ", Max_displ_km==bf & Mort
alityRate==mt, select=SPAPercMortality), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_", ip
, "[((a-1)*length(Mortality_rate))+b,8] <-sum(subset(RTD_percloss_O
uter_Thames_Estuary_SPA_consented_", ip, ", Max_displ_km==bf & SPAP
ercLoss>0, select=RingArea), na.rm=TRUE)}, silent=TRUE)")))
      b<-b+1
```

```
    }
    a<-a+1
  }
}
#Export as csv
setwd("C:/Users/44755/OneDrive - University of Strathclyde/1. Thesi
s/12. Thesis V2")
#If using hundred within gradient save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_3,"
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_3_Hundred_Wit
hin.csv")
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_5,"
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_5_Hundred_Wit
hin.csv")
#If using basic gradient save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_3,"
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_3_Gradient.cs
v")
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_5,"
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_5_Gradient.cs
v")

#Sum individual OWF impacts

#Individual OWFs summed
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_sum <- data.f
rame()
a<-1
for (ip in OWF_consented_SPA) {
  eval(parse(text = paste0("RTD_percloss_total_Outer_Thames_Estuary
_SPA_consented_sum <- rbind(RTD_percloss_total_Outer_Thames_Estuary
_SPA_consented_sum, RTD_percloss_total_Outer_Thames_Estuary_SPA_con
sented_", OWF_consented_SPA[a], ")")))
  a<-a+1
}
#Save
#If using hundred within gradient save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_sum
,"RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_allOWFs_Hun
dred_Within.csv")
#If using basic gradient save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_sum
,"RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_allOWFs_Gra
dient.csv")

#All OWFs summed
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_sum_total <-
aggregate(RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_sum
[,4:7],by=list(Max_displ_km = RTD_percloss_total_Outer_Thames_Estua
ry_SPA_consented_sum$Max_displ_km,MortalityRate = RTD_percloss_tota
l_Outer_Thames_Estuary_SPA_consented_sum$MortalityRate),sum)
#Save
```

```
#If using hundred within gradient save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_sum
_total,"RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_sum_t
otal_Hundred_Within.csv")
#If using basic gradient save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_sum
_total,"RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_sum_t
otal_Gradient.csv")
```

PREPLANNING Impacted multiple times

```
#Select preplanning OWFs only
OWF_preplanning_only <- OWF.sprepro[OWF.sprepro@data$Inf_Status ==
"Pre-planning Application",]
#Split into individual OWFs
for (ip in 1:length(OWF_preplanning_only)) {
  eval(parse(text = paste0("OWF_preplanning_", ip, " <- OWF_preplan
ning_only[ip,]")))
}
#Make rings around in planning OWFs only
for (ip in 1:length(OWF_preplanning_only)) {
  #Make buffers
  eval(parse(text = paste0("OWF_0km_buf_preplanning_", ip, " <- OWF
_preplanning_", ip, "")))
  buffer <- 1:16
  for (bf in buffer) {
    eval(parse(text = paste0("OWF_", bf, "km_buf_preplanning_", ip,
" <- gBuffer(OWF_preplanning_", ip, ", width = bf*1000, byid=TRUE)"
)))
  }
  #Create rings from buffers
  eval(parse(text = paste0("OWF_0km_ring_preplanning_", ip, " <- OW
F_preplanning_", ip, "
    OWF_1km_ring_preplanning_", ip, " <- erase(OWF_1km_buf_preplann
ing_", ip, ", OWF_preplanning_", ip, ")")))
  buffer <- 1:16
  for (bf in buffer[2:16]) {
    eval(parse(text = paste0("OWF_", bf, "km_ring_preplanning_", ip
, " <- erase(OWF_", bf, "km_buf_preplanning_", ip, ", OWF_", bf - 1
, "km_buf_preplanning_", ip, ")")))
  }
}
#Crop density to preplanning OWF and buffers
for (ip in 1:length(OWF_preplanning_only)) {
  buffer <- 0:16
  for (bf in buffer) {
    try(eval(parse(text = paste0("RTD_density_Outer_Thames_Estuary_
SPA_OWF_", bf, "km_ring_preplanning_", ip, " <-raster::intersect(RT
D_density_Outer_Thames_Estuary_SPA, OWF_", bf, "km_ring_preplanning
_", ip, ")"))))
  }
}
```

```
#Check which OWF intersect SPA
OWF_preplanning_SPA <- c()
for (ip in 1:length(OWF_preplanning_only)) {
  eval(parse(text = paste0("try(if(!is.null(RTD_density_Outer_Thame
s_Estuary_SPA_OWF_16km_ring_preplanning_", ip, ")){OWF_preplanning_
SPA <- append(OWF_preplanning_SPA,ip)})")))
}
```

Calculate area

```
#Calculate area
Individual_preplanning_OWFs <- c(2)
#Table
Individual_preplanning_area <- data.frame(OWF=NA, Ring=NA, Area=NA)
a<-1
for(ip in Individual_preplanning_OWFs){
  b<-1
  for(fb in buffer){
    try(eval(parse(text = paste0("Individual_preplanning_area[((a-1
)*length(buffer))+b,1] <- ip
        Individual_preplanning_area[((a-1)*length(buffer))+b,2] <-
fb
        Individual_preplanning_area[((a-1)*length(buffer))+b,3] <-
area(OWF_", fb,"km_ring_preplanning_", ip,")/1000000"))))
    b<-b+1
  }
  a<-a+1
}
#Save
setwd("Y:/Marine Species/Rebecca Hall/Laptop files/PhD work/Future
cumulative displ/Results tables")
write.csv(Individual_preplanning_area,"Individual_preplanning_area.
csv")
#Crop to SPA
a<-1
for(ip in Individual_preplanning_OWFs){
  b<-1
  for(fb in buffer){
    try(eval(parse(text = paste0("OWF_", fb,"km_ring_preplanning_",
ip,"_OTESPA <- raster::intersect(Outer_Thames_Estuary_SPA, OWF_", f
b,"km_ring_preplanning_", ip,")"))))
    b<-b+1
  }
  a<-a+1
}
#Table
Individual_preplanning_area_OTESPA <- data.frame(OWF=NA, Ring=NA, A
rea=NA)
a<-1
for(ip in Individual_preplanning_OWFs){
  b<-1
  for(fb in buffer){
```

```
    try(eval(parse(text = paste0("Individual_preplanning_area_OTESP
A[((a-1)*length(buffer))+b,1] <- ip
        Individual_preplanning_area_OTESPA[((a-1)*length(buffer))+b
,2] <- fb
        Individual_preplanning_area_OTESPA[((a-1)*length(buffer))+b
,3] <- area(OWF_", fb,"km_ring_preplanning_", ip,"_OTESPA)/1000000"
))))
    b<-b+1
  }
  a<-a+1
}
#Save
setwd("Y:/Marine Species/Rebecca Hall/Laptop files/PhD work/Future
cumulative displ/Results tables")
write.csv(Individual_preplanning_area_OTESPA,"Individual_preplannin
g_area_OTESPA.csv")
```

Displace birds in buffers & rings

```
#Displace birds using displacement gradient
for (ip in OWF_preplanning_SPA) {
  for (fb in buffer){
    for(bf in buffer){
      eval(parse(text = paste0("if(exists('RTD_density_Outer_Thames
_Estuary_SPA_OWF_",fb,"km_ring_preplanning_", ip, "')){if(!is.null(
RTD_density_Outer_Thames_Estuary_SPA_OWF_",fb,"km_ring_preplanning_
", ip, ")){RTD_density_Outer_Thames_Estuary_SPA_OWF_",fb,"km_ring_p
replanning_", ip, "@data$RH_D_MaxDispl",bf," <- as.numeric(sapply((
1-(Displ_together[(bf*17)+(fb+1),Displ_grad])/100),'*',RTD_density_
Outer_Thames_Estuary_SPA_OWF_",fb,"km_ring_preplanning_", ip, "@dat
a$RH_D))}}")))
    }
  }
}
```

Calculate numbers of birds displaced and mortality and as proportion of SPA

```
#No. birds in SPA
RTD_density_Outer_Thames_Estuary_SPA_sum <- sum((area(RTD_density_O
uter_Thames_Estuary_SPA)/1000000)*RTD_density_Outer_Thames_Estuary_
SPA@data$RH_D)
#Percentage loss
for (ip in OWF_preplanning_SPA) {
  for (rg in ring) {
    eval(parse(text = paste0("try(if(!is.null(RTD_density_Outer_Tha
mes_Estuary_SPA_OWF_", rg, "km_ring_preplanning_", ip, ")){RTD_dens
ity_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_preplanning_", ip,
"_sum <-sum((area(RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "
km_ring_preplanning_", ip, ")/1000000)*RTD_density_Outer_Thames_Est
uary_SPA_OWF_", rg, "km_ring_preplanning_", ip, "@data$RH_D)})")))
    for (bf in ring) {
      eval(parse(text = paste0("try(if(!is.null(RTD_density_Outer_T
hames_Estuary_SPA_OWF_", rg, "km_ring_preplanning_", ip, ")){
```

```
      RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_prep
lanning_", ip, "_sum_", bf, " <-sum((area(RTD_density_Outer_Thames_
Estuary_SPA_OWF_", rg, "km_ring_preplanning_", ip, ")/1000000)*RTD_
density_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_preplanning_",
ip, "@data$RH_D_MaxDispl", bf, ")
      RTD_percloss_Outer_Thames_Estuary_SPA_OWF_", rg, "km_ring_pre
planning_", ip, "_", bf, " <- ((RTD_density_Outer_Thames_Estuary_SP
A_OWF_", rg, "km_ring_preplanning_", ip, "_sum - RTD_density_Outer_
Thames_Estuary_SPA_OWF_", rg, "km_ring_preplanning_", ip, "_sum_",
bf, ")/RTD_density_Outer_Thames_Estuary_SPA_sum)*100})")))
    }
  }
}
#Calculate numbers of bird casualties and as proportion of SPA
Mortality_rate <- 1:10
#Put into table
for (ip in OWF_preplanning_SPA) {
  eval(parse(text = paste0("RTD_percloss_Outer_Thames_Estuary_SPA_p
replanning_", ip, " <- data.frame(Max_displ_km=NA, Ring=NA, Mortali
tyRate=NA, RingArea=NA, NoBirds=NA, NoBirdLoss=NA, SPAPercLoss=NA,
NoBirdMortality=NA, SPAPercMortality=NA)")))
  a<-1
  for (bf in ring) {
    b<-1
    for (rg in ring) {
      c<-1
      for (mt in Mortality_rate) {
        eval(parse(text = paste0("try(if(!is.null(RTD_density_Outer
_Thames_Estuary_SPA_OWF_", rg, "km_ring_preplanning_", ip, ")){
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_", ip,
"[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortali
ty_rate))+c,1] <- bf
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_", ip,
"[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortali
ty_rate))+c,2] <- rg
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_", ip,
"[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortali
ty_rate))+c,3] <- mt
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_", ip,
"[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortali
ty_rate))+c,4] <-sum(area(RTD_density_Outer_Thames_Estuary_SPA_OWF_
", rg, "km_ring_preplanning_", ip, ")/1000000)
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_", ip,
"[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortali
ty_rate))+c,5] <-RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "k
m_ring_preplanning_", ip, "_sum
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_", ip,
"[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortali
ty_rate))+c,6] <-RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "k
m_ring_preplanning_", ip, "_sum - RTD_density_Outer_Thames_Estuary_
SPA_OWF_", rg, "km_ring_preplanning_", ip, "_sum_", bf, "
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_", ip,
```

```
"[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortali
ty_rate))+c,7] <-RTD_percloss_Outer_Thames_Estuary_SPA_OWF_", rg, "
km_ring_preplanning_", ip, "_", bf, "
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_", ip,
"[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortali
ty_rate))+c,8] <-(RTD_density_Outer_Thames_Estuary_SPA_OWF_", rg, "
km_ring_preplanning_", ip, "_sum - RTD_density_Outer_Thames_Estuary
_SPA_OWF_", rg, "km_ring_preplanning_", ip, "_sum_", bf, ")/100*mt
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_", ip,
"[((a-1)*length(Mortality_rate)*length(ring))+((b-1)*length(Mortali
ty_rate))+c,9] <-(RTD_percloss_Outer_Thames_Estuary_SPA_OWF_", rg,
"km_ring_preplanning_", ip, "_", bf, ")/100*mt})")))
        c<-c+1
      }
      b<-b+1
    }
    a<-a+1
  }
}
#Sum % birds for each scenario
for (ip in OWF_preplanning_SPA) {
  eval(parse(text = paste0("RTD_percloss_total_Outer_Thames_Estuary
_SPA_preplanning_", ip, " <- data.frame(OWF_num=NA, Max_displ_km=NA
, MortalityRate=NA, NoBirdLoss=NA, SPAPercLoss=NA, NoBirdMortality=
NA, SPAPercMortality=NA, Area=NA)")))
  a<-1
  for (bf in ring) {
    b<-1
    for (mt in Mortality_rate) {
      eval(parse(text = paste0("
        RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_",
ip, "[((a-1)*length(Mortality_rate))+b,1] <- ip
        RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_",
ip, "[((a-1)*length(Mortality_rate))+b,2] <- bf
        RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_",
ip, "[((a-1)*length(Mortality_rate))+b,3] <- mt
        try({RTD_percloss_total_Outer_Thames_Estuary_SPA_preplannin
g_", ip, "[((a-1)*length(Mortality_rate))+b,4] <-sum(subset(RTD_per
closs_Outer_Thames_Estuary_SPA_preplanning_", ip, ", Max_displ_km==
bf & MortalityRate==mt, select=NoBirdLoss), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_",
ip, "[((a-1)*length(Mortality_rate))+b,5] <-sum(subset(RTD_percloss
_Outer_Thames_Estuary_SPA_preplanning_", ip, ", Max_displ_km==bf &
MortalityRate==mt, select=SPAPercLoss), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_",
ip, "[((a-1)*length(Mortality_rate))+b,6] <-sum(subset(RTD_percloss
_Outer_Thames_Estuary_SPA_preplanning_", ip, ", Max_displ_km==bf &
MortalityRate==mt, select=NoBirdMortality), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_",
ip, "[((a-1)*length(Mortality_rate))+b,7] <-sum(subset(RTD_percloss
_Outer_Thames_Estuary_SPA_preplanning_", ip, ", Max_displ_km==bf &
MortalityRate==mt, select=SPAPercMortality), na.rm=TRUE)
```

```
        RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_",
ip, "[((a-1)*length(Mortality_rate))+b,8] <-sum(subset(RTD_percloss
_Outer_Thames_Estuary_SPA_preplanning_", ip, ", Max_displ_km==bf &
SPAPercLoss>0, select=RingArea), na.rm=TRUE)}, silent=TRUE)")))
      b<-b+1
    }
    a<-a+1
  }
}
#Export as csv
setwd("C:/Users/44755/OneDrive - University of Strathclyde/1. Thesi
s/12. Thesis V2")
#If using hundred within displacement gradient, save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_3
,"RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_3_Hundred
_Within.csv")
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_5
,"RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_5_Hundred
_Within.csv")
#If using basic displacement gradient, save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_3
,"RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_3_Gradien
t.csv")
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_5
,"RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_5_Gradien
t.csv")

#Sum individual OWF impacts

#Individual OWFs summed
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_sum <- data
.frame()
a<-1
for (ip in OWF_preplanning_SPA) {
  eval(parse(text = paste0("RTD_percloss_total_Outer_Thames_Estuary
_SPA_preplanning_sum <- rbind(RTD_percloss_total_Outer_Thames_Estua
ry_SPA_preplanning_sum, RTD_percloss_total_Outer_Thames_Estuary_SPA
_preplanning_", OWF_preplanning_SPA[a], ")")))
  a<-a+1
}

#Save
#If using hundred within displacement gradient, save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_s
um,"RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_allOWFs
_Hundred_Within.csv")
#If using basic displacement gradient, save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_s
um,"RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_allOWFs
_Gradient.csv")

#All OWFs summed
```

```
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_sum_total <
- aggregate(RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning
_sum[,4:7],by=list(Max_displ_km = RTD_percloss_total_Outer_Thames_E
stuary_SPA_preplanning_sum$Max_displ_km,MortalityRate = RTD_perclos
s_total_Outer_Thames_Estuary_SPA_preplanning_sum$MortalityRate),sum
)
#Save
#If using hundred within displacement gradient, save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_s
um_total,"RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_s
um_total_Hundred_Within.csv")
#If using basic displacement gradient, save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_s
um_total,"RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_s
um_total_Gradient.csv")
```

~~~~~ Impacted once in order ~~~~~

##OPERATIONAL Impacted once in order

```
#Pull out operational OWFs by order of construction starting
OWF_operational_order_1 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "Scroby Sands",]
OWF_operational_order_2 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "Kentish Flats",]
OWF_operational_order_3 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "Gunfleet Sands I" | OWF.sprepro@data$Name_Prop == "Gunfleet Sand
s II",]
OWF_operational_order_3 <- aggregate(OWF_operational_order_3,dissol
ve=TRUE)
OWF_operational_order_4 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "Thanet",]
OWF_operational_order_5 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "Greater Gabbard",]
OWF_operational_order_6 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "London Array",]
OWF_operational_order_7 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "Gunfleet Sands Demo",]
OWF_operational_order_8 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "Kentish Flats Extension",]
OWF_operational_order_9 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "Galloper",]
OWF_operational_order_10 <- OWF.sprepro[OWF.sprepro@data$Name_Prop
== "East Anglia ONE",]
```

Make buffers

```
#Make 0km buffers for each OWF (i.e. call the OWF 0km)
for(ip in 1:10){
  eval(parse(text = paste0("OWF_0km_buf_operational_order_", ip," <
- OWF_operational_order_", ip,"")))
}
#Make buffers around each OWF
```

```
buffer <- 0:16
for(ip in 1:10){
  for (bf in buffer) {
    eval(parse(text = paste0("OWF_", bf, "km_buf_operational_order_
", ip," <- gBuffer(OWF_operational_order_", ip,", width = bf*1000,
byid=TRUE)")))
  }
}
#When max displ is "fb" (call it displ_"fb" and keep last item "fb"
km buf)
#Erase buffers from one another
for(fb in buffer){
  eval(parse(text = paste0("OWF_0km_buf_operational_order_1_displ_"
, fb, "_erased <- OWF_0km_buf_operational_order_1
    OWF_0km_buf_operational_order_2_displ_", fb, "_erased <- erase(
OWF_0km_buf_operational_order_2,OWF_", fb, "km_buf_operational_orde
r_1)")))
  for (bf in buffer[2:17]) {
    eval(parse(text = paste0("OWF_", bf, "km_buf_operational_order_
1_displ_", fb, "_erased <- OWF_", bf, "km_buf_operational_order_1
      OWF_", bf, "km_buf_operational_order_2_displ_", fb, "_erased
<- erase(OWF_", bf, "km_buf_operational_order_2,OWF_", fb, "km_buf_
operational_order_1)")))
  }
}
#Do for all other buffers
for(fb in buffer){
  for(bf in buffer){
    try(eval(parse(text = paste0("
      #Erase OWF 3
      OWF_", bf, "km_buf_operational_order_3_displ_", fb, "_erased_
takeaway2 <- erase(OWF_", bf, "km_buf_operational_order_3,OWF_", fb
, "km_buf_operational_order_2)
      OWF_", bf, "km_buf_operational_order_3_displ_", fb, "_erased_
takeaway1 <- erase(OWF_", bf, "km_buf_operational_order_3_displ_",
fb, "_erased_takeaway2,OWF_", fb, "km_buf_operational_order_1)
      OWF_", bf, "km_buf_operational_order_3_displ_", fb, "_erased
<- OWF_", bf, "km_buf_operational_order_3_displ_", fb, "_erased_tak
eaway1
      #Erase OWF 4
      OWF_", bf, "km_buf_operational_order_4_displ_", fb, "_erased_
takeaway3 <- erase(OWF_", bf, "km_buf_operational_order_4,OWF_", fb
, "km_buf_operational_order_3)
      OWF_", bf, "km_buf_operational_order_4_displ_", fb, "_erased_
takeaway2 <- erase(OWF_", bf, "km_buf_operational_order_4_displ_",
fb, "_erased_takeaway3,OWF_", fb, "km_buf_operational_order_2)
      OWF_", bf, "km_buf_operational_order_4_displ_", fb, "_erased_
takeaway1 <- erase(OWF_", bf, "km_buf_operational_order_4_displ_",
fb, "_erased_takeaway2,OWF_", fb, "km_buf_operational_order_1)
      OWF_", bf, "km_buf_operational_order_4_displ_", fb, "_erased
<- OWF_", bf, "km_buf_operational_order_4_displ_", fb, "_erased_tak
eaway1
```

```
      #Erase OWF 5
      OWF_", bf, "km_buf_operational_order_5_displ_", fb, "_erased_
takeaway4 <- erase(OWF_", bf, "km_buf_operational_order_5,OWF_", fb
, "km_buf_operational_order_4)
      OWF_", bf, "km_buf_operational_order_5_displ_", fb, "_erased_
takeaway3 <- erase(OWF_", bf, "km_buf_operational_order_5_displ_",
fb, "_erased_takeaway4,OWF_", fb, "km_buf_operational_order_3)
      OWF_", bf, "km_buf_operational_order_5_displ_", fb, "_erased_
takeaway2 <- erase(OWF_", bf, "km_buf_operational_order_5_displ_",
fb, "_erased_takeaway3,OWF_", fb, "km_buf_operational_order_2)
      OWF_", bf, "km_buf_operational_order_5_displ_", fb, "_erased_
takeaway1 <- erase(OWF_", bf, "km_buf_operational_order_5_displ_",
fb, "_erased_takeaway2,OWF_", fb, "km_buf_operational_order_1)
      OWF_", bf, "km_buf_operational_order_5_displ_", fb, "_erased
<- OWF_", bf, "km_buf_operational_order_5_displ_", fb, "_erased_tak
eaway1
      #Erase OWF 6
      OWF_", bf, "km_buf_operational_order_6_displ_", fb, "_erased_
takeaway5 <- erase(OWF_", bf, "km_buf_operational_order_6,OWF_", fb
, "km_buf_operational_order_5)
      OWF_", bf, "km_buf_operational_order_6_displ_", fb, "_erased_
takeaway4 <- erase(OWF_", bf, "km_buf_operational_order_6_displ_",
fb, "_erased_takeaway5,OWF_", fb, "km_buf_operational_order_4)
      OWF_", bf, "km_buf_operational_order_6_displ_", fb, "_erased_
takeaway3 <- erase(OWF_", bf, "km_buf_operational_order_6_displ_",
fb, "_erased_takeaway4,OWF_", fb, "km_buf_operational_order_3)
      OWF_", bf, "km_buf_operational_order_6_displ_", fb, "_erased_
takeaway2 <- erase(OWF_", bf, "km_buf_operational_order_6_displ_",
fb, "_erased_takeaway3,OWF_", fb, "km_buf_operational_order_2)
      OWF_", bf, "km_buf_operational_order_6_displ_", fb, "_erased_
takeaway1 <- erase(OWF_", bf, "km_buf_operational_order_6_displ_",
fb, "_erased_takeaway2,OWF_", fb, "km_buf_operational_order_1)
      OWF_", bf, "km_buf_operational_order_6_displ_", fb, "_erased
<- OWF_", bf, "km_buf_operational_order_6_displ_", fb, "_erased_tak
eaway1
      #Erase OWF 7
      OWF_", bf, "km_buf_operational_order_7_displ_", fb, "_erased_
takeaway6 <- erase(OWF_", bf, "km_buf_operational_order_7,OWF_", fb
, "km_buf_operational_order_6)
      OWF_", bf, "km_buf_operational_order_7_displ_", fb, "_erased_
takeaway5 <- erase(OWF_", bf, "km_buf_operational_order_7_displ_",
fb, "_erased_takeaway6,OWF_", fb, "km_buf_operational_order_5)
      OWF_", bf, "km_buf_operational_order_7_displ_", fb, "_erased_
takeaway4 <- erase(OWF_", bf, "km_buf_operational_order_7_displ_",
fb, "_erased_takeaway5,OWF_", fb, "km_buf_operational_order_4)
      OWF_", bf, "km_buf_operational_order_7_displ_", fb, "_erased_
takeaway3 <- erase(OWF_", bf, "km_buf_operational_order_7_displ_",
fb, "_erased_takeaway4,OWF_", fb, "km_buf_operational_order_3)
      OWF_", bf, "km_buf_operational_order_7_displ_", fb, "_erased_
takeaway2 <- erase(OWF_", bf, "km_buf_operational_order_7_displ_",
fb, "_erased_takeaway3,OWF_", fb, "km_buf_operational_order_2)
      OWF_", bf, "km_buf_operational_order_7_displ_", fb, "_erased_
```

```
takeaway1 <- erase(OWF_", bf, "km_buf_operational_order_7_displ_",
fb, "_erased_takeaway2,OWF_", fb, "km_buf_operational_order_1)
      OWF_", bf, "km_buf_operational_order_7_displ_", fb, "_erased
<- OWF_", bf, "km_buf_operational_order_7_displ_", fb, "_erased_tak
eaway1
      #Erase OWF 8
      OWF_", bf, "km_buf_operational_order_8_displ_", fb, "_erased_
takeaway7 <- erase(OWF_", bf, "km_buf_operational_order_8,OWF_", fb
, "km_buf_operational_order_7)
      OWF_", bf, "km_buf_operational_order_8_displ_", fb, "_erased_
takeaway6 <- erase(OWF_", bf, "km_buf_operational_order_8_displ_",
fb, "_erased_takeaway7,OWF_", fb, "km_buf_operational_order_6)
      OWF_", bf, "km_buf_operational_order_8_displ_", fb, "_erased_
takeaway5 <- erase(OWF_", bf, "km_buf_operational_order_8_displ_",
fb, "_erased_takeaway6,OWF_", fb, "km_buf_operational_order_5)
      OWF_", bf, "km_buf_operational_order_8_displ_", fb, "_erased_
takeaway4 <- erase(OWF_", bf, "km_buf_operational_order_8_displ_",
fb, "_erased_takeaway5,OWF_", fb, "km_buf_operational_order_4)
      OWF_", bf, "km_buf_operational_order_8_displ_", fb, "_erased_
takeaway3 <- erase(OWF_", bf, "km_buf_operational_order_8_displ_",
fb, "_erased_takeaway4,OWF_", fb, "km_buf_operational_order_3)
      OWF_", bf, "km_buf_operational_order_8_displ_", fb, "_erased_
takeaway2 <- erase(OWF_", bf, "km_buf_operational_order_8_displ_",
fb, "_erased_takeaway3,OWF_", fb, "km_buf_operational_order_2)
      OWF_", bf, "km_buf_operational_order_8_displ_", fb, "_erased_
takeaway1 <- erase(OWF_", bf, "km_buf_operational_order_8_displ_",
fb, "_erased_takeaway2,OWF_", fb, "km_buf_operational_order_1)
      OWF_", bf, "km_buf_operational_order_8_displ_", fb, "_erased
<- OWF_", bf, "km_buf_operational_order_8_displ_", fb, "_erased_tak
eaway1
      #Erase OWF 9
      OWF_", bf, "km_buf_operational_order_9_displ_", fb, "_erased_
takeaway8 <- erase(OWF_", bf, "km_buf_operational_order_9,OWF_", fb
, "km_buf_operational_order_8)
      OWF_", bf, "km_buf_operational_order_9_displ_", fb, "_erased_
takeaway7 <- erase(OWF_", bf, "km_buf_operational_order_9_displ_",
fb, "_erased_takeaway8,OWF_", fb, "km_buf_operational_order_7)
      OWF_", bf, "km_buf_operational_order_9_displ_", fb, "_erased_
takeaway6 <- erase(OWF_", bf, "km_buf_operational_order_9_displ_",
fb, "_erased_takeaway7,OWF_", fb, "km_buf_operational_order_6)
      OWF_", bf, "km_buf_operational_order_9_displ_", fb, "_erased_
takeaway5 <- erase(OWF_", bf, "km_buf_operational_order_9_displ_",
fb, "_erased_takeaway6,OWF_", fb, "km_buf_operational_order_5)
      OWF_", bf, "km_buf_operational_order_9_displ_", fb, "_erased_
takeaway4 <- erase(OWF_", bf, "km_buf_operational_order_9_displ_",
fb, "_erased_takeaway5,OWF_", fb, "km_buf_operational_order_4)
      OWF_", bf, "km_buf_operational_order_9_displ_", fb, "_erased_
takeaway3 <- erase(OWF_", bf, "km_buf_operational_order_9_displ_",
fb, "_erased_takeaway4,OWF_", fb, "km_buf_operational_order_3)
      OWF_", bf, "km_buf_operational_order_9_displ_", fb, "_erased_
takeaway2 <- erase(OWF_", bf, "km_buf_operational_order_9_displ_",
fb, "_erased_takeaway3,OWF_", fb, "km_buf_operational_order_2)
```

```
      OWF_", bf, "km_buf_operational_order_9_displ_", fb, "_erased_
takeaway1 <- erase(OWF_", bf, "km_buf_operational_order_9_displ_",
fb, "_erased_takeaway2,OWF_", fb, "km_buf_operational_order_1)
      OWF_", bf, "km_buf_operational_order_9_displ_", fb, "_erased
<- OWF_", bf, "km_buf_operational_order_9_displ_", fb, "_erased_tak
eaway1
      #Erase OWF 1
      OWF_", bf, "km_buf_operational_order_10_displ_", fb, "_erased
_takeaway9 <- erase(OWF_", bf, "km_buf_operational_order_10,OWF_",
fb, "km_buf_operational_order_9)
      OWF_", bf, "km_buf_operational_order_10_displ_", fb, "_erased
_takeaway8 <- erase(OWF_", bf, "km_buf_operational_order_10_displ_"
, fb, "_erased_takeaway9,OWF_", fb, "km_buf_operational_order_8)
      OWF_", bf, "km_buf_operational_order_10_displ_", fb, "_erased
_takeaway7 <- erase(OWF_", bf, "km_buf_operational_order_10_displ_"
, fb, "_erased_takeaway8,OWF_", fb, "km_buf_operational_order_7)
      OWF_", bf, "km_buf_operational_order_10_displ_", fb, "_erased
_takeaway6 <- erase(OWF_", bf, "km_buf_operational_order_10_displ_"
, fb, "_erased_takeaway7,OWF_", fb, "km_buf_operational_order_6)
      OWF_", bf, "km_buf_operational_order_10_displ_", fb, "_erased
_takeaway5 <- erase(OWF_", bf, "km_buf_operational_order_10_displ_"
, fb, "_erased_takeaway6,OWF_", fb, "km_buf_operational_order_5)
      OWF_", bf, "km_buf_operational_order_10_displ_", fb, "_erased
_takeaway4 <- erase(OWF_", bf, "km_buf_operational_order_10_displ_"
, fb, "_erased_takeaway5,OWF_", fb, "km_buf_operational_order_4)
      OWF_", bf, "km_buf_operational_order_10_displ_", fb, "_erased
_takeaway3 <- erase(OWF_", bf, "km_buf_operational_order_10_displ_"
, fb, "_erased_takeaway4,OWF_", fb, "km_buf_operational_order_3)
      OWF_", bf, "km_buf_operational_order_10_displ_", fb, "_erased
_takeaway2 <- erase(OWF_", bf, "km_buf_operational_order_10_displ_"
, fb, "_erased_takeaway3,OWF_", fb, "km_buf_operational_order_2)
      OWF_", bf, "km_buf_operational_order_10_displ_", fb, "_erased
_takeaway1 <- erase(OWF_", bf, "km_buf_operational_order_10_displ_"
, fb, "_erased_takeaway2,OWF_", fb, "km_buf_operational_order_1)
      OWF_", bf, "km_buf_operational_order_10_displ_", fb, "_erased
<- OWF_", bf, "km_buf_operational_order_10_displ_", fb, "_erased_ta
keaway1"))))
  }
}
```

Make rings

```
#Create rings from buffers
for(fb in buffer){
  for(ip in 1:10){
    try(eval(parse(text = paste0("OWF_0km_ring_operational_order_",
ip, "_displ_", fb, "_erased <- OWF_0km_buf_operational_order_", ip,
"_displ_", fb, "_erased
      OWF_1km_ring_operational_order_", ip, "_displ_", fb, "_erased
<- erase(OWF_1km_buf_operational_order_", ip, "_displ_", fb, "_eras
ed, OWF_0km_buf_operational_order_", ip, "_displ_", fb, "_erased)")
)))
```

```
    for (bf in buffer[3:17]) {
      try(eval(parse(text = paste0("OWF_", bf, "km_ring_operational
_order_", ip, "_displ_", fb, "_erased <- erase(OWF_", bf, "km_buf_o
perational_order_", ip, "_displ_", fb, "_erased, OWF_", bf -1, "km_
buf_operational_order_", ip, "_displ_", fb, "_erased)"))))
    }
  }
}
```

Calculate area of rings

```
#Calculate area of rings
Operational_order_area <- data.frame(OWF=NA, Ring=NA, Area=NA)
a<-1
for(ip in 1:10){
  b<-1
  for(fb in buffer){
    try(eval(parse(text = paste0("
        Operational_order_area[((a-1)*length(buffer))+b,1] <- ip
        Operational_order_area[((a-1)*length(buffer))+b,2] <- fb
        Operational_order_area[((a-1)*length(buffer))+b,3] <- area(
OWF_", fb, "km_ring_operational_order_", ip, "_displ_16_erased)/100
0000"))))
    b<-b+1
  }
  a<-a+1
}
#Save
setwd("Y:/Marine Species/Rebecca Hall/Laptop files/PhD work/Future
cumulative displ/Results tables")
write.csv(Operational_order_area,"Operational_order_area.csv")
#Crop to SPA
for(ip in 1:10){
  for(bf in buffer){
    for(fb in buffer){
      try(eval(parse(text = paste0("OWF_", fb, "km_ring_operational
_order_", ip, "_displ_", bf, "_erased_OTESPA <- raster::intersect(O
uter_Thames_Estuary_SPA, OWF_", fb, "km_ring_operational_order_", i
p, "_displ_", bf, "_erased)"))))
    }
  }
}
#Table
Operational_order_area_OTESPA <- data.frame(MaxDispl=NA, OWF=NA, Ri
ng=NA, Area=NA)
a<-1
for(bf in buffer){
  b<-1
  for(ip in 1:10){
    c<-1
    for(fb in buffer){
      try(eval(parse(text = paste0("
```

```
          Operational_order_area_OTESPA[((a-1)*length(buffer)*10)+(
(b-1)*length(buffer))+c,1] <- bf
          Operational_order_area_OTESPA[((a-1)*length(buffer)*10)+(
(b-1)*length(buffer))+c,2] <- ip
          Operational_order_area_OTESPA[((a-1)*length(buffer)*10)+(
(b-1)*length(buffer))+c,3] <- fb
          Operational_order_area_OTESPA[((a-1)*length(buffer)*10)+(
(b-1)*length(buffer))+c,4] <- area(OWF_", fb, "km_ring_operational_
order_", ip, "_displ_", bf, "_erased_OTESPA)/1000000"))))
      c<-c+1
    }
    b<-b+1
  }
  a<-a+1
}
#Save
setwd("Y:/Marine Species/Rebecca Hall/Laptop files/PhD work/Future
cumulative displ/Results tables")
write.csv(Operational_order_area_OTESPA,"Operational_order_area_OTE
SPA.csv")
```

Crop density to OWFs & rings

```
#Crop density
for(fb in buffer){
  for (ip in 1:10) {
    for (bf in buffer) {
      try(eval(parse(text = paste0("RTD_density_Outer_Thames_Estuar
y_SPA_OWF_", bf, "km_ring_operational_order_", ip, "_displ_", fb, "
_erased <-raster::intersect(RTD_density_Outer_Thames_Estuary_SPA, O
WF_", bf, "km_ring_operational_order_", ip, "_displ_", fb, "_erased
)"))))
    }
  }
}
```

Displace birds

```
#Displace birds using displacement gradient
for (ip in 1:10) {
  for (fb in buffer){
    for(bf in buffer){
      eval(parse(text = paste0("if(exists('RTD_density_Outer_Thames
_Estuary_SPA_OWF_", bf, "km_ring_operational_order_", ip, "_displ_"
, fb, "_erased')){if(!is.null(RTD_density_Outer_Thames_Estuary_SPA_
OWF_", bf, "km_ring_operational_order_", ip, "_displ_", fb, "_erase
d)){RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_operat
ional_order_", ip, "_displ_", fb, "_erased@data$RH_D_MaxDispl",fb,"
<- as.numeric(sapply((1-(Displ_together[(fb*17)+(bf+1),Displ_grad])
/100),'*',RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_
operational_order_", ip, "_displ_", fb, "_erased@data$RH_D))}}")))
    }
```

```
  }
}
```

Calculate numbers of birds displaced and mortality and as proportion of SPA

```
#No. birds in SPA
RTD_density_Outer_Thames_Estuary_SPA_sum <- sum((area(RTD_density_Outer_Thames_Estuary_SPA)/1000000)*RTD_density_Outer_Thames_Estuary_SPA@data$RH_D)
for (ip in 1:10) {
  for (fb in buffer){
    for(bf in 0:fb){
      try(eval(parse(text = paste0("
        RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_operational_order_", ip, "_displ_", fb, "_erased_sum <- sum((area(RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_operational_order_", ip, "_displ_", fb, "_erased)/1000000)*RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_operational_order_", ip, "_displ_", fb, "_erased@data$RH_D)
        RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_operational_order_", ip, "_displ_", fb, "_erased_sum_", fb, " <-sum((area(RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_operational_order_", ip, "_displ_", fb, "_erased)/1000000)*RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_operational_order_", ip, "_displ_", fb, "_erased@data$RH_D_MaxDispl", fb, ")
        RTD_percloss_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_operational_order_", ip, "_displ_", fb, "_erased <- ((RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_operational_order_", ip, "_displ_", fb, "_erased_sum - RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_operational_order_", ip, "_displ_", fb, "_erased_sum_", fb, ")/RTD_density_Outer_Thames_Estuary_SPA_sum)*100"))))
    }
  }
}
#Calculate numbers of bird casualties and as proportion of SPA
Mortality_rate <- 1:10
#Put into table
for (ip in 1:10) {
  eval(parse(text = paste0("RTD_percloss_Outer_Thames_Estuary_SPA_operational_order_", ip, " <- data.frame(Max_displ_km=NA, Ring=NA, MortalityRate=NA, RingArea=NA, NoBirds=NA, NoBirdLoss=NA, SPAPercLoss=NA, NoBirdMortality=NA, SPAPercMortality=NA)")))
  a<-1
  for (fb in buffer) {
    b<-1
    for (bf in 0:fb) {
      c<-1
      for (mt in Mortality_rate) {
        eval(parse(text = paste0("try(if(!is.null(RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_operational_order_", ip, "_displ_", fb, "_erased)){
          RTD_percloss_Outer_Thames_Estuary_SPA_operational_order_"
```

```
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,1] <- fb
          RTD_percloss_Outer_Thames_Estuary_SPA_operational_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,2] <- bf
          RTD_percloss_Outer_Thames_Estuary_SPA_operational_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,3] <- mt
          RTD_percloss_Outer_Thames_Estuary_SPA_operational_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,4] <-sum(area(RTD_density_Outer_Thames_Estuary_
SPA_OWF_", bf, "km_ring_operational_order_", ip, "_displ_", fb, "_e
rased)/1000000)
          RTD_percloss_Outer_Thames_Estuary_SPA_operational_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,5] <-RTD_density_Outer_Thames_Estuary_SPA_OWF_"
, bf, "km_ring_operational_order_", ip, "_displ_", fb, "_erased_sum
          RTD_percloss_Outer_Thames_Estuary_SPA_operational_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,6] <-RTD_density_Outer_Thames_Estuary_SPA_OWF_"
, bf, "km_ring_operational_order_", ip, "_displ_", fb, "_erased_sum
- RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_operatio
nal_order_", ip, "_displ_", fb, "_erased_sum_", fb, "
          RTD_percloss_Outer_Thames_Estuary_SPA_operational_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,7] <-RTD_percloss_Outer_Thames_Estuary_SPA_OWF_
", bf, "km_ring_operational_order_", ip, "_displ_", fb, "_erased
          RTD_percloss_Outer_Thames_Estuary_SPA_operational_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,8] <-(RTD_density_Outer_Thames_Estuary_SPA_OWF_
", bf, "km_ring_operational_order_", ip, "_displ_", fb, "_erased_su
m - RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_operat
ional_order_", ip, "_displ_", fb, "_erased_sum_", fb, ")/100*mt
          RTD_percloss_Outer_Thames_Estuary_SPA_operational_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,9] <-(RTD_percloss_Outer_Thames_Estuary_SPA_OWF
_", bf, "km_ring_operational_order_", ip, "_displ_", fb, "_erased)/
100*mt})")))
        c<-c+1
      }
      b<-b+1
    }
    a<-a+1
  }
}
#Remova NAs
for (ip in 1:10) {
  eval(parse(text = paste0("RTD_percloss_Outer_Thames_Estuary_SPA_o
perational_order_", ip, "<-na.omit(RTD_percloss_Outer_Thames_Estuar
y_SPA_operational_order_", ip, ")")))
}
#Sum % birds for each scenario
```

```
for (ip in 1:10) {
  eval(parse(text = paste0("RTD_percloss_total_Outer_Thames_Estuary
_SPA_operational_order_", ip, " <- data.frame(OWF_num=NA, Max_displ
_km=NA, MortalityRate=NA, NoBirdLoss=NA, SPAPercLoss=NA, NoBirdMort
ality=NA, SPAPercMortality=NA, Area=NA)")))
  a<-1
  for (fb in buffer) {
    b<-1
    for (mt in Mortality_rate) {
      eval(parse(text = paste0("
        RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_ord
er_", ip, "[((a-1)*length(Mortality_rate))+b,1] <- ip
        RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_ord
er_", ip, "[((a-1)*length(Mortality_rate))+b,2] <- fb
        RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_ord
er_", ip, "[((a-1)*length(Mortality_rate))+b,3] <- mt
        try({RTD_percloss_total_Outer_Thames_Estuary_SPA_operationa
l_order_", ip, "[((a-1)*length(Mortality_rate))+b,4] <-sum(subset(R
TD_percloss_Outer_Thames_Estuary_SPA_operational_order_", ip, ", Ma
x_displ_km==fb & MortalityRate==mt, select=NoBirdLoss), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_ord
er_", ip, "[((a-1)*length(Mortality_rate))+b,5] <-sum(subset(RTD_pe
rcloss_Outer_Thames_Estuary_SPA_operational_order_", ip, ", Max_dis
pl_km==fb & MortalityRate==mt, select=SPAPercLoss), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_ord
er_", ip, "[((a-1)*length(Mortality_rate))+b,6] <-sum(subset(RTD_pe
rcloss_Outer_Thames_Estuary_SPA_operational_order_", ip, ", Max_dis
pl_km==fb & MortalityRate==mt, select=NoBirdMortality), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_ord
er_", ip, "[((a-1)*length(Mortality_rate))+b,7] <-sum(subset(RTD_pe
rcloss_Outer_Thames_Estuary_SPA_operational_order_", ip, ", Max_dis
pl_km==fb & MortalityRate==mt, select=SPAPercMortality), na.rm=TRUE
)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_ord
er_", ip, "[((a-1)*length(Mortality_rate))+b,8] <-sum(subset(RTD_pe
rcloss_Outer_Thames_Estuary_SPA_operational_order_", ip, ", Max_dis
pl_km==fb & SPAPercLoss>0, select=RingArea), na.rm=TRUE)}, silent=T
RUE)")))
      b<-b+1
    }
    a<-a+1
  }
}
#Sum all OWFs
RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_order_sum <
- data.frame()
a<-1
for (ip in Mortality_rate) {
  eval(parse(text = paste0("RTD_percloss_total_Outer_Thames_Estuary
_SPA_operational_order_sum <- rbind(RTD_percloss_total_Outer_Thames
_Estuary_SPA_operational_order_sum, RTD_percloss_total_Outer_Thames
_Estuary_SPA_operational_order_", Mortality_rate[a], ")")))
```

```
  a<-a+1
}
#Save
setwd("c:/Users/44755/OneDrive - University of Strathlcyde/1. Thesi
s/12. Thesis V2")
#If using hundred within displacement gradient, save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_o
rder_sum,"RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_o
rder_sum_Hundred_Within.csv")
#If using basic gradient displacement gradient, save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_o
rder_sum,"RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_o
rder_sum_Gradient.csv")
```

##CONSENTED ONE FIRST Impacted once in order

```
#Pull out consented OWFs by order of construction starting
OWF_consented_order_1 <- OWF.sprepro[OWF.sprepro@data$Name_Prop ==
"Scroby Sands",]
OWF_consented_order_2 <- OWF.sprepro[OWF.sprepro@data$Name_Prop ==
"Kentish Flats",]
OWF_consented_order_3 <- GunfleetSands.sprepro
OWF_consented_order_4 <- OWF.sprepro[OWF.sprepro@data$Name_Prop ==
"Thanet",]
OWF_consented_order_5 <- OWF.sprepro[OWF.sprepro@data$Name_Prop ==
"Greater Gabbard",]
OWF_consented_order_6 <- OWF.sprepro[OWF.sprepro@data$Name_Prop ==
"London Array",]
OWF_consented_order_7 <- OWF.sprepro[OWF.sprepro@data$Name_Prop ==
"Gunfleet Sands Demo",]
OWF_consented_order_8 <- OWF.sprepro[OWF.sprepro@data$Name_Prop ==
"Kentish Flats Extension",]
OWF_consented_order_9 <- OWF.sprepro[OWF.sprepro@data$Name_Prop ==
"East Anglia ONE",]
OWF_consented_order_10 <- OWF.sprepro[OWF.sprepro@data$Name_Prop ==
"East Anglia ONE NORTH",]
OWF_consented_order_11 <- OWF.sprepro[OWF.sprepro@data$Name_Prop ==
"East Anglia TWO",]
consented_OWFs <- 1:11
```

Make buffers

```
#Make 0km buffers for each OWF (i.e. call the OWF 0km)
for(ip in consented_OWFs){
  eval(parse(text = paste0("OWF_0km_buf_consented_order_", ip," <-
OWF_consented_order_", ip,"")))
}
#Make buffers around each OWF
buffer <- 0:16
for(ip in consented_OWFs){
  for (bf in buffer) {
    eval(parse(text = paste0("OWF_", bf, "km_buf_consented_order_",
ip," <- gBuffer(OWF_consented_order_", ip,", width = bf*1000, byid=
```

```
TRUE)")))
  }
}
#When max displ is "fb" (call it displ_"fb" and keep last item "fb"
km buf)
#Erase buffers from one another
for(fb in buffer){
  try(eval(parse(text = paste0("OWF_0km_buf_consented_order_1_displ
_", fb, "_erased <- OWF_0km_buf_consented_order_1if(gContainsProper
ly(OWF_", fb, "km_buf_consented_order_1,OWF_0km_buf_consented_order
_2)==FALSE){OWF_0km_buf_consented_order_2_displ_", fb, "_erased <-
erase(OWF_0km_buf_consented_order_2,OWF_", fb, "km_buf_consented_or
der_1)}"))))
}
for(fb in buffer){
  for (bf in buffer[2:17]) {
    try(eval(parse(text = paste0("OWF_", bf, "km_buf_consented_orde
r_1_displ_", fb, "_erased <- OWF_", bf, "km_buf_consented_order_1if
(gContainsProperly(OWF_", fb, "km_buf_consented_order_1,OWF_", bf,
"km_buf_consented_order_2)==FALSE){OWF_", bf, "km_buf_consented_ord
er_2_displ_", fb, "_erased <- erase(OWF_", bf, "km_buf_consented_or
der_2,OWF_", fb, "km_buf_consented_order_1)}"))))
  }
}
#Do for all other buffers
for(fb in buffer){
  for(bf in buffer){
    try(eval(parse(text = paste0("
      #Erase OWF 3
      if(gContainsProperly(OWF_", fb, "km_buf_consented_order_2,OWF
_", bf, "km_buf_consented_order_3)==FALSE){OWF_", bf, "km_buf_conse
nted_order_3_displ_", fb, "_erased_takeaway2 <- erase(OWF_", bf, "k
m_buf_consented_order_3,OWF_", fb, "km_buf_consented_order_2)}
      if(exists('OWF_", bf, "km_buf_consented_order_3_displ_", fb,
"_erased_takeaway2')){OWF_", bf, "km_buf_consented_order_3_displ_",
fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_consented_order_
3_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_consented_orde
r_1)}
      if(exists('OWF_", bf, "km_buf_consented_order_3_displ_", fb,
"_erased_takeaway1')){OWF_", bf, "km_buf_consented_order_3_displ_",
fb, "_erased <- OWF_", bf, "km_buf_consented_order_3_displ_", fb, "
_erased_takeaway1}
      #Erase OWF 4
      if(gContainsProperly(OWF_", fb, "km_buf_consented_order_3,OWF
_", bf, "km_buf_consented_order_4)==FALSE){OWF_", bf, "km_buf_conse
nted_order_4_displ_", fb, "_erased_takeaway3 <- erase(OWF_", bf, "k
m_buf_consented_order_4,OWF_", fb, "km_buf_consented_order_3)}
      if(exists('OWF_", bf, "km_buf_consented_order_4_displ_", fb,
"_erased_takeaway3')){OWF_", bf, "km_buf_consented_order_4_displ_",
fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_consented_order_
4_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_consented_orde
r_2)}
```

```
      if(exists('OWF_", bf, "km_buf_consented_order_4_displ_", fb,
"_erased_takeaway2')){OWF_", bf, "km_buf_consented_order_4_displ_",
fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_consented_order_
4_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_consented_orde
r_1)}
      if(exists('OWF_", bf, "km_buf_consented_order_4_displ_", fb,
"_erased_takeaway1')){OWF_", bf, "km_buf_consented_order_4_displ_",
fb, "_erased <- OWF_", bf, "km_buf_consented_order_4_displ_", fb, "
_erased_takeaway1}
      #Erase OWF 5
      if(gContainsProperly(OWF_", fb, "km_buf_consented_order_4,OWF
_", bf, "km_buf_consented_order_5)==FALSE){OWF_", bf, "km_buf_conse
nted_order_5_displ_", fb, "_erased_takeaway4 <- erase(OWF_", bf, "k
m_buf_consented_order_5,OWF_", fb, "km_buf_consented_order_4)}
      if(exists('OWF_", bf, "km_buf_consented_order_5_displ_", fb,
"_erased_takeaway4')){OWF_", bf, "km_buf_consented_order_5_displ_",
fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_consented_order_
5_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_consented_orde
r_3)}
      if(exists('OWF_", bf, "km_buf_consented_order_5_displ_", fb,
"_erased_takeaway3')){OWF_", bf, "km_buf_consented_order_5_displ_",
fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_consented_order_
5_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_consented_orde
r_2)}
      if(exists('OWF_", bf, "km_buf_consented_order_5_displ_", fb,
"_erased_takeaway2')){OWF_", bf, "km_buf_consented_order_5_displ_",
fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_consented_order_
5_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_consented_orde
r_1)}
      if(exists('OWF_", bf, "km_buf_consented_order_5_displ_", fb,
"_erased_takeaway1')){OWF_", bf, "km_buf_consented_order_5_displ_",
fb, "_erased <- OWF_", bf, "km_buf_consented_order_5_displ_", fb, "
_erased_takeaway1}
      #Erase OWF 6
      if(gContainsProperly(OWF_", fb, "km_buf_consented_order_5,OWF
_", bf, "km_buf_consented_order_6)==FALSE){OWF_", bf, "km_buf_conse
nted_order_6_displ_", fb, "_erased_takeaway5 <- erase(OWF_", bf, "k
m_buf_consented_order_6,OWF_", fb, "km_buf_consented_order_5)}
      if(exists('OWF_", bf, "km_buf_consented_order_6_displ_", fb,
"_erased_takeaway5')){OWF_", bf, "km_buf_consented_order_6_displ_",
fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_consented_order_
6_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_consented_orde
r_4)}
      if(exists('OWF_", bf, "km_buf_consented_order_6_displ_", fb,
"_erased_takeaway4')){OWF_", bf, "km_buf_consented_order_6_displ_",
fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_consented_order_
6_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_consented_orde
r_3)}
      if(exists('OWF_", bf, "km_buf_consented_order_6_displ_", fb,
"_erased_takeaway3')){OWF_", bf, "km_buf_consented_order_6_displ_",
fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_consented_order_
6_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_consented_orde
```

```
r_2)}
      if(exists('OWF_", bf, "km_buf_consented_order_6_displ_", fb,
"_erased_takeaway2')){OWF_", bf, "km_buf_consented_order_6_displ_",
fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_consented_order_
6_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_consented_orde
r_1)}
      if(exists('OWF_", bf, "km_buf_consented_order_6_displ_", fb,
"_erased_takeaway1')){OWF_", bf, "km_buf_consented_order_6_displ_",
fb, "_erased <- OWF_", bf, "km_buf_consented_order_6_displ_", fb, "
_erased_takeaway1}
      #Erase OWF 7
      if(gContainsProperly(OWF_", fb, "km_buf_consented_order_6,OWF
_", bf, "km_buf_consented_order_7)==FALSE){OWF_", bf, "km_buf_conse
nted_order_7_displ_", fb, "_erased_takeaway6 <- erase(OWF_", bf, "k
m_buf_consented_order_7,OWF_", fb, "km_buf_consented_order_6)}
      if(exists('OWF_", bf, "km_buf_consented_order_7_displ_", fb,
"_erased_takeaway6')){OWF_", bf, "km_buf_consented_order_7_displ_",
fb, "_erased_takeaway5 <- erase(OWF_", bf, "km_buf_consented_order_
7_displ_", fb, "_erased_takeaway6,OWF_", fb, "km_buf_consented_orde
r_5)}
      if(exists('OWF_", bf, "km_buf_consented_order_7_displ_", fb,
"_erased_takeaway5')){OWF_", bf, "km_buf_consented_order_7_displ_",
fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_consented_order_
7_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_consented_orde
r_4)}
      if(exists('OWF_", bf, "km_buf_consented_order_7_displ_", fb,
"_erased_takeaway4')){OWF_", bf, "km_buf_consented_order_7_displ_",
fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_consented_order_
7_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_consented_orde
r_3)}
      if(exists('OWF_", bf, "km_buf_consented_order_7_displ_", fb,
"_erased_takeaway3')){OWF_", bf, "km_buf_consented_order_7_displ_",
fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_consented_order_
7_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_consented_orde
r_2)}
      if(exists('OWF_", bf, "km_buf_consented_order_7_displ_", fb,
"_erased_takeaway2')){OWF_", bf, "km_buf_consented_order_7_displ_",
fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_consented_order_
7_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_consented_orde
r_1)}
      if(exists('OWF_", bf, "km_buf_consented_order_7_displ_", fb,
"_erased_takeaway1')){OWF_", bf, "km_buf_consented_order_7_displ_",
fb, "_erased <- OWF_", bf, "km_buf_consented_order_7_displ_", fb, "
_erased_takeaway1}
      #Erase OWF 8
      if(gContainsProperly(OWF_", fb, "km_buf_consented_order_7,OWF
_", bf, "km_buf_consented_order_8)==FALSE){OWF_", bf, "km_buf_conse
nted_order_8_displ_", fb, "_erased_takeaway7 <- erase(OWF_", bf, "k
m_buf_consented_order_8,OWF_", fb, "km_buf_consented_order_7)}
      if(exists('OWF_", bf, "km_buf_consented_order_8_displ_", fb,
"_erased_takeaway7')){OWF_", bf, "km_buf_consented_order_8_displ_",
fb, "_erased_takeaway6 <- erase(OWF_", bf, "km_buf_consented_order_
```

```
8_displ_", fb, "_erased_takeaway7,OWF_", fb, "km_buf_consented_orde
r_6)}
      if(exists('OWF_", bf, "km_buf_consented_order_8_displ_", fb,
"_erased_takeaway6')){OWF_", bf, "km_buf_consented_order_8_displ_",
fb, "_erased_takeaway5 <- erase(OWF_", bf, "km_buf_consented_order_
8_displ_", fb, "_erased_takeaway6,OWF_", fb, "km_buf_consented_orde
r_5)}
      if(exists('OWF_", bf, "km_buf_consented_order_8_displ_", fb,
"_erased_takeaway5')){OWF_", bf, "km_buf_consented_order_8_displ_",
fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_consented_order_
8_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_consented_orde
r_4)}
      if(exists('OWF_", bf, "km_buf_consented_order_8_displ_", fb,
"_erased_takeaway4')){OWF_", bf, "km_buf_consented_order_8_displ_",
fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_consented_order_
8_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_consented_orde
r_3)}
      if(exists('OWF_", bf, "km_buf_consented_order_8_displ_", fb,
"_erased_takeaway3')){OWF_", bf, "km_buf_consented_order_8_displ_",
fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_consented_order_
8_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_consented_orde
r_2)}
      if(exists('OWF_", bf, "km_buf_consented_order_8_displ_", fb,
"_erased_takeaway2')){OWF_", bf, "km_buf_consented_order_8_displ_",
fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_consented_order_
8_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_consented_orde
r_1)}
      if(exists('OWF_", bf, "km_buf_consented_order_8_displ_", fb,
"_erased_takeaway1')){OWF_", bf, "km_buf_consented_order_8_displ_",
fb, "_erased <- OWF_", bf, "km_buf_consented_order_8_displ_", fb, "
_erased_takeaway1}
      Erase OWF 9
      if(gContainsProperly(OWF_", fb, "km_buf_consented_order_8,OWF
_", bf, "km_buf_consented_order_9)==FALSE){OWF_", bf, "km_buf_conse
nted_order_9_displ_", fb, "_erased_takeaway8 <- erase(OWF_", bf, "k
m_buf_consented_order_9,OWF_", fb, "km_buf_consented_order_8)}
      if(exists('OWF_", bf, "km_buf_consented_order_9_displ_", fb,
"_erased_takeaway8')){OWF_", bf, "km_buf_consented_order_9_displ_",
fb, "_erased_takeaway7 <- erase(OWF_", bf, "km_buf_consented_order_
9_displ_", fb, "_erased_takeaway8,OWF_", fb, "km_buf_consented_orde
r_7)}
      if(exists('OWF_", bf, "km_buf_consented_order_9_displ_", fb,
"_erased_takeaway7')){OWF_", bf, "km_buf_consented_order_9_displ_",
fb, "_erased_takeaway6 <- erase(OWF_", bf, "km_buf_consented_order_
9_displ_", fb, "_erased_takeaway7,OWF_", fb, "km_buf_consented_orde
r_6)}
      if(exists('OWF_", bf, "km_buf_consented_order_9_displ_", fb,
"_erased_takeaway6')){OWF_", bf, "km_buf_consented_order_9_displ_",
fb, "_erased_takeaway5 <- erase(OWF_", bf, "km_buf_consented_order_
9_displ_", fb, "_erased_takeaway6,OWF_", fb, "km_buf_consented_orde
r_5)}
      if(exists('OWF_", bf, "km_buf_consented_order_9_displ_", fb,
```

```
"_erased_takeaway5')){OWF_", bf, "km_buf_consented_order_9_displ_",
fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_consented_order_
9_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_consented_orde
r_4)}
      if(exists('OWF_", bf, "km_buf_consented_order_9_displ_", fb,
"_erased_takeaway4')){OWF_", bf, "km_buf_consented_order_9_displ_",
fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_consented_order_
9_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_consented_orde
r_3)}
      if(exists('OWF_", bf, "km_buf_consented_order_9_displ_", fb,
"_erased_takeaway3')){OWF_", bf, "km_buf_consented_order_9_displ_",
fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_consented_order_
9_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_consented_orde
r_2)}
      if(exists('OWF_", bf, "km_buf_consented_order_9_displ_", fb,
"_erased_takeaway2')){OWF_", bf, "km_buf_consented_order_9_displ_",
fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_consented_order_
9_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_consented_orde
r_1)}
      if(exists('OWF_", bf, "km_buf_consented_order_9_displ_", fb,
"_erased_takeaway1')){OWF_", bf, "km_buf_consented_order_9_displ_",
fb, "_erased <- OWF_", bf, "km_buf_consented_order_9_displ_", fb, "
_erased_takeaway1}
      #Erase OWF 10
      if(gContainsProperly(OWF_", fb, "km_buf_consented_order_9,OWF
_", bf, "km_buf_consented_order_10)==FALSE){OWF_", bf, "km_buf_cons
ented_order_10_displ_", fb, "_erased_takeaway9 <- erase(OWF_", bf,
"km_buf_consented_order_10,OWF_", fb, "km_buf_consented_order_9)}
      if(exists('OWF_", bf, "km_buf_consented_order_10_displ_", fb,
"_erased_takeaway9')){OWF_", bf, "km_buf_consented_order_10_displ_"
, fb, "_erased_takeaway8 <- erase(OWF_", bf, "km_buf_consented_orde
r_10_displ_", fb, "_erased_takeaway9,OWF_", fb, "km_buf_consented_o
rder_8)}
      if(exists('OWF_", bf, "km_buf_consented_order_10_displ_", fb,
"_erased_takeaway8')){OWF_", bf, "km_buf_consented_order_10_displ_"
, fb, "_erased_takeaway7 <- erase(OWF_", bf, "km_buf_consented_orde
r_10_displ_", fb, "_erased_takeaway8,OWF_", fb, "km_buf_consented_o
rder_7)}
      if(exists('OWF_", bf, "km_buf_consented_order_10_displ_", fb,
"_erased_takeaway7')){OWF_", bf, "km_buf_consented_order_10_displ_"
, fb, "_erased_takeaway6 <- erase(OWF_", bf, "km_buf_consented_orde
r_10_displ_", fb, "_erased_takeaway7,OWF_", fb, "km_buf_consented_o
rder_6)}
      if(exists('OWF_", bf, "km_buf_consented_order_10_displ_", fb,
"_erased_takeaway6')){OWF_", bf, "km_buf_consented_order_10_displ_"
, fb, "_erased_takeaway5 <- erase(OWF_", bf, "km_buf_consented_orde
r_10_displ_", fb, "_erased_takeaway6,OWF_", fb, "km_buf_consented_o
rder_5)}
      if(exists('OWF_", bf, "km_buf_consented_order_10_displ_", fb,
"_erased_takeaway5')){OWF_", bf, "km_buf_consented_order_10_displ_"
, fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_consented_orde
r_10_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_consented_o
```

```
rder_4)}
      if(exists('OWF_", bf, "km_buf_consented_order_10_displ_", fb,
"_erased_takeaway4')){OWF_", bf, "km_buf_consented_order_10_displ_"
, fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_consented_orde
r_10_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_consented_o
rder_3)}
      if(exists('OWF_", bf, "km_buf_consented_order_10_displ_", fb,
"_erased_takeaway3')){OWF_", bf, "km_buf_consented_order_10_displ_"
, fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_consented_orde
r_10_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_consented_o
rder_2)}
      if(exists('OWF_", bf, "km_buf_consented_order_10_displ_", fb,
"_erased_takeaway2')){OWF_", bf, "km_buf_consented_order_10_displ_"
, fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_consented_orde
r_10_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_consented_o
rder_1)}
      if(exists('OWF_", bf, "km_buf_consented_order_10_displ_", fb,
"_erased_takeaway1')){OWF_", bf, "km_buf_consented_order_10_displ_"
, fb, "_erased <- OWF_", bf, "km_buf_consented_order_10_displ_", fb
, "_erased_takeaway1}
      #Erase OWF 11
      if(gContainsProperly(OWF_", fb, "km_buf_consented_order_10,OW
F_", bf, "km_buf_consented_order_11)==FALSE){OWF_", bf, "km_buf_con
sented_order_11_displ_", fb, "_erased_takeaway10 <- erase(OWF_", bf
, "km_buf_consented_order_11,OWF_", fb, "km_buf_consented_order_10)
}
      if(exists('OWF_", bf, "km_buf_consented_order_11_displ_", fb,
"_erased_takeaway10')){OWF_", bf, "km_buf_consented_order_11_displ_
", fb, "_erased_takeaway9 <- erase(OWF_", bf, "km_buf_consented_ord
er_11_displ_", fb, "_erased_takeaway10,OWF_", fb, "km_buf_consented
_order_9)}
      if(exists('OWF_", bf, "km_buf_consented_order_11_displ_", fb,
"_erased_takeaway9')){OWF_", bf, "km_buf_consented_order_11_displ_"
, fb, "_erased_takeaway8 <- erase(OWF_", bf, "km_buf_consented_orde
r_11_displ_", fb, "_erased_takeaway9,OWF_", fb, "km_buf_consented_o
rder_8)}
      if(exists('OWF_", bf, "km_buf_consented_order_11_displ_", fb,
"_erased_takeaway8')){OWF_", bf, "km_buf_consented_order_11_displ_"
, fb, "_erased_takeaway7 <- erase(OWF_", bf, "km_buf_consented_orde
r_11_displ_", fb, "_erased_takeaway8,OWF_", fb, "km_buf_consented_o
rder_7)}
      if(exists('OWF_", bf, "km_buf_consented_order_11_displ_", fb,
"_erased_takeaway7')){OWF_", bf, "km_buf_consented_order_11_displ_"
, fb, "_erased_takeaway6 <- erase(OWF_", bf, "km_buf_consented_orde
r_11_displ_", fb, "_erased_takeaway7,OWF_", fb, "km_buf_consented_o
rder_6)}
      if(exists('OWF_", bf, "km_buf_consented_order_11_displ_", fb,
"_erased_takeaway6')){OWF_", bf, "km_buf_consented_order_11_displ_"
, fb, "_erased_takeaway5 <- erase(OWF_", bf, "km_buf_consented_orde
r_11_displ_", fb, "_erased_takeaway6,OWF_", fb, "km_buf_consented_o
rder_5)}
      if(exists('OWF_", bf, "km_buf_consented_order_11_displ_", fb,
```

```
"_erased_takeaway5')){OWF_", bf, "km_buf_consented_order_11_displ_"
, fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_consented_orde
r_11_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_consented_o
rder_4)}
      if(exists('OWF_", bf, "km_buf_consented_order_11_displ_", fb,
"_erased_takeaway4')){OWF_", bf, "km_buf_consented_order_11_displ_"
, fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_consented_orde
r_11_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_consented_o
rder_3)}
      if(exists('OWF_", bf, "km_buf_consented_order_11_displ_", fb,
"_erased_takeaway3')){OWF_", bf, "km_buf_consented_order_11_displ_"
, fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_consented_orde
r_11_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_consented_o
rder_2)}
      if(exists('OWF_", bf, "km_buf_consented_order_11_displ_", fb,
"_erased_takeaway2')){OWF_", bf, "km_buf_consented_order_11_displ_"
, fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_consented_orde
r_11_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_consented_o
rder_1)}
      if(exists('OWF_", bf, "km_buf_consented_order_11_displ_", fb,
"_erased_takeaway1')){OWF_", bf, "km_buf_consented_order_11_displ_"
, fb, "_erased <- OWF_", bf, "km_buf_consented_order_11_displ_", fb
, "_erased_takeaway1}"))))
  }
}
```

Make rings

```
#Create rings from buffers
for(fb in buffer){
  for(ip in consented_OWFs){
    try(eval(parse(text = paste0("
      OWF_0km_ring_consented_order_", ip, "_displ_", fb, "_erased <
- OWF_0km_buf_consented_order_", ip, "_displ_", fb, "_erased
      OWF_1km_ring_consented_order_", ip, "_displ_", fb, "_erased <
- erase(OWF_1km_buf_consented_order_", ip, "_displ_", fb, "_erased,
OWF_0km_buf_consented_order_", ip, "_displ_", fb, "_erased)"))))
    for (bf in buffer[3:17]) {
      try(eval(parse(text = paste0("OWF_", bf, "km_ring_consented_o
rder_", ip, "_displ_", fb, "_erased <- erase(OWF_", bf, "km_buf_con
sented_order_", ip, "_displ_", fb, "_erased, OWF_", bf -1, "km_buf_
consented_order_", ip, "_displ_", fb, "_erased)"))))
    }
  }
}
```

Calculate area of rings

```
#Calculate area of rings
consented_order_area <- data.frame(OWF=NA, Ring=NA, Area=NA)
a<-1
for(ip in consented_OWFs){
  b<-1
```

```
  for(fb in buffer){
    try(eval(parse(text = paste0("
        consented_order_area[((a-1)*length(buffer))+b,1] <- ip
        consented_order_area[((a-1)*length(buffer))+b,2] <- fb
        consented_order_area[((a-1)*length(buffer))+b,3] <- area(OW
F_", fb, "km_ring_consented_order_", ip, "_displ_16_erased)/1000000
"))))
    b<-b+1
  }
  a<-a+1
}
#Save
setwd("Y:/Marine Species/Rebecca Hall/Laptop files/PhD work/Future
cumulative displ/Results tables")
write.csv(consented_order_area,"consented_order_area.csv")
#Crop to SPA
for(ip in consented_OWFs){
  for(bf in buffer){
    for(fb in buffer){
      try(eval(parse(text = paste0("OWF_", fb, "km_ring_consented_o
rder_", ip, "_displ_", bf, "_erased_OTESPA <- raster::intersect(Out
er_Thames_Estuary_SPA, OWF_", fb, "km_ring_consented_order_", ip, "
_displ_", bf, "_erased)"))))
    }
  }
}
#Table
consented_order_area_OTESPA <- data.frame(MaxDispl=NA, OWF=NA, Ring
=NA, Area=NA)
a<-1
for(bf in buffer){
  b<-1
  for(ip in consented_OWFs){
    c<-1
    for(fb in buffer){
      try(eval(parse(text = paste0("
          consented_order_area_OTESPA[((a-1)*length(buffer)*length(
consented_OWFs))+((b-1)*length(buffer))+c,1] <- bf
          consented_order_area_OTESPA[((a-1)*length(buffer)*length(
consented_OWFs))+((b-1)*length(buffer))+c,2] <- ip
          consented_order_area_OTESPA[((a-1)*length(buffer)*length(
consented_OWFs))+((b-1)*length(buffer))+c,3] <- fb
          consented_order_area_OTESPA[((a-1)*length(buffer)*length(
consented_OWFs))+((b-1)*length(buffer))+c,4] <- area(OWF_", fb, "km
_ring_consented_order_", ip, "_displ_", bf, "_erased_OTESPA)/100000
0"))))
      c<-c+1
    }
    b<-b+1
  }
  a<-a+1
}
```

```
#Save
setwd("Y:/Marine Species/Rebecca Hall/Laptop files/PhD work/Future
cumulative displ/Results tables")
write.csv(consented_order_area_OTESPA,"Consented_order_area_OTESPA_
OneNorth_first.csv")
```

Crop density to OWFs & rings

```
#Crop density
for(fb in buffer){
  for (ip in consented_OWFs) {
    for (bf in buffer) {
      try(eval(parse(text = paste0("RTD_density_Outer_Thames_Estuar
y_SPA_OWF_", bf, "km_ring_consented_order_", ip, "_displ_", fb, "_e
rased <-raster::intersect(RTD_density_Outer_Thames_Estuary_SPA, OWF
_", bf, "km_ring_consented_order_", ip, "_displ_", fb, "_erased)"))
))
    }
  }
}
```

Displace birds

```
#Displace birds using displacement gradient
for (ip in consented_OWFs) {
  for (fb in buffer){
    for(bf in buffer){
      eval(parse(text = paste0("if(exists('RTD_density_Outer_Thames
_Estuary_SPA_OWF_", bf, "km_ring_consented_order_", ip, "_displ_",
fb, "_erased')){if(!is.null(RTD_density_Outer_Thames_Estuary_SPA_OW
F_", bf, "km_ring_consented_order_", ip, "_displ_", fb, "_erased)){
RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_consented_
order_", ip, "_displ_", fb, "_erased@data$RH_D_MaxDispl",fb," <- as
.numeric(sapply((1-(Displ_together[(fb*17)+(bf+1),Displ_grad])/100)
,'*',RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_conse
nted_order_", ip, "_displ_", fb, "_erased@data$RH_D))}}")))
    }
  }
}
```

Calculate numbers of birds displaced and mortality and as proportion of SPA

```
#No. birds in SPA
RTD_density_Outer_Thames_Estuary_SPA_sum <- sum((area(RTD_density_O
uter_Thames_Estuary_SPA)/1000000)*RTD_density_Outer_Thames_Estuary_
SPA@data$RH_D)
for (ip in consented_OWFs) {
  for (fb in buffer){
    for(bf in 0:fb){
      try(eval(parse(text = paste0("
          RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_
consented_order_", ip, "_displ_", fb, "_erased_sum <- sum((area(RTD
_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_consented_ord
er_", ip, "_displ_", fb, "_erased)/1000000)*RTD_density_Outer_Thame
```

```
s_Estuary_SPA_OWF_", bf, "km_ring_consented_order_", ip, "_displ_",
fb, "_erased@data$RH_D)
          RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_
consented_order_", ip, "_displ_", fb, "_erased_sum_", fb, " <-sum((
area(RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_conse
nted_order_", ip, "_displ_", fb, "_erased)/1000000)*RTD_density_Out
er_Thames_Estuary_SPA_OWF_", bf, "km_ring_consented_order_", ip, "_
displ_", fb, "_erased@data$RH_D_MaxDispl", fb, ")
          RTD_percloss_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring
_consented_order_", ip, "_displ_", fb, "_erased <- ((RTD_density_Ou
ter_Thames_Estuary_SPA_OWF_", bf, "km_ring_consented_order_", ip, "
_displ_", fb, "_erased_sum - RTD_density_Outer_Thames_Estuary_SPA_O
WF_", bf, "km_ring_consented_order_", ip, "_displ_", fb, "_erased_s
um_", fb, ")/RTD_density_Outer_Thames_Estuary_SPA_sum)*100"))))
    }
  }
}
#Calculate numbers of bird casualties and as proportion of SPA
Mortality_rate <- 1:10
#Put into table
for (ip in consented_OWFs) {
  eval(parse(text = paste0("RTD_percloss_Outer_Thames_Estuary_SPA_c
onsented_order_", ip, " <- data.frame(Max_displ_km=NA, Ring=NA, Mor
talityRate=NA, RingArea=NA, NoBirds=NA, NoBirdLoss=NA, SPAPercLoss=
NA, NoBirdMortality=NA, SPAPercMortality=NA)")))
  a<-1
  for (fb in buffer) {
    b<-1
    for (bf in 0:fb) {
      c<-1
      for (mt in Mortality_rate) {
        eval(parse(text = paste0("try(if(!is.null(RTD_density_Outer
_Thames_Estuary_SPA_OWF_", bf, "km_ring_consented_order_", ip, "_di
spl_", fb, "_erased)){
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_order_",
ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length(M
ortality_rate))+c,1] <- fb
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_order_",
ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length(M
ortality_rate))+c,2] <- bf
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_order_",
ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length(M
ortality_rate))+c,3] <- mt
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_order_",
ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length(M
ortality_rate))+c,4] <-sum(area(RTD_density_Outer_Thames_Estuary_SP
A_OWF_", bf, "km_ring_consented_order_", ip, "_displ_", fb, "_erase
d)/1000000)
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_order_",
ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length(M
ortality_rate))+c,5] <-RTD_density_Outer_Thames_Estuary_SPA_OWF_",
bf, "km_ring_consented_order_", ip, "_displ_", fb, "_erased_sum
```

```
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_order_",
ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length(M
ortality_rate))+c,6] <-RTD_density_Outer_Thames_Estuary_SPA_OWF_",
bf, "km_ring_consented_order_", ip, "_displ_", fb, "_erased_sum - R
TD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_consented_o
rder_", ip, "_displ_", fb, "_erased_sum_", fb, "
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_order_",
ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length(M
ortality_rate))+c,7] <-RTD_percloss_Outer_Thames_Estuary_SPA_OWF_",
bf, "km_ring_consented_order_", ip, "_displ_", fb, "_erased
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_order_",
ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length(M
ortality_rate))+c,8] <-(RTD_density_Outer_Thames_Estuary_SPA_OWF_",
bf, "km_ring_consented_order_", ip, "_displ_", fb, "_erased_sum - R
TD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_consented_o
rder_", ip, "_displ_", fb, "_erased_sum_", fb, ")/100*mt
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_order_",
ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length(M
ortality_rate))+c,9] <-(RTD_percloss_Outer_Thames_Estuary_SPA_OWF_"
, bf, "km_ring_consented_order_", ip, "_displ_", fb, "_erased)/100*
mt})")))
        c<-c+1
      }
      b<-b+1
    }
    a<-a+1
  }
}
#Remova NAs
for (ip in consented_OWFs) {
  eval(parse(text = paste0("RTD_percloss_Outer_Thames_Estuary_SPA_c
onsented_order_", ip, "<-na.omit(RTD_percloss_Outer_Thames_Estuary_
SPA_consented_order_", ip, ")")))
}
#Sum % birds for each scenario
for (ip in consented_OWFs) {
  eval(parse(text = paste0("RTD_percloss_total_Outer_Thames_Estuary
_SPA_consented_order_", ip, " <- data.frame(OWF_num=NA, Max_displ_k
m=NA, MortalityRate=NA, NoBirdLoss=NA, SPAPercLoss=NA, NoBirdMortal
ity=NA, SPAPercMortality=NA, Area=NA)")))
  a<-1
  for (fb in buffer) {
    b<-1
    for (mt in Mortality_rate) {
      eval(parse(text = paste0("
        RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order
_", ip, "[((a-1)*length(Mortality_rate))+b,1] <- ip
        RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order
_", ip, "[((a-1)*length(Mortality_rate))+b,2] <- fb
        RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order
_", ip, "[((a-1)*length(Mortality_rate))+b,3] <- mt
        try({RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_
```

```
order_", ip, "[((a-1)*length(Mortality_rate))+b,4] <-sum(subset(RTD
_percloss_Outer_Thames_Estuary_SPA_consented_order_", ip, ", Max_di
spl_km==fb & MortalityRate==mt, select=NoBirdLoss), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order
_", ip, "[((a-1)*length(Mortality_rate))+b,5] <-sum(subset(RTD_perc
loss_Outer_Thames_Estuary_SPA_consented_order_", ip, ", Max_displ_k
m==fb & MortalityRate==mt, select=SPAPercLoss), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order
_", ip, "[((a-1)*length(Mortality_rate))+b,6] <-sum(subset(RTD_perc
loss_Outer_Thames_Estuary_SPA_consented_order_", ip, ", Max_displ_k
m==fb & MortalityRate==mt, select=NoBirdMortality), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order
_", ip, "[((a-1)*length(Mortality_rate))+b,7] <-sum(subset(RTD_perc
loss_Outer_Thames_Estuary_SPA_consented_order_", ip, ", Max_displ_k
m==fb & MortalityRate==mt, select=SPAPercMortality), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order
_", ip, "[((a-1)*length(Mortality_rate))+b,8] <-sum(subset(RTD_perc
loss_Outer_Thames_Estuary_SPA_consented_order_", ip, ", Max_displ_k
m==fb & SPAPercLoss>0, select=RingArea), na.rm=TRUE)}, silent=TRUE)
")))
      b<-b+1
    }
    a<-a+1
  }
}
#Sum all OWFs
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_sum <-
data.frame()
a<-1
for (ip in consented_OWFs) {
  eval(parse(text = paste0("RTD_percloss_total_Outer_Thames_Estuary
_SPA_consented_order_sum <- rbind(RTD_percloss_total_Outer_Thames_E
stuary_SPA_consented_order_sum, RTD_percloss_total_Outer_Thames_Est
uary_SPA_consented_order_", consented_OWFs[a], ")")))
  a<-a+1
}
#Save
setwd("C:/Users/44755/OneDrive - University of Strathclyde/1. Thesi
s/12. Thesis V2")
#If using hundred within displacement gradient, save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_ord
er_sum,"RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order
_OneNorth_first_sum_Hundred_Within.csv")
#If using basic displacement gradient, save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_ord
er_sum,"RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order
_OneNorth_first_sum_Gradient.csv")
```

CONSENTED TWO FIRST Impacted once in order

```
#Pull out consented OWFs by order of construction starting
OWF_consented_order_1 <- OWF.sprepro[OWF.sprepro@data$Name_Prop ==
```

```
"Scroby Sands",]
OWF_consented_order_2 <- OWF.sprepro[OWF.sprepro@data$Name_Prop ==
"Kentish Flats",]
OWF_consented_order_3 <- GunfleetSands.sprepro
OWF_consented_order_4 <- OWF.sprepro[OWF.sprepro@data$Name_Prop ==
"Thanet",]
OWF_consented_order_5 <- OWF.sprepro[OWF.sprepro@data$Name_Prop ==
"Greater Gabbard",]
OWF_consented_order_6 <- OWF.sprepro[OWF.sprepro@data$Name_Prop ==
"London Array",]
OWF_consented_order_7 <- OWF.sprepro[OWF.sprepro@data$Name_Prop ==
"Gunfleet Sands Demo",]
OWF_consented_order_8 <- OWF.sprepro[OWF.sprepro@data$Name_Prop ==
"Kentish Flats Extension",]
OWF_consented_order_9 <- OWF.sprepro[OWF.sprepro@data$Name_Prop ==
"East Anglia ONE",]
OWF_consented_order_10 <- OWF.sprepro[OWF.sprepro@data$Name_Prop ==
"East Anglia TWO",]
OWF_consented_order_11 <- OWF.sprepro[OWF.sprepro@data$Name_Prop ==
"East Anglia ONE NORTH",]
consented_OWFs <- 1:11
```

Make buffers

```
#Make 0km buffers for each OWF (i.e. call the OWF 0km)
for(ip in consented_OWFs){
  eval(parse(text = paste0("OWF_0km_buf_consented_order_", ip," <-
OWF_consented_order_", ip,"")))
}
#Make buffers around each OWF
buffer <- 0:16
for(ip in consented_OWFs){
  for (bf in buffer) {
    eval(parse(text = paste0("OWF_", bf, "km_buf_consented_order_",
ip," <- gBuffer(OWF_consented_order_", ip,", width = bf*1000, byid=
TRUE)")))
  }
}
#When max displ is "fb" (call it displ_"fb" and keep last item "fb"
km buf)
#Erase buffers from one another
for(fb in buffer){
  try(eval(parse(text = paste0("OWF_0km_buf_consented_order_1_displ
_", fb, "_erased <- OWF_0km_buf_consented_order_1if(gContainsProper
ly(OWF_", fb, "km_buf_consented_order_1,OWF_0km_buf_consented_order
_2)==FALSE){OWF_0km_buf_consented_order_2_displ_", fb, "_erased <-
erase(OWF_0km_buf_consented_order_2,OWF_", fb, "km_buf_consented_or
der_1)}"))))
}
for(fb in buffer){
  for (bf in buffer[2:17]) {
    try(eval(parse(text = paste0("OWF_", bf, "km_buf_consented_orde
```

```
r_1_displ_", fb, "_erased <- OWF_", bf, "km_buf_consented_order_1
      if(gContainsProperly(OWF_", fb, "km_buf_consented_order_1,OWF
_", bf, "km_buf_consented_order_2)==FALSE){OWF_", bf, "km_buf_conse
nted_order_2_displ_", fb, "_erased <- erase(OWF_", bf, "km_buf_cons
ented_order_2,OWF_", fb, "km_buf_consented_order_1)}"))))
  }
}
#Do for other buffers
for(fb in buffer){
  for(bf in buffer){
    try(eval(parse(text = paste0("
      #Erase OWF 3
      if(gContainsProperly(OWF_", fb, "km_buf_consented_order_2,OWF
_", bf, "km_buf_consented_order_3)==FALSE){OWF_", bf, "km_buf_conse
nted_order_3_displ_", fb, "_erased_takeaway2 <- erase(OWF_", bf, "k
m_buf_consented_order_3,OWF_", fb, "km_buf_consented_order_2)}
      if(exists('OWF_", bf, "km_buf_consented_order_3_displ_", fb,
"_erased_takeaway2')){OWF_", bf, "km_buf_consented_order_3_displ_",
fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_consented_order_
3_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_consented_orde
r_1)}
      if(exists('OWF_", bf, "km_buf_consented_order_3_displ_", fb,
"_erased_takeaway1')){OWF_", bf, "km_buf_consented_order_3_displ_",
fb, "_erased <- OWF_", bf, "km_buf_consented_order_3_displ_", fb, "
_erased_takeaway1}
      #Erase OWF 4
      if(gContainsProperly(OWF_", fb, "km_buf_consented_order_3,OWF
_", bf, "km_buf_consented_order_4)==FALSE){OWF_", bf, "km_buf_conse
nted_order_4_displ_", fb, "_erased_takeaway3 <- erase(OWF_", bf, "k
m_buf_consented_order_4,OWF_", fb, "km_buf_consented_order_3)}
      if(exists('OWF_", bf, "km_buf_consented_order_4_displ_", fb,
"_erased_takeaway3')){OWF_", bf, "km_buf_consented_order_4_displ_",
fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_consented_order_
4_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_consented_orde
r_2)}
      if(exists('OWF_", bf, "km_buf_consented_order_4_displ_", fb,
"_erased_takeaway2')){OWF_", bf, "km_buf_consented_order_4_displ_",
fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_consented_order_
4_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_consented_orde
r_1)}
      if(exists('OWF_", bf, "km_buf_consented_order_4_displ_", fb,
"_erased_takeaway1')){OWF_", bf, "km_buf_consented_order_4_displ_",
fb, "_erased <- OWF_", bf, "km_buf_consented_order_4_displ_", fb, "
_erased_takeaway1}
      #Erase OWF 5
      if(gContainsProperly(OWF_", fb, "km_buf_consented_order_4,OWF
_", bf, "km_buf_consented_order_5)==FALSE){OWF_", bf, "km_buf_conse
nted_order_5_displ_", fb, "_erased_takeaway4 <- erase(OWF_", bf, "k
m_buf_consented_order_5,OWF_", fb, "km_buf_consented_order_4)}
      if(exists('OWF_", bf, "km_buf_consented_order_5_displ_", fb,
"_erased_takeaway4')){OWF_", bf, "km_buf_consented_order_5_displ_",
fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_consented_order_
```

```
5_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_consented_orde
r_3))}
      if(exists('OWF_", bf, "km_buf_consented_order_5_displ_", fb,
"_erased_takeaway3')){OWF_", bf, "km_buf_consented_order_5_displ_",
fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_consented_order_
5_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_consented_orde
r_2)}
      if(exists('OWF_", bf, "km_buf_consented_order_5_displ_", fb,
"_erased_takeaway2')){OWF_", bf, "km_buf_consented_order_5_displ_",
fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_consented_order_
5_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_consented_orde
r_1)}
      if(exists('OWF_", bf, "km_buf_consented_order_5_displ_", fb,
"_erased_takeaway1')){OWF_", bf, "km_buf_consented_order_5_displ_",
fb, "_erased <- OWF_", bf, "km_buf_consented_order_5_displ_", fb, "
_erased_takeaway1}
      #Erase OWF 6
      if(gContainsProperly(OWF_", fb, "km_buf_consented_order_5,OWF
_", bf, "km_buf_consented_order_6)==FALSE){OWF_", bf, "km_buf_conse
nted_order_6_displ_", fb, "_erased_takeaway5 <- erase(OWF_", bf, "k
m_buf_consented_order_6,OWF_", fb, "km_buf_consented_order_5)}
      if(exists('OWF_", bf, "km_buf_consented_order_6_displ_", fb,
"_erased_takeaway5')){OWF_", bf, "km_buf_consented_order_6_displ_",
fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_consented_order_
6_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_consented_orde
r_4)}
      if(exists('OWF_", bf, "km_buf_consented_order_6_displ_", fb,
"_erased_takeaway4')){OWF_", bf, "km_buf_consented_order_6_displ_",
fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_consented_order_
6_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_consented_orde
r_3)}
      if(exists('OWF_", bf, "km_buf_consented_order_6_displ_", fb,
"_erased_takeaway3')){OWF_", bf, "km_buf_consented_order_6_displ_",
fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_consented_order_
6_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_consented_orde
r_2)}
      if(exists('OWF_", bf, "km_buf_consented_order_6_displ_", fb,
"_erased_takeaway2')){OWF_", bf, "km_buf_consented_order_6_displ_",
fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_consented_order_
6_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_consented_orde
r_1)}
      if(exists('OWF_", bf, "km_buf_consented_order_6_displ_", fb,
"_erased_takeaway1')){OWF_", bf, "km_buf_consented_order_6_displ_",
fb, "_erased <- OWF_", bf, "km_buf_consented_order_6_displ_", fb, "
_erased_takeaway1}
      #Erase OWF 7
      if(gContainsProperly(OWF_", fb, "km_buf_consented_order_6,OWF
_", bf, "km_buf_consented_order_7)==FALSE){OWF_", bf, "km_buf_conse
nted_order_7_displ_", fb, "_erased_takeaway6 <- erase(OWF_", bf, "k
m_buf_consented_order_7,OWF_", fb, "km_buf_consented_order_6)}
      if(exists('OWF_", bf, "km_buf_consented_order_7_displ_", fb,
"_erased_takeaway6')){OWF_", bf, "km_buf_consented_order_7_displ_",
```

```
fb, "_erased_takeaway5 <- erase(OWF_", bf, "km_buf_consented_order_
7_displ_", fb, "_erased_takeaway6,OWF_", fb, "km_buf_consented_orde
r_5))}
      if(exists('OWF_", bf, "km_buf_consented_order_7_displ_", fb,
"_erased_takeaway5')){OWF_", bf, "km_buf_consented_order_7_displ_",
fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_consented_order_
7_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_consented_orde
r_4))}
      if(exists('OWF_", bf, "km_buf_consented_order_7_displ_", fb,
"_erased_takeaway4')){OWF_", bf, "km_buf_consented_order_7_displ_",
fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_consented_order_
7_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_consented_orde
r_3))}
      if(exists('OWF_", bf, "km_buf_consented_order_7_displ_", fb,
"_erased_takeaway3')){OWF_", bf, "km_buf_consented_order_7_displ_",
fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_consented_order_
7_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_consented_orde
r_2))}
      if(exists('OWF_", bf, "km_buf_consented_order_7_displ_", fb,
"_erased_takeaway2')){OWF_", bf, "km_buf_consented_order_7_displ_",
fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_consented_order_
7_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_consented_orde
r_1))}
      if(exists('OWF_", bf, "km_buf_consented_order_7_displ_", fb,
"_erased_takeaway1')){OWF_", bf, "km_buf_consented_order_7_displ_",
fb, "_erased <- OWF_", bf, "km_buf_consented_order_7_displ_", fb, "
_erased_takeaway1}
      #Erase OWF 8
      if(gContainsProperly(OWF_", fb, "km_buf_consented_order_7,OWF
_", bf, "km_buf_consented_order_8)==FALSE){OWF_", bf, "km_buf_conse
nted_order_8_displ_", fb, "_erased_takeaway7 <- erase(OWF_", bf, "k
m_buf_consented_order_8,OWF_", fb, "km_buf_consented_order_7)}
      if(exists('OWF_", bf, "km_buf_consented_order_8_displ_", fb,
"_erased_takeaway7')){OWF_", bf, "km_buf_consented_order_8_displ_",
fb, "_erased_takeaway6 <- erase(OWF_", bf, "km_buf_consented_order_
8_displ_", fb, "_erased_takeaway7,OWF_", fb, "km_buf_consented_orde
r_6))}
      if(exists('OWF_", bf, "km_buf_consented_order_8_displ_", fb,
"_erased_takeaway6')){OWF_", bf, "km_buf_consented_order_8_displ_",
fb, "_erased_takeaway5 <- erase(OWF_", bf, "km_buf_consented_order_
8_displ_", fb, "_erased_takeaway6,OWF_", fb, "km_buf_consented_orde
r_5))}
      if(exists('OWF_", bf, "km_buf_consented_order_8_displ_", fb,
"_erased_takeaway5')){OWF_", bf, "km_buf_consented_order_8_displ_",
fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_consented_order_
8_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_consented_orde
r_4))}
      if(exists('OWF_", bf, "km_buf_consented_order_8_displ_", fb,
"_erased_takeaway4')){OWF_", bf, "km_buf_consented_order_8_displ_",
fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_consented_order_
8_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_consented_orde
r_3))}
```

```
      if(exists('OWF_", bf, "km_buf_consented_order_8_displ_", fb,
"_erased_takeaway3')){OWF_", bf, "km_buf_consented_order_8_displ_",
fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_consented_order_
8_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_consented_orde
r_2)}
      if(exists('OWF_", bf, "km_buf_consented_order_8_displ_", fb,
"_erased_takeaway2')){OWF_", bf, "km_buf_consented_order_8_displ_",
fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_consented_order_
8_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_consented_orde
r_1)}
      if(exists('OWF_", bf, "km_buf_consented_order_8_displ_", fb,
"_erased_takeaway1')){OWF_", bf, "km_buf_consented_order_8_displ_",
fb, "_erased <- OWF_", bf, "km_buf_consented_order_8_displ_", fb, "
_erased_takeaway1}
      #Erase OWF 9
      if(gContainsProperly(OWF_", fb, "km_buf_consented_order_8,OWF
_", bf, "km_buf_consented_order_9)==FALSE){OWF_", bf, "km_buf_conse
nted_order_9_displ_", fb, "_erased_takeaway8 <- erase(OWF_", bf, "k
m_buf_consented_order_9,OWF_", fb, "km_buf_consented_order_8)}
      if(exists('OWF_", bf, "km_buf_consented_order_9_displ_", fb,
"_erased_takeaway8')){OWF_", bf, "km_buf_consented_order_9_displ_",
fb, "_erased_takeaway7 <- erase(OWF_", bf, "km_buf_consented_order_
9_displ_", fb, "_erased_takeaway8,OWF_", fb, "km_buf_consented_orde
r_7)}
      if(exists('OWF_", bf, "km_buf_consented_order_9_displ_", fb,
"_erased_takeaway7')){OWF_", bf, "km_buf_consented_order_9_displ_",
fb, "_erased_takeaway6 <- erase(OWF_", bf, "km_buf_consented_order_
9_displ_", fb, "_erased_takeaway7,OWF_", fb, "km_buf_consented_orde
r_6)}
      if(exists('OWF_", bf, "km_buf_consented_order_9_displ_", fb,
"_erased_takeaway6')){OWF_", bf, "km_buf_consented_order_9_displ_",
fb, "_erased_takeaway5 <- erase(OWF_", bf, "km_buf_consented_order_
9_displ_", fb, "_erased_takeaway6,OWF_", fb, "km_buf_consented_orde
r_5)}
      if(exists('OWF_", bf, "km_buf_consented_order_9_displ_", fb,
"_erased_takeaway5')){OWF_", bf, "km_buf_consented_order_9_displ_",
fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_consented_order_
9_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_consented_orde
r_4)}
      if(exists('OWF_", bf, "km_buf_consented_order_9_displ_", fb,
"_erased_takeaway4')){OWF_", bf, "km_buf_consented_order_9_displ_",
fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_consented_order_
9_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_consented_orde
r_3)}
      if(exists('OWF_", bf, "km_buf_consented_order_9_displ_", fb,
"_erased_takeaway3')){OWF_", bf, "km_buf_consented_order_9_displ_",
fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_consented_order_
9_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_consented_orde
r_2)}
      if(exists('OWF_", bf, "km_buf_consented_order_9_displ_", fb,
"_erased_takeaway2')){OWF_", bf, "km_buf_consented_order_9_displ_",
fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_consented_order_
```

```
9_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_consented_orde
r_1))}
      if(exists('OWF_", bf, "km_buf_consented_order_9_displ_", fb,
"_erased_takeaway1')){OWF_", bf, "km_buf_consented_order_9_displ_",
fb, "_erased <- OWF_", bf, "km_buf_consented_order_9_displ_", fb, "
_erased_takeaway1}
      #Erase OWF 10
      if(gContainsProperly(OWF_", fb, "km_buf_consented_order_9,OWF
_", bf, "km_buf_consented_order_10)==FALSE){OWF_", bf, "km_buf_cons
ented_order_10_displ_", fb, "_erased_takeaway9 <- erase(OWF_", bf,
"km_buf_consented_order_10,OWF_", fb, "km_buf_consented_order_9)}
      if(exists('OWF_", bf, "km_buf_consented_order_10_displ_", fb,
"_erased_takeaway9')){OWF_", bf, "km_buf_consented_order_10_displ_"
, fb, "_erased_takeaway8 <- erase(OWF_", bf, "km_buf_consented_orde
r_10_displ_", fb, "_erased_takeaway9,OWF_", fb, "km_buf_consented_o
rder_8)}
      if(exists('OWF_", bf, "km_buf_consented_order_10_displ_", fb,
"_erased_takeaway8')){OWF_", bf, "km_buf_consented_order_10_displ_"
, fb, "_erased_takeaway7 <- erase(OWF_", bf, "km_buf_consented_orde
r_10_displ_", fb, "_erased_takeaway8,OWF_", fb, "km_buf_consented_o
rder_7)}
      if(exists('OWF_", bf, "km_buf_consented_order_10_displ_", fb,
"_erased_takeaway7')){OWF_", bf, "km_buf_consented_order_10_displ_"
, fb, "_erased_takeaway6 <- erase(OWF_", bf, "km_buf_consented_orde
r_10_displ_", fb, "_erased_takeaway7,OWF_", fb, "km_buf_consented_o
rder_6)}
      if(exists('OWF_", bf, "km_buf_consented_order_10_displ_", fb,
"_erased_takeaway6')){OWF_", bf, "km_buf_consented_order_10_displ_"
, fb, "_erased_takeaway5 <- erase(OWF_", bf, "km_buf_consented_orde
r_10_displ_", fb, "_erased_takeaway6,OWF_", fb, "km_buf_consented_o
rder_5)}
      if(exists('OWF_", bf, "km_buf_consented_order_10_displ_", fb,
"_erased_takeaway5')){OWF_", bf, "km_buf_consented_order_10_displ_"
, fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_consented_orde
r_10_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_consented_o
rder_4)}
      if(exists('OWF_", bf, "km_buf_consented_order_10_displ_", fb,
"_erased_takeaway4')){OWF_", bf, "km_buf_consented_order_10_displ_"
, fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_consented_orde
r_10_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_consented_o
rder_3)}
      if(exists('OWF_", bf, "km_buf_consented_order_10_displ_", fb,
"_erased_takeaway3')){OWF_", bf, "km_buf_consented_order_10_displ_"
, fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_consented_orde
r_10_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_consented_o
rder_2)}
      if(exists('OWF_", bf, "km_buf_consented_order_10_displ_", fb,
"_erased_takeaway2')){OWF_", bf, "km_buf_consented_order_10_displ_"
, fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_consented_orde
r_10_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_consented_o
rder_1)}
      if(exists('OWF_", bf, "km_buf_consented_order_10_displ_", fb,
```

```
"_erased_takeaway1')){OWF_", bf, "km_buf_consented_order_10_displ_"
, fb, "_erased <- OWF_", bf, "km_buf_consented_order_10_displ_", fb
, "_erased_takeaway1}
      #Erase OWF 11
      if(gContainsProperly(OWF_", fb, "km_buf_consented_order_10,OW
F_", bf, "km_buf_consented_order_11)==FALSE){OWF_", bf, "km_buf_con
sented_order_11_displ_", fb, "_erased_takeaway10 <- erase(OWF_", bf
, "km_buf_consented_order_11,OWF_", fb, "km_buf_consented_order_10)
}
      if(exists('OWF_", bf, "km_buf_consented_order_11_displ_", fb,
"_erased_takeaway10')){OWF_", bf, "km_buf_consented_order_11_displ_
", fb, "_erased_takeaway9 <- erase(OWF_", bf, "km_buf_consented_ord
er_11_displ_", fb, "_erased_takeaway10,OWF_", fb, "km_buf_consented
_order_9)}
      if(exists('OWF_", bf, "km_buf_consented_order_11_displ_", fb,
"_erased_takeaway9')){OWF_", bf, "km_buf_consented_order_11_displ_"
, fb, "_erased_takeaway8 <- erase(OWF_", bf, "km_buf_consented_orde
r_11_displ_", fb, "_erased_takeaway9,OWF_", fb, "km_buf_consented_o
rder_8)}
      if(exists('OWF_", bf, "km_buf_consented_order_11_displ_", fb,
"_erased_takeaway8')){OWF_", bf, "km_buf_consented_order_11_displ_"
, fb, "_erased_takeaway7 <- erase(OWF_", bf, "km_buf_consented_orde
r_11_displ_", fb, "_erased_takeaway8,OWF_", fb, "km_buf_consented_o
rder_7)}
      if(exists('OWF_", bf, "km_buf_consented_order_11_displ_", fb,
"_erased_takeaway7')){OWF_", bf, "km_buf_consented_order_11_displ_"
, fb, "_erased_takeaway6 <- erase(OWF_", bf, "km_buf_consented_orde
r_11_displ_", fb, "_erased_takeaway7,OWF_", fb, "km_buf_consented_o
rder_6)}
      if(exists('OWF_", bf, "km_buf_consented_order_11_displ_", fb,
"_erased_takeaway6')){OWF_", bf, "km_buf_consented_order_11_displ_"
, fb, "_erased_takeaway5 <- erase(OWF_", bf, "km_buf_consented_orde
r_11_displ_", fb, "_erased_takeaway6,OWF_", fb, "km_buf_consented_o
rder_5)}
      if(exists('OWF_", bf, "km_buf_consented_order_11_displ_", fb,
"_erased_takeaway5')){OWF_", bf, "km_buf_consented_order_11_displ_"
, fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_consented_orde
r_11_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_consented_o
rder_4)}
      if(exists('OWF_", bf, "km_buf_consented_order_11_displ_", fb,
"_erased_takeaway4')){OWF_", bf, "km_buf_consented_order_11_displ_"
, fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_consented_orde
r_11_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_consented_o
rder_3)}
      if(exists('OWF_", bf, "km_buf_consented_order_11_displ_", fb,
"_erased_takeaway3')){OWF_", bf, "km_buf_consented_order_11_displ_"
, fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_consented_orde
r_11_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_consented_o
rder_2)}
      if(exists('OWF_", bf, "km_buf_consented_order_11_displ_", fb,
"_erased_takeaway2')){OWF_", bf, "km_buf_consented_order_11_displ_"
, fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_consented_orde
```

```
r_11_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_consented_o
rder_1)}
      if(exists('OWF_", bf, "km_buf_consented_order_11_displ_", fb,
"_erased_takeaway1')){OWF_", bf, "km_buf_consented_order_11_displ_"
, fb, "_erased <- OWF_", bf, "km_buf_consented_order_11_displ_", fb
, "_erased_takeaway1}"))))
  }
}
```

Make rings

```
#Create rings from buffers
for(fb in buffer){
  for(ip in consented_OWFs){
    try(eval(parse(text = paste0("
      OWF_0km_ring_consented_order_", ip, "_displ_", fb, "_erased <
- OWF_0km_buf_consented_order_", ip, "_displ_", fb, "_erased
      OWF_1km_ring_consented_order_", ip, "_displ_", fb, "_erased <
- erase(OWF_1km_buf_consented_order_", ip, "_displ_", fb, "_erased,
OWF_0km_buf_consented_order_", ip, "_displ_", fb, "_erased)"))))
    for (bf in buffer[3:17]) {
      try(eval(parse(text = paste0("OWF_", bf, "km_ring_consented_o
rder_", ip, "_displ_", fb, "_erased <- erase(OWF_", bf, "km_buf_con
sented_order_", ip, "_displ_", fb, "_erased, OWF_", bf -1, "km_buf_
consented_order_", ip, "_displ_", fb, "_erased)"))))
    }
  }
}
```

Calculate area of rings

```
#Calculate area
consented_order_area <- data.frame(OWF=NA, Ring=NA, Area=NA)
a<-1
for(ip in consented_OWFs){
  b<-1
  for(fb in buffer){
    try(eval(parse(text = paste0("
        consented_order_area[((a-1)*length(buffer))+b,1] <- ip
        consented_order_area[((a-1)*length(buffer))+b,2] <- fb
        consented_order_area[((a-1)*length(buffer))+b,3] <- area(OW
F_", fb, "km_ring_consented_order_", ip, "_displ_16_erased)/1000000
"))))
    b<-b+1
  }
  a<-a+1
}
#Save
setwd("Y:/Marine Species/Rebecca Hall/Laptop files/PhD work/Future
cumulative displ/Results tables")
write.csv(consented_order_area,"consented_order_area.csv")
#Crop to SPA
for(ip in consented_OWFs){
```

```
  for(bf in buffer){
    for(fb in buffer){
      try(eval(parse(text = paste0("OWF_", fb, "km_ring_consented_order_", ip, "_displ_", bf, "_erased_OTESPA <- raster::intersect(Outer_Thames_Estuary_SPA, OWF_", fb, "km_ring_consented_order_", ip, "_displ_", bf, "_erased)"))))
    }
  }
}
#Table
consented_order_area_OTESPA <- data.frame(MaxDispl=NA, OWF=NA, Ring=NA, Area=NA)
a<-1
for(bf in buffer){
  b<-1
  for(ip in consented_OWFs){
    c<-1
    for(fb in buffer){
      try(eval(parse(text = paste0("
          consented_order_area_OTESPA[((a-1)*length(buffer)*length(consented_OWFs))+((b-1)*length(buffer))+c,1] <- bf
          consented_order_area_OTESPA[((a-1)*length(buffer)*length(consented_OWFs))+((b-1)*length(buffer))+c,2] <- ip
          consented_order_area_OTESPA[((a-1)*length(buffer)*length(consented_OWFs))+((b-1)*length(buffer))+c,3] <- fb
          consented_order_area_OTESPA[((a-1)*length(buffer)*length(consented_OWFs))+((b-1)*length(buffer))+c,4] <- area(OWF_", fb, "km_ring_consented_order_", ip, "_displ_", bf, "_erased_OTESPA)/1000000"))))
      c<-c+1
    }
    b<-b+1
  }
  a<-a+1
}
#Save
setwd("Y:/Marine Species/Rebecca Hall/Laptop files/PhD work/Future cumulative displ/Results tables")
write.csv(consented_order_area_OTESPA,"Consented_order_area_OTESPA_Two_first.csv")
```

Crop density to OWFs & rings

```
#Crop density
for(fb in buffer){
  for (ip in consented_OWFs) {
    for (bf in buffer) {
      try(eval(parse(text = paste0("RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_consented_order_", ip, "_displ_", fb, "_erased <-raster::intersect(RTD_density_Outer_Thames_Estuary_SPA, OWF_", bf, "km_ring_consented_order_", ip, "_displ_", fb, "_erased)"))))
```

```
    }
  }
}
```

Displace birds

```
#Displace birds using displacement gradient
for (ip in consented_OWFs) {
  for (fb in buffer){
    for(bf in buffer){eval(parse(text = paste0("if(exists('RTD_dens
ity_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_consented_order_",
ip, "_displ_", fb, "_erased')){if(!is.null(RTD_density_Outer_Thames
_Estuary_SPA_OWF_", bf, "km_ring_consented_order_", ip, "_displ_",
fb, "_erased)){RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_
ring_consented_order_", ip, "_displ_", fb, "_erased@data$RH_D_MaxDi
spl",fb," <- as.numeric(sapply((1-(Displ_together[(fb*17)+(bf+1),Di
spl_grad])/100),'*',RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf,
"km_ring_consented_order_", ip, "_displ_", fb, "_erased@data$RH_D))
}}")))
    }
  }
}
```

Calculate numbers of birds displaced and mortality and as proportion of SPA

```
#No. birds in SPA
RTD_density_Outer_Thames_Estuary_SPA_sum <- sum((area(RTD_density_O
uter_Thames_Estuary_SPA)/1000000)*RTD_density_Outer_Thames_Estuary_
SPA@data$RH_D)
for (ip in consented_OWFs) {
  for (fb in buffer){
    for(bf in 0:fb){
      try(eval(parse(text = paste0("
          RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_
consented_order_", ip, "_displ_", fb, "_erased_sum <- sum((area(RTD
_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_consented_ord
er_", ip, "_displ_", fb, "_erased)/1000000)*RTD_density_Outer_Thame
s_Estuary_SPA_OWF_", bf, "km_ring_consented_order_", ip, "_displ_",
fb, "_erased@data$RH_D)
          RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_
consented_order_", ip, "_displ_", fb, "_erased_sum_", fb, " <-sum((
area(RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_conse
nted_order_", ip, "_displ_", fb, "_erased)/1000000)*RTD_density_Out
er_Thames_Estuary_SPA_OWF_", bf, "km_ring_consented_order_", ip, "_
displ_", fb, "_erased@data$RH_D_MaxDispl", fb, ")
          RTD_percloss_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring
_consented_order_", ip, "_displ_", fb, "_erased <- ((RTD_density_Ou
ter_Thames_Estuary_SPA_OWF_", bf, "km_ring_consented_order_", ip, "
_displ_", fb, "_erased_sum - RTD_density_Outer_Thames_Estuary_SPA_O
WF_", bf, "km_ring_consented_order_", ip, "_displ_", fb, "_erased_s
um_", fb, ")/RTD_density_Outer_Thames_Estuary_SPA_sum)*100"))))
    }
  }
```

```
}
#Calculate numbers of bird casualties and as proportion of SPA
Mortality_rate <- 1:10
#Put into table
for (ip in consented_OWFs) {
  eval(parse(text = paste0("RTD_percloss_Outer_Thames_Estuary_SPA_c
onsented_order_", ip, " <- data.frame(Max_displ_km=NA, Ring=NA, Mor
talityRate=NA, RingArea=NA, NoBirds=NA, NoBirdLoss=NA, SPAPercLoss=
NA, NoBirdMortality=NA, SPAPercMortality=NA)")))
  a<-1
  for (fb in buffer) {
    b<-1
    for (bf in 0:fb) {
      c<-1
      for (mt in Mortality_rate) {
        eval(parse(text = paste0("try(if(!is.null(RTD_density_Outer
_Thames_Estuary_SPA_OWF_", bf, "km_ring_consented_order_", ip, "_di
spl_", fb, "_erased)){
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_order_",
ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length(M
ortality_rate))+c,1] <- fb
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_order_",
ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length(M
ortality_rate))+c,2] <- bf
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_order_",
ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length(M
ortality_rate))+c,3] <- mt
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_order_",
ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length(M
ortality_rate))+c,4] <-sum(area(RTD_density_Outer_Thames_Estuary_SP
A_OWF_", bf, "km_ring_consented_order_", ip, "_displ_", fb, "_erase
d)/1000000)
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_order_",
ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length(M
ortality_rate))+c,5] <-RTD_density_Outer_Thames_Estuary_SPA_OWF_",
bf, "km_ring_consented_order_", ip, "_displ_", fb, "_erased_sum
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_order_",
ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length(M
ortality_rate))+c,6] <-RTD_density_Outer_Thames_Estuary_SPA_OWF_",
bf, "km_ring_consented_order_", ip, "_displ_", fb, "_erased_sum - R
TD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_consented_o
rder_", ip, "_displ_", fb, "_erased_sum_", fb, "
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_order_",
ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length(M
ortality_rate))+c,7] <-RTD_percloss_Outer_Thames_Estuary_SPA_OWF_",
bf, "km_ring_consented_order_", ip, "_displ_", fb, "_erased
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_order_",
ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length(M
ortality_rate))+c,8] <-(RTD_density_Outer_Thames_Estuary_SPA_OWF_",
bf, "km_ring_consented_order_", ip, "_displ_", fb, "_erased_sum - R
TD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_consented_o
rder_", ip, "_displ_", fb, "_erased_sum_", fb, ")/100*mt
```

```
          RTD_percloss_Outer_Thames_Estuary_SPA_consented_order_",
ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length(M
ortality_rate))+c,9] <-(RTD_percloss_Outer_Thames_Estuary_SPA_OWF_"
, bf, "km_ring_consented_order_", ip, "_displ_", fb, "_erased)/100*
mt})")))
        c<-c+1
      }
      b<-b+1
    }
    a<-a+1
  }
}
#Remova NAs
for (ip in consented_OWFs) {
  eval(parse(text = paste0("RTD_percloss_Outer_Thames_Estuary_SPA_c
onsented_order_", ip, "<-na.omit(RTD_percloss_Outer_Thames_Estuary_
SPA_consented_order_", ip, ")")))
}
#Sum % birds for each scenario
for (ip in consented_OWFs) {
  eval(parse(text = paste0("RTD_percloss_total_Outer_Thames_Estuary
_SPA_consented_order_", ip, " <- data.frame(OWF_num=NA, Max_displ_k
m=NA, MortalityRate=NA, NoBirdLoss=NA, SPAPercLoss=NA, NoBirdMortal
ity=NA, SPAPercMortality=NA, Area=NA)")))
  a<-1
  for (fb in buffer) {
    b<-1
    for (mt in Mortality_rate) {
      eval(parse(text = paste0("
        RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order
_", ip, "[((a-1)*length(Mortality_rate))+b,1] <- ip
        RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order
_", ip, "[((a-1)*length(Mortality_rate))+b,2] <- fb
        RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order
_", ip, "[((a-1)*length(Mortality_rate))+b,3] <- mt
        try({RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_
order_", ip, "[((a-1)*length(Mortality_rate))+b,4] <-sum(subset(RTD
_percloss_Outer_Thames_Estuary_SPA_consented_order_", ip, ", Max_di
spl_km==fb & MortalityRate==mt, select=NoBirdLoss), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order
_", ip, "[((a-1)*length(Mortality_rate))+b,5] <-sum(subset(RTD_perc
loss_Outer_Thames_Estuary_SPA_consented_order_", ip, ", Max_displ_k
m==fb & MortalityRate==mt, select=SPAPercLoss), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order
_", ip, "[((a-1)*length(Mortality_rate))+b,6] <-sum(subset(RTD_perc
loss_Outer_Thames_Estuary_SPA_consented_order_", ip, ", Max_displ_k
m==fb & MortalityRate==mt, select=NoBirdMortality), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order
_", ip, "[((a-1)*length(Mortality_rate))+b,7] <-sum(subset(RTD_perc
loss_Outer_Thames_Estuary_SPA_consented_order_", ip, ", Max_displ_k
m==fb & MortalityRate==mt, select=SPAPercMortality), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order
```

```
_", ip, "[((a-1)*length(Mortality_rate))+b,8] <-sum(subset(RTD_perc
loss_Outer_Thames_Estuary_SPA_consented_order_", ip, ", Max_displ_k
m==fb & SPAPercLoss>0, select=RingArea), na.rm=TRUE)}, silent=TRUE)
")))
      b<-b+1
    }
    a<-a+1
  }
}
#Sum all OWFs
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_sum <-
data.frame()
a<-1
for (ip in consented_OWFs) {
  eval(parse(text = paste0("RTD_percloss_total_Outer_Thames_Estuary
_SPA_consented_order_sum <- rbind(RTD_percloss_total_Outer_Thames_E
stuary_SPA_consented_order_sum, RTD_percloss_total_Outer_Thames_Est
uary_SPA_consented_order_", consented_OWFs[a], ")")))
  a<-a+1
}
#Save
setwd("C:/Users/44755/OneDrive - University of Strathclyde/1. Thesi
s/12. Thesis V2")
#If using hundred within displacement gradient, save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_ord
er_sum,"RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order
_Two_first_sum_Hundred_Within.csv")
#If using basic displacement gradient, save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_ord
er_sum,"RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order
_Two_first_sum_Gradient.csv")
```

PREPLANNING ONE NORTH FIRST Impacted once in order

```
#Pull out preplanning OWFs by order of construction starting
OWF_preplanning_order_1 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "Scroby Sands",]
OWF_preplanning_order_2 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "Kentish Flats",]
OWF_preplanning_order_3 <- GunfleetSands.sprepro
OWF_preplanning_order_3 <- aggregate(OWF_preplanning_order_3,dissol
ve=TRUE)
OWF_preplanning_order_4 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "Thanet",]
OWF_preplanning_order_5 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "Greater Gabbard",]
OWF_preplanning_order_6 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "London Array",]
OWF_preplanning_order_7 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "Gunfleet Sands Demo",]
OWF_preplanning_order_8 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "Kentish Flats Extension",]
```

```
OWF_preplanning_order_9 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "East Anglia ONE",]
OWF_preplanning_order_10 <- OWF.sprepro[OWF.sprepro@data$Name_Prop
== "East Anglia ONE NORTH",]
OWF_preplanning_order_11 <- OWF.sprepro[OWF.sprepro@data$Name_Prop
== "East Anglia TWO",]
OWF_preplanning_order_12 <- OWF.sprepro[OWF.sprepro@data$Name_Prop
== "North Falls",]
preplanning_OWFs <- 1:12
```

Make buffers

```
#Make 0km buffers for each OWF (i.e. call the OWF 0km)
for(ip in preplanning_OWFs){
  eval(parse(text = paste0("OWF_0km_buf_preplanning_order_", ip," <
- OWF_preplanning_order_", ip,"")))
}
#Make buffers around each OWF
buffer <- 0:16
for(ip in preplanning_OWFs){
  for (bf in buffer) {
    eval(parse(text = paste0("OWF_", bf, "km_buf_preplanning_order_
", ip," <- gBuffer(OWF_preplanning_order_", ip,", width = bf*1000,
byid=TRUE)")))
  }
}
#When max displ is "fb" (call it displ_"fb" and keep last item "fb"
km buf)
#Erase buffers from one another
for(fb in buffer){
  try(eval(parse(text = paste0("OWF_0km_buf_preplanning_order_1_dis
pl_", fb, "_erased <- OWF_0km_buf_preplanning_order_1if(gContainsPr
operly(OWF_", fb, "km_buf_preplanning_order_1,OWF_0km_buf_preplanni
ng_order_2)==FALSE){OWF_0km_buf_preplanning_order_2_displ_", fb, "_
erased <- erase(OWF_0km_buf_preplanning_order_2,OWF_", fb, "km_buf_
preplanning_order_1)}"))))
}
for(fb in buffer){
  for (bf in buffer[2:17]) {
    try(eval(parse(text = paste0("OWF_", bf, "km_buf_preplanning_or
der_1_displ_", fb, "_erased <- OWF_", bf, "km_buf_preplanning_order
_1if(gContainsProperly(OWF_", fb, "km_buf_preplanning_order_1,OWF_"
, bf, "km_buf_preplanning_order_2)==FALSE){OWF_", bf, "km_buf_prepl
anning_order_2_displ_", fb, "_erased <- erase(OWF_", bf, "km_buf_pr
eplanning_order_2,OWF_", fb, "km_buf_preplanning_order_1)}"))))
  }
}
#Erase 1 to 7
for(fb in buffer){
  for(bf in buffer){
    try(eval(parse(text = paste0("
      #Erase OWF 3
```

```
      if(gContainsProperly(OWF_", fb, "km_buf_preplanning_order_2,O
WF_", bf, "km_buf_preplanning_order_3)==FALSE){OWF_", bf, "km_buf_p
replanning_order_3_displ_", fb, "_erased_takeaway2 <- erase(OWF_",
bf, "km_buf_preplanning_order_3,OWF_", fb, "km_buf_preplanning_orde
r_2)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_3_displ_", fb
, "_erased_takeaway2')){OWF_", bf, "km_buf_preplanning_order_3_disp
l_", fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_preplanning
_order_3_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_preplan
ning_order_1)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_3_displ_", fb
, "_erased_takeaway1')){OWF_", bf, "km_buf_preplanning_order_3_disp
l_", fb, "_erased <- OWF_", bf, "km_buf_preplanning_order_3_displ_"
, fb, "_erased_takeaway1}
      #Erase OWF 4
      if(gContainsProperly(OWF_", fb, "km_buf_preplanning_order_3,O
WF_", bf, "km_buf_preplanning_order_4)==FALSE){OWF_", bf, "km_buf_p
replanning_order_4_displ_", fb, "_erased_takeaway3 <- erase(OWF_",
bf, "km_buf_preplanning_order_4,OWF_", fb, "km_buf_preplanning_orde
r_3)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_4_displ_", fb
, "_erased_takeaway3')){OWF_", bf, "km_buf_preplanning_order_4_disp
l_", fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_preplanning
_order_4_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_preplan
ning_order_2)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_4_displ_", fb
, "_erased_takeaway2')){OWF_", bf, "km_buf_preplanning_order_4_disp
l_", fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_preplanning
_order_4_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_preplan
ning_order_1)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_4_displ_", fb
, "_erased_takeaway1')){OWF_", bf, "km_buf_preplanning_order_4_disp
l_", fb, "_erased <- OWF_", bf, "km_buf_preplanning_order_4_displ_"
, fb, "_erased_takeaway1}
      #Erase OWF 5
      if(gContainsProperly(OWF_", fb, "km_buf_preplanning_order_4,O
WF_", bf, "km_buf_preplanning_order_5)==FALSE){OWF_", bf, "km_buf_p
replanning_order_5_displ_", fb, "_erased_takeaway4 <- erase(OWF_",
bf, "km_buf_preplanning_order_5,OWF_", fb, "km_buf_preplanning_orde
r_4)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_5_displ_", fb
, "_erased_takeaway4')){OWF_", bf, "km_buf_preplanning_order_5_disp
l_", fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_preplanning
_order_5_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_preplan
ning_order_3)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_5_displ_", fb
, "_erased_takeaway3')){OWF_", bf, "km_buf_preplanning_order_5_disp
l_", fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_preplanning
_order_5_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_preplan
ning_order_2)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_5_displ_", fb
, "_erased_takeaway2')){OWF_", bf, "km_buf_preplanning_order_5_disp
```

```
l_", fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_preplanning
_order_5_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_preplan
ning_order_1)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_5_displ_", fb
, "_erased_takeaway1')){OWF_", bf, "km_buf_preplanning_order_5_disp
l_", fb, "_erased <- OWF_", bf, "km_buf_preplanning_order_5_displ_"
, fb, "_erased_takeaway1}
      #Erase OWF 6
      if(gContainsProperly(OWF_", fb, "km_buf_preplanning_order_5,O
WF_", bf, "km_buf_preplanning_order_6)==FALSE){OWF_", bf, "km_buf_p
replanning_order_6_displ_", fb, "_erased_takeaway5 <- erase(OWF_",
bf, "km_buf_preplanning_order_6,OWF_", fb, "km_buf_preplanning_orde
r_5)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_6_displ_", fb
, "_erased_takeaway5')){OWF_", bf, "km_buf_preplanning_order_6_disp
l_", fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_preplanning
_order_6_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_preplan
ning_order_4)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_6_displ_", fb
, "_erased_takeaway4')){OWF_", bf, "km_buf_preplanning_order_6_disp
l_", fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_preplanning
_order_6_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_preplan
ning_order_3)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_6_displ_", fb
, "_erased_takeaway3')){OWF_", bf, "km_buf_preplanning_order_6_disp
l_", fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_preplanning
_order_6_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_preplan
ning_order_2)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_6_displ_", fb
, "_erased_takeaway2')){OWF_", bf, "km_buf_preplanning_order_6_disp
l_", fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_preplanning
_order_6_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_preplan
ning_order_1)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_6_displ_", fb
, "_erased_takeaway1')){OWF_", bf, "km_buf_preplanning_order_6_disp
l_", fb, "_erased <- OWF_", bf, "km_buf_preplanning_order_6_displ_"
, fb, "_erased_takeaway1}
      #Erase OWF 7
      if(gContainsProperly(OWF_", fb, "km_buf_preplanning_order_6,O
WF_", bf, "km_buf_preplanning_order_7)==FALSE){OWF_", bf, "km_buf_p
replanning_order_7_displ_", fb, "_erased_takeaway6 <- erase(OWF_",
bf, "km_buf_preplanning_order_7,OWF_", fb, "km_buf_preplanning_orde
r_6)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_7_displ_", fb
, "_erased_takeaway6')){OWF_", bf, "km_buf_preplanning_order_7_disp
l_", fb, "_erased_takeaway5 <- erase(OWF_", bf, "km_buf_preplanning
_order_7_displ_", fb, "_erased_takeaway6,OWF_", fb, "km_buf_preplan
ning_order_5)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_7_displ_", fb
, "_erased_takeaway5')){OWF_", bf, "km_buf_preplanning_order_7_disp
l_", fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_preplanning
_order_7_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_preplan
```

```
ning_order_4)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_7_displ_", fb
, "_erased_takeaway4')){OWF_", bf, "km_buf_preplanning_order_7_disp
l_", fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_preplanning
_order_7_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_preplan
ning_order_3)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_7_displ_", fb
, "_erased_takeaway3')){OWF_", bf, "km_buf_preplanning_order_7_disp
l_", fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_preplanning
_order_7_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_preplan
ning_order_2)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_7_displ_", fb
, "_erased_takeaway2')){OWF_", bf, "km_buf_preplanning_order_7_disp
l_", fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_preplanning
_order_7_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_preplan
ning_order_1)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_7_displ_", fb
, "_erased_takeaway1')){OWF_", bf, "km_buf_preplanning_order_7_disp
l_", fb, "_erased <- OWF_", bf, "km_buf_preplanning_order_7_displ_"
, fb, "_erased_takeaway1}"))))
  }
}
#Erase 8
for(fb in buffer){
  for(bf in buffer){
    try(eval(parse(text = paste0("
      #Erase OWF 8
      if(gContainsProperly(OWF_", fb, "km_buf_preplanning_order_7,O
WF_", bf, "km_buf_preplanning_order_8)==FALSE){OWF_", bf, "km_buf_p
replanning_order_8_displ_", fb, "_erased_takeaway7 <- erase(OWF_",
bf, "km_buf_preplanning_order_8,OWF_", fb, "km_buf_preplanning_orde
r_7)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_8_displ_", fb
, "_erased_takeaway7')){OWF_", bf, "km_buf_preplanning_order_8_disp
l_", fb, "_erased_takeaway6 <- erase(OWF_", bf, "km_buf_preplanning
_order_8_displ_", fb, "_erased_takeaway7,OWF_", fb, "km_buf_preplan
ning_order_6)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_8_displ_", fb
, "_erased_takeaway6')){OWF_", bf, "km_buf_preplanning_order_8_disp
l_", fb, "_erased_takeaway5 <- erase(OWF_", bf, "km_buf_preplanning
_order_8_displ_", fb, "_erased_takeaway6,OWF_", fb, "km_buf_preplan
ning_order_5)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_8_displ_", fb
, "_erased_takeaway5')){OWF_", bf, "km_buf_preplanning_order_8_disp
l_", fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_preplanning
_order_8_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_preplan
ning_order_4)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_8_displ_", fb
, "_erased_takeaway4')){OWF_", bf, "km_buf_preplanning_order_8_disp
l_", fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_preplanning
_order_8_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_preplan
ning_order_3)}
```

```
      if(exists('OWF_", bf, "km_buf_preplanning_order_8_displ_", fb
, "_erased_takeaway3')){OWF_", bf, "km_buf_preplanning_order_8_disp
l_", fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_preplanning
_order_8_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_preplan
ning_order_2)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_8_displ_", fb
, "_erased_takeaway2')){OWF_", bf, "km_buf_preplanning_order_8_disp
l_", fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_preplanning
_order_8_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_preplan
ning_order_1)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_8_displ_", fb
, "_erased_takeaway1')){OWF_", bf, "km_buf_preplanning_order_8_disp
l_", fb, "_erased <- OWF_", bf, "km_buf_preplanning_order_8_displ_"
, fb, "_erased_takeaway1}"))))
  }
}
#Erase 9
for(fb in buffer){
  for(bf in buffer){
    try(eval(parse(text = paste0("
      #Erase OWF 9
      if(gContainsProperly(OWF_", fb, "km_buf_preplanning_order_8,O
WF_", bf, "km_buf_preplanning_order_9)==FALSE){OWF_", bf, "km_buf_p
replanning_order_9_displ_", fb, "_erased_takeaway8 <- erase(OWF_",
bf, "km_buf_preplanning_order_9,OWF_", fb, "km_buf_preplanning_orde
r_8)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_9_displ_", fb
, "_erased_takeaway8')){OWF_", bf, "km_buf_preplanning_order_9_disp
l_", fb, "_erased_takeaway7 <- erase(OWF_", bf, "km_buf_preplanning
_order_9_displ_", fb, "_erased_takeaway8,OWF_", fb, "km_buf_preplan
ning_order_7)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_9_displ_", fb
, "_erased_takeaway7')){OWF_", bf, "km_buf_preplanning_order_9_disp
l_", fb, "_erased_takeaway6 <- erase(OWF_", bf, "km_buf_preplanning
_order_9_displ_", fb, "_erased_takeaway7,OWF_", fb, "km_buf_preplan
ning_order_6)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_9_displ_", fb
, "_erased_takeaway6')){OWF_", bf, "km_buf_preplanning_order_9_disp
l_", fb, "_erased_takeaway5 <- erase(OWF_", bf, "km_buf_preplanning
_order_9_displ_", fb, "_erased_takeaway6,OWF_", fb, "km_buf_preplan
ning_order_5)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_9_displ_", fb
, "_erased_takeaway5')){OWF_", bf, "km_buf_preplanning_order_9_disp
l_", fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_preplanning
_order_9_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_preplan
ning_order_4)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_9_displ_", fb
, "_erased_takeaway4')){OWF_", bf, "km_buf_preplanning_order_9_disp
l_", fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_preplanning
_order_9_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_preplan
ning_order_3)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_9_displ_", fb
```

```
, "_erased_takeaway3'')){OWF_", bf, "km_buf_preplanning_order_9_disp
l_", fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_preplanning
_order_9_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_preplan
ning_order_2)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_9_displ_", fb
, "_erased_takeaway2'')){OWF_", bf, "km_buf_preplanning_order_9_disp
l_", fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_preplanning
_order_9_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_preplan
ning_order_1)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_9_displ_", fb
, "_erased_takeaway1'')){OWF_", bf, "km_buf_preplanning_order_9_disp
l_", fb, "_erased <- OWF_", bf, "km_buf_preplanning_order_9_displ_"
, fb, "_erased_takeaway1}")))
  }
}
#Erase 10
for(fb in buffer){
  for(bf in buffer){
    try(eval(parse(text = paste0("
      #Erase OWF 10
      if(gContainsProperly(OWF_", fb, "km_buf_preplanning_order_9,O
WF_", bf, "km_buf_preplanning_order_10)==FALSE){OWF_", bf, "km_buf_
preplanning_order_10_displ_", fb, "_erased_takeaway9 <- erase(OWF_"
, bf, "km_buf_preplanning_order_10,OWF_", fb, "km_buf_preplanning_o
rder_9)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_10_displ_", f
b, "_erased_takeaway9'')){OWF_", bf, "km_buf_preplanning_order_10_di
spl_", fb, "_erased_takeaway8 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_10_displ_", fb, "_erased_takeaway9,OWF_", fb, "km_buf_prep
lanning_order_8)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_10_displ_", f
b, "_erased_takeaway8'')){OWF_", bf, "km_buf_preplanning_order_10_di
spl_", fb, "_erased_takeaway7 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_10_displ_", fb, "_erased_takeaway8,OWF_", fb, "km_buf_prep
lanning_order_7)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_10_displ_", f
b, "_erased_takeaway7'')){OWF_", bf, "km_buf_preplanning_order_10_di
spl_", fb, "_erased_takeaway6 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_10_displ_", fb, "_erased_takeaway7,OWF_", fb, "km_buf_prep
lanning_order_6)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_10_displ_", f
b, "_erased_takeaway6'')){OWF_", bf, "km_buf_preplanning_order_10_di
spl_", fb, "_erased_takeaway5 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_10_displ_", fb, "_erased_takeaway6,OWF_", fb, "km_buf_prep
lanning_order_5)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_10_displ_", f
b, "_erased_takeaway5'')){OWF_", bf, "km_buf_preplanning_order_10_di
spl_", fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_10_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_prep
lanning_order_4)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_10_displ_", f
b, "_erased_takeaway4'')){OWF_", bf, "km_buf_preplanning_order_10_di
```

```
spl_", fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_10_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_prep
lanning_order_3)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_10_displ_", f
b, "_erased_takeaway3')){OWF_", bf, "km_buf_preplanning_order_10_di
spl_", fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_10_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_prep
lanning_order_2)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_10_displ_", f
b, "_erased_takeaway2')){OWF_", bf, "km_buf_preplanning_order_10_di
spl_", fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_10_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_prep
lanning_order_1)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_10_displ_", f
b, "_erased_takeaway1')){OWF_", bf, "km_buf_preplanning_order_10_di
spl_", fb, "_erased <- OWF_", bf, "km_buf_preplanning_order_10_disp
l_", fb, "_erased_takeaway1}"))))
  }
}
#Erase 11
for(fb in buffer){
  for(bf in buffer){
    try(eval(parse(text = paste0("
      #Erase OWF 11
      if(gContainsProperly(OWF_", fb, "km_buf_preplanning_order_10,
OWF_", bf, "km_buf_preplanning_order_11)==FALSE){OWF_", bf, "km_buf
_preplanning_order_11_displ_", fb, "_erased_takeaway10 <- erase(OWF
_", bf, "km_buf_preplanning_order_11,OWF_", fb, "km_buf_preplanning
_order_10)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_11_displ_", f
b, "_erased_takeaway10')){OWF_", bf, "km_buf_preplanning_order_11_d
ispl_", fb, "_erased_takeaway9 <- erase(OWF_", bf, "km_buf_preplann
ing_order_11_displ_", fb, "_erased_takeaway10,OWF_", fb, "km_buf_pr
eplanning_order_9)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_11_displ_", f
b, "_erased_takeaway9')){OWF_", bf, "km_buf_preplanning_order_11_di
spl_", fb, "_erased_takeaway8 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_11_displ_", fb, "_erased_takeaway9,OWF_", fb, "km_buf_prep
lanning_order_8)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_11_displ_", f
b, "_erased_takeaway8')){OWF_", bf, "km_buf_preplanning_order_11_di
spl_", fb, "_erased_takeaway7 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_11_displ_", fb, "_erased_takeaway8,OWF_", fb, "km_buf_prep
lanning_order_7)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_11_displ_", f
b, "_erased_takeaway7')){OWF_", bf, "km_buf_preplanning_order_11_di
spl_", fb, "_erased_takeaway6 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_11_displ_", fb, "_erased_takeaway7,OWF_", fb, "km_buf_prep
lanning_order_6)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_11_displ_", f
b, "_erased_takeaway6')){OWF_", bf, "km_buf_preplanning_order_11_di
spl_", fb, "_erased_takeaway5 <- erase(OWF_", bf, "km_buf_preplanni
```

```
ng_order_11_displ_", fb, "_erased_takeaway6,OWF_", fb, "km_buf_prep
lanning_order_5)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_11_displ_", f
b, "_erased_takeaway5')){OWF_", bf, "km_buf_preplanning_order_11_di
spl_", fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_11_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_prep
lanning_order_4)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_11_displ_", f
b, "_erased_takeaway4')){OWF_", bf, "km_buf_preplanning_order_11_di
spl_", fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_11_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_prep
lanning_order_3)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_11_displ_", f
b, "_erased_takeaway3')){OWF_", bf, "km_buf_preplanning_order_11_di
spl_", fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_11_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_prep
lanning_order_2)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_11_displ_", f
b, "_erased_takeaway2')){OWF_", bf, "km_buf_preplanning_order_11_di
spl_", fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_11_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_prep
lanning_order_1)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_11_displ_", f
b, "_erased_takeaway1')){OWF_", bf, "km_buf_preplanning_order_11_di
spl_", fb, "_erased <- OWF_", bf, "km_buf_preplanning_order_11_disp
l_", fb, "_erased_takeaway1}"))))
  }
}
#Erase 12
for(fb in buffer){
  for(bf in buffer){
    try(eval(parse(text = paste0("
      #Erase OWF 12
      if(gContainsProperly(OWF_", fb, "km_buf_preplanning_order_11,
OWF_", bf, "km_buf_preplanning_order_12)==FALSE){OWF_", bf, "km_buf
_preplanning_order_12_displ_", fb, "_erased_takeaway11 <- erase(OWF
_", bf, "km_buf_preplanning_order_12,OWF_", fb, "km_buf_preplanning
_order_11)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_12_displ_", f
b, "_erased_takeaway11')){OWF_", bf, "km_buf_preplanning_order_12_d
ispl_", fb, "_erased_takeaway10 <- erase(OWF_", bf, "km_buf_preplan
ning_order_12_displ_", fb, "_erased_takeaway11,OWF_", fb, "km_buf_p
replanning_order_10)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_12_displ_", f
b, "_erased_takeaway10')){OWF_", bf, "km_buf_preplanning_order_12_d
ispl_", fb, "_erased_takeaway9 <- erase(OWF_", bf, "km_buf_preplann
ing_order_12_displ_", fb, "_erased_takeaway10,OWF_", fb, "km_buf_pr
eplanning_order_9)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_12_displ_", f
b, "_erased_takeaway9')){OWF_", bf, "km_buf_preplanning_order_12_di
spl_", fb, "_erased_takeaway8 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_12_displ_", fb, "_erased_takeaway9,OWF_", fb, "km_buf_prep
```

```
lanning_order_8)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_12_displ_", f
b, "_erased_takeaway8')){OWF_", bf, "km_buf_preplanning_order_12_di
spl_", fb, "_erased_takeaway7 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_12_displ_", fb, "_erased_takeaway8,OWF_", fb, "km_buf_prep
lanning_order_7)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_12_displ_", f
b, "_erased_takeaway7')){OWF_", bf, "km_buf_preplanning_order_12_di
spl_", fb, "_erased_takeaway6 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_12_displ_", fb, "_erased_takeaway7,OWF_", fb, "km_buf_prep
lanning_order_6)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_12_displ_", f
b, "_erased_takeaway6')){OWF_", bf, "km_buf_preplanning_order_12_di
spl_", fb, "_erased_takeaway5 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_12_displ_", fb, "_erased_takeaway6,OWF_", fb, "km_buf_prep
lanning_order_5)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_12_displ_", f
b, "_erased_takeaway5')){OWF_", bf, "km_buf_preplanning_order_12_di
spl_", fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_12_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_prep
lanning_order_4)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_12_displ_", f
b, "_erased_takeaway4')){OWF_", bf, "km_buf_preplanning_order_12_di
spl_", fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_12_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_prep
lanning_order_3)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_12_displ_", f
b, "_erased_takeaway3')){OWF_", bf, "km_buf_preplanning_order_12_di
spl_", fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_12_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_prep
lanning_order_2)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_12_displ_", f
b, "_erased_takeaway2')){OWF_", bf, "km_buf_preplanning_order_12_di
spl_", fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_12_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_prep
lanning_order_1)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_12_displ_", f
b, "_erased_takeaway1')){OWF_", bf, "km_buf_preplanning_order_12_di
spl_", fb, "_erased <- OWF_", bf, "km_buf_preplanning_order_12_disp
l_", fb, "_erased_takeaway1}"))))
  }
}
```

Make rings

```
#Create rings from buffers
for(fb in buffer){
  for(ip in preplanning_OWFs){
    try(eval(parse(text = paste0("
      OWF_0km_ring_preplanning_order_", ip, "_displ_", fb, "_erased
<- OWF_0km_buf_preplanning_order_", ip, "_displ_", fb, "_erased
      OWF_1km_ring_preplanning_order_", ip, "_displ_", fb, "_erased
```

```
<- erase(OWF_1km_buf_preplanning_order_", ip, "_displ_", fb, "_eras
ed, OWF_0km_buf_preplanning_order_", ip, "_displ_", fb, "_erased)")
)))
    for (bf in buffer[3:17]) {
      try(eval(parse(text = paste0("OWF_", bf, "km_ring_preplanning
_order_", ip, "_displ_", fb, "_erased <- erase(OWF_", bf, "km_buf_p
replanning_order_", ip, "_displ_", fb, "_erased, OWF_", bf -1, "km_
buf_preplanning_order_", ip, "_displ_", fb, "_erased)"))))
    }
  }
}
```

Calculate area of rings

```
#Calculate area
preplanning_order_area <- data.frame(OWF=NA, Ring=NA, Area=NA)
a<-1
for(ip in preplanning_OWFs){
  b<-1
  for(fb in buffer){
    try(eval(parse(text = paste0("
        preplanning_order_area[((a-1)*length(buffer))+b,1] <- ip
        preplanning_order_area[((a-1)*length(buffer))+b,2] <- fb
        preplanning_order_area[((a-1)*length(buffer))+b,3] <- area(
OWF_", fb, "km_ring_preplanning_order_", ip, "_displ_16_erased)/100
0000"))))
    b<-b+1
  }
  a<-a+1
}
#Save
setwd("Y:/Marine Species/Rebecca Hall/Laptop files/PhD work/Future
cumulative displ/Results tables")
write.csv(preplanning_order_area,"preplanning_order_area.csv")
#Crop to SPA
for(ip in preplanning_OWFs){
  for(bf in buffer){
    for(fb in buffer){
      try(eval(parse(text = paste0("OWF_", fb, "km_ring_preplanning
_order_", ip, "_displ_", bf, "_erased_OTESPA <- raster::intersect(O
uter_Thames_Estuary_SPA, OWF_", fb, "km_ring_preplanning_order_", i
p, "_displ_", bf, "_erased)"))))
    }
  }
}
#Table
preplanning_order_area_OTESPA <- data.frame(MaxDispl=NA, OWF=NA, Ri
ng=NA, Area=NA)
a<-1
for(bf in buffer){
  b<-1
  for(ip in preplanning_OWFs){
```

```
    c<-1
    for(fb in buffer){
      try(eval(parse(text = paste0("
          preplanning_order_area_OTESPA[((a-1)*length(buffer)*lengt
h(preplanning_OWFs))+((b-1)*length(buffer))+c,1] <- bf
          preplanning_order_area_OTESPA[((a-1)*length(buffer)*lengt
h(preplanning_OWFs))+((b-1)*length(buffer))+c,2] <- ip
          preplanning_order_area_OTESPA[((a-1)*length(buffer)*lengt
h(preplanning_OWFs))+((b-1)*length(buffer))+c,3] <- fb
          preplanning_order_area_OTESPA[((a-1)*length(buffer)*lengt
h(preplanning_OWFs))+((b-1)*length(buffer))+c,4] <- area(OWF_", fb,
"km_ring_preplanning_order_", ip, "_displ_", bf, "_erased_OTESPA)/1
000000"))))
      c<-c+1
    }
    b<-b+1
  }
  a<-a+1
}
#Save
setwd("Y:/Marine Species/Rebecca Hall/Laptop files/PhD work/Future
cumulative displ/Results tables")
write.csv(preplanning_order_area_OTESPA,"preplanning_order_area_OTE
SPA_OneNorth_first.csv")
```

Crop density to OWFs & rings

```
#Crop density
for(fb in buffer){
  for (ip in preplanning_OWFs) {
    for (bf in buffer) {
      try(eval(parse(text = paste0("RTD_density_Outer_Thames_Estuar
y_SPA_OWF_", bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "
_erased <-raster::intersect(RTD_density_Outer_Thames_Estuary_SPA, O
WF_", bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "_erased
)"))))
    }
  }
}
```

Displace birds

```
#Displace birds using displacement gradient
for (ip in preplanning_OWFs) {
  for (fb in buffer){
    for(bf in buffer){
      eval(parse(text = paste0("if(exists('RTD_density_Outer_Thames
_Estuary_SPA_OWF_", bf, "km_ring_preplanning_order_", ip, "_displ_"
, fb, "_erased')){if(!is.null(RTD_density_Outer_Thames_Estuary_SPA_
OWF_", bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "_erase
d)){RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_prepla
nning_order_", ip, "_displ_", fb, "_erased@data$RH_D_MaxDispl",fb,"
<- as.numeric(sapply((1-(Displ_together[(fb*17)+(bf+1),Displ_grad])
```

```
/100),'*',RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_
preplanning_order_", ip, "_displ_", fb, "_erased@data$RH_D))}}")))
    }
  }
}
```

Calculate numbers of birds displaced and mortality and as proportion of SPA

```
#No. birds in SPA
RTD_density_Outer_Thames_Estuary_SPA_sum <- sum((area(RTD_density_O
uter_Thames_Estuary_SPA)/1000000)*RTD_density_Outer_Thames_Estuary_
SPA@data$RH_D)
for (ip in preplanning_OWFs) {
  for (fb in buffer){
    for(bf in 0:fb){
      try(eval(parse(text = paste0("
          RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_
preplanning_order_", ip, "_displ_", fb, "_erased_sum <- sum((area(R
TD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_preplanning
_order_", ip, "_displ_", fb, "_erased)/1000000)*RTD_density_Outer_T
hames_Estuary_SPA_OWF_", bf, "km_ring_preplanning_order_", ip, "_di
spl_", fb, "_erased@data$RH_D)
          RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_
preplanning_order_", ip, "_displ_", fb, "_erased_sum_", fb, " <-sum
((area(RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_pre
planning_order_", ip, "_displ_", fb, "_erased)/1000000)*RTD_density
_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_preplanning_order_",
ip, "_displ_", fb, "_erased@data$RH_D_MaxDispl", fb, ")
          RTD_percloss_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring
_preplanning_order_", ip, "_displ_", fb, "_erased <- ((RTD_density_
Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_preplanning_order_", i
p, "_displ_", fb, "_erased_sum - RTD_density_Outer_Thames_Estuary_S
PA_OWF_", bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "_er
ased_sum_", fb, ")/RTD_density_Outer_Thames_Estuary_SPA_sum)*100"))
))
    }
  }
}
#Calculate numbers of bird casualties and as proportion of SPA
Mortality_rate <- 1:10
#Put into table
for (ip in preplanning_OWFs) {
  eval(parse(text = paste0("RTD_percloss_Outer_Thames_Estuary_SPA_p
replanning_order_", ip, " <- data.frame(Max_displ_km=NA, Ring=NA, M
ortalityRate=NA, RingArea=NA, NoBirds=NA, NoBirdLoss=NA, SPAPercLos
s=NA, NoBirdMortality=NA, SPAPercMortality=NA)")))
  a<-1
  for (fb in buffer) {
    b<-1
    for (bf in 0:fb) {
      c<-1
      for (mt in Mortality_rate) {
```

```
        eval(parse(text = paste0("try(if(!is.null(RTD_density_Outer
_Thames_Estuary_SPA_OWF_", bf, "km_ring_preplanning_order_", ip, "_
displ_", fb, "_erased)){
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,1] <- fb
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,2] <- bf
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,3] <- mt
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,4] <-sum(area(RTD_density_Outer_Thames_Estuary_
SPA_OWF_", bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "_e
rased)/1000000)
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,5] <-RTD_density_Outer_Thames_Estuary_SPA_OWF_"
, bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "_erased_sum
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,6] <-RTD_density_Outer_Thames_Estuary_SPA_OWF_"
, bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "_erased_sum
- RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_preplann
ing_order_", ip, "_displ_", fb, "_erased_sum_", fb, "
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,7] <-RTD_percloss_Outer_Thames_Estuary_SPA_OWF_
", bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "_erased
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,8] <-(RTD_density_Outer_Thames_Estuary_SPA_OWF_
", bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "_erased_su
m - RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_prepla
nning_order_", ip, "_displ_", fb, "_erased_sum_", fb, ")/100*mt
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,9] <-(RTD_percloss_Outer_Thames_Estuary_SPA_OWF
_", bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "_erased)/
100*mt})")))
        c<-c+1
      }
      b<-b+1
    }
    a<-a+1
  }
}
#Remova NAs
for (ip in preplanning_OWFs) {
  eval(parse(text = paste0("RTD_percloss_Outer_Thames_Estuary_SPA_p
```

```
replanning_order_", ip, "<-na.omit(RTD_percloss_Outer_Thames_Estuar
y_SPA_preplanning_order_", ip, ")")))
}
#Sum % birds for each scenario
for (ip in preplanning_OWFs) {
  eval(parse(text = paste0("RTD_percloss_total_Outer_Thames_Estuary
_SPA_preplanning_order_", ip, " <- data.frame(OWF_num=NA, Max_displ
_km=NA, MortalityRate=NA, NoBirdLoss=NA, SPAPercLoss=NA, NoBirdMort
ality=NA, SPAPercMortality=NA, Area=NA)")))
  a<-1
  for (fb in buffer) {
    b<-1
    for (mt in Mortality_rate) {
      eval(parse(text = paste0("
        RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_ord
er_", ip, "[((a-1)*length(Mortality_rate))+b,1] <- ip
        RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_ord
er_", ip, "[((a-1)*length(Mortality_rate))+b,2] <- fb
        RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_ord
er_", ip, "[((a-1)*length(Mortality_rate))+b,3] <- mt
        try({RTD_percloss_total_Outer_Thames_Estuary_SPA_preplannin
g_order_", ip, "[((a-1)*length(Mortality_rate))+b,4] <-sum(subset(R
TD_percloss_Outer_Thames_Estuary_SPA_preplanning_order_", ip, ", Ma
x_displ_km==fb & MortalityRate==mt, select=NoBirdLoss), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_ord
er_", ip, "[((a-1)*length(Mortality_rate))+b,5] <-sum(subset(RTD_pe
rcloss_Outer_Thames_Estuary_SPA_preplanning_order_", ip, ", Max_dis
pl_km==fb & MortalityRate==mt, select=SPAPercLoss), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_ord
er_", ip, "[((a-1)*length(Mortality_rate))+b,6] <-sum(subset(RTD_pe
rcloss_Outer_Thames_Estuary_SPA_preplanning_order_", ip, ", Max_dis
pl_km==fb & MortalityRate==mt, select=NoBirdMortality), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_ord
er_", ip, "[((a-1)*length(Mortality_rate))+b,7] <-sum(subset(RTD_pe
rcloss_Outer_Thames_Estuary_SPA_preplanning_order_", ip, ", Max_dis
pl_km==fb & MortalityRate==mt, select=SPAPercMortality), na.rm=TRUE
)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_ord
er_", ip, "[((a-1)*length(Mortality_rate))+b,8] <-sum(subset(RTD_pe
rcloss_Outer_Thames_Estuary_SPA_preplanning_order_", ip, ", Max_dis
pl_km==fb & SPAPercLoss>0, select=RingArea), na.rm=TRUE)}, silent=T
RUE)")))
      b<-b+1
    }
    a<-a+1
  }
}
#Sum all OWFs
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_sum <
- data.frame()
a<-1
for (ip in preplanning_OWFs) {
```

```
  eval(parse(text = paste0("RTD_percloss_total_Outer_Thames_Estuary
_SPA_preplanning_order_sum <- rbind(RTD_percloss_total_Outer_Thames
_Estuary_SPA_preplanning_order_sum, RTD_percloss_total_Outer_Thames
_Estuary_SPA_preplanning_order_", preplanning_OWFs[a], ")")))
  a<-a+1
}
#Save
setwd("c:/Users/44755/OneDrive - University of Strathclyde/1. Thesi
s/12. Thesis V2")
#If using hundred within displacement gradient, save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_o
rder_sum,"RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_o
rder_OneNorth_first_sum_Hundred_Within.csv")
#If using basic displacement gradient, save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_o
rder_sum,"RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_o
rder_OneNorth_first_sum_Gradient.csv")
```

PREPLANNING TWO FIRST Impacted once in order

```
#Pull out preplanning OWFs by order of construction starting
OWF_preplanning_order_1 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "Scroby Sands",]
OWF_preplanning_order_2 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "Kentish Flats",]
OWF_preplanning_order_3 <- GunfleetSands.sprepro
OWF_preplanning_order_3 <- aggregate(OWF_preplanning_order_3,dissol
ve=TRUE)
OWF_preplanning_order_4 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "Thanet",]
OWF_preplanning_order_5 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "Greater Gabbard",]
OWF_preplanning_order_6 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "London Array",]
OWF_preplanning_order_7 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "Gunfleet Sands Demo",]
OWF_preplanning_order_8 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "Kentish Flats Extension",]
OWF_preplanning_order_9 <- OWF.sprepro[OWF.sprepro@data$Name_Prop =
= "East Anglia ONE",]
OWF_preplanning_order_10 <- OWF.sprepro[OWF.sprepro@data$Name_Prop
== "East Anglia TWO",]
OWF_preplanning_order_11 <- OWF.sprepro[OWF.sprepro@data$Name_Prop
== "East Anglia ONE NORTH",]
OWF_preplanning_order_12 <- OWF.sprepro[OWF.sprepro@data$Name_Prop
== "North Falls",]
preplanning_OWFs <- 1:12
```

Make buffers

```
#Make 0km buffers for each OWF (i.e. call the OWF 0km)
for(ip in preplanning_OWFs){
  eval(parse(text = paste0("OWF_0km_buf_preplanning_order_", ip," <
```

```
- OWF_preplanning_order_", ip,"")))
}
#Make buffers around each OWF
buffer <- 0:16
for(ip in preplanning_OWFs){
  for (bf in buffer) {
    eval(parse(text = paste0("OWF_", bf, "km_buf_preplanning_order_
", ip," <- gBuffer(OWF_preplanning_order_", ip,", width = bf*1000,
byid=TRUE)")))
  }
}
#When max displ is "fb" (call it displ_"fb" and keep last item "fb"
km buf)
#Erase buffers from one another
for(fb in buffer){
  try(eval(parse(text = paste0("OWF_0km_buf_preplanning_order_1_dis
pl_", fb, "_erased <- OWF_0km_buf_preplanning_order_1if(gContainsPr
operly(OWF_", fb, "km_buf_preplanning_order_1,OWF_0km_buf_preplanni
ng_order_2)==FALSE){OWF_0km_buf_preplanning_order_2_displ_", fb, "_
erased <- erase(OWF_0km_buf_preplanning_order_2,OWF_", fb, "km_buf_
preplanning_order_1)}"))))
}
for(fb in buffer){
  for (bf in buffer[2:17]) {
    try(eval(parse(text = paste0("OWF_", bf, "km_buf_preplanning_or
der_1_displ_", fb, "_erased <- OWF_", bf, "km_buf_preplanning_order
_1if(gContainsProperly(OWF_", fb, "km_buf_preplanning_order_1,OWF_"
, bf, "km_buf_preplanning_order_2)==FALSE){OWF_", bf, "km_buf_prepl
anning_order_2_displ_", fb, "_erased <- erase(OWF_", bf, "km_buf_pr
eplanning_order_2,OWF_", fb, "km_buf_preplanning_order_1)}"))))
  }
}
#Erase 1 to 7
for(fb in buffer){
  for(bf in buffer){
    try(eval(parse(text = paste0("
      #Erase OWF 3
      if(gContainsProperly(OWF_", fb, "km_buf_preplanning_order_2,O
WF_", bf, "km_buf_preplanning_order_3)==FALSE){OWF_", bf, "km_buf_p
replanning_order_3_displ_", fb, "_erased_takeaway2 <- erase(OWF_",
bf, "km_buf_preplanning_order_3,OWF_", fb, "km_buf_preplanning_orde
r_2)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_3_displ_", fb
, "_erased_takeaway2')){OWF_", bf, "km_buf_preplanning_order_3_disp
l_", fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_preplanning
_order_3_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_preplan
ning_order_1)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_3_displ_", fb
, "_erased_takeaway1')){OWF_", bf, "km_buf_preplanning_order_3_disp
l_", fb, "_erased <- OWF_", bf, "km_buf_preplanning_order_3_displ_"
, fb, "_erased_takeaway1}
      #Erase OWF 4
```

```
      if(gContainsProperly(OWF_", fb, "km_buf_preplanning_order_3,O
WF_", bf, "km_buf_preplanning_order_4)==FALSE){OWF_", bf, "km_buf_p
replanning_order_4_displ_", fb, "_erased_takeaway3 <- erase(OWF_",
bf, "km_buf_preplanning_order_4,OWF_", fb, "km_buf_preplanning_orde
r_3)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_4_displ_", fb
, "_erased_takeaway3')){OWF_", bf, "km_buf_preplanning_order_4_disp
l_", fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_preplanning
_order_4_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_preplan
ning_order_2)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_4_displ_", fb
, "_erased_takeaway2')){OWF_", bf, "km_buf_preplanning_order_4_disp
l_", fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_preplanning
_order_4_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_preplan
ning_order_1)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_4_displ_", fb
, "_erased_takeaway1')){OWF_", bf, "km_buf_preplanning_order_4_disp
l_", fb, "_erased <- OWF_", bf, "km_buf_preplanning_order_4_displ_"
, fb, "_erased_takeaway1}
      #Erase OWF 5
      if(gContainsProperly(OWF_", fb, "km_buf_preplanning_order_4,O
WF_", bf, "km_buf_preplanning_order_5)==FALSE){OWF_", bf, "km_buf_p
replanning_order_5_displ_", fb, "_erased_takeaway4 <- erase(OWF_",
bf, "km_buf_preplanning_order_5,OWF_", fb, "km_buf_preplanning_orde
r_4)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_5_displ_", fb
, "_erased_takeaway4')){OWF_", bf, "km_buf_preplanning_order_5_disp
l_", fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_preplanning
_order_5_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_preplan
ning_order_3)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_5_displ_", fb
, "_erased_takeaway3')){OWF_", bf, "km_buf_preplanning_order_5_disp
l_", fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_preplanning
_order_5_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_preplan
ning_order_2)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_5_displ_", fb
, "_erased_takeaway2')){OWF_", bf, "km_buf_preplanning_order_5_disp
l_", fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_preplanning
_order_5_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_preplan
ning_order_1)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_5_displ_", fb
, "_erased_takeaway1')){OWF_", bf, "km_buf_preplanning_order_5_disp
l_", fb, "_erased <- OWF_", bf, "km_buf_preplanning_order_5_displ_"
, fb, "_erased_takeaway1}
      #Erase OWF 6
      if(gContainsProperly(OWF_", fb, "km_buf_preplanning_order_5,O
WF_", bf, "km_buf_preplanning_order_6)==FALSE){OWF_", bf, "km_buf_p
replanning_order_6_displ_", fb, "_erased_takeaway5 <- erase(OWF_",
bf, "km_buf_preplanning_order_6,OWF_", fb, "km_buf_preplanning_orde
r_5)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_6_displ_", fb
, "_erased_takeaway5')){OWF_", bf, "km_buf_preplanning_order_6_disp
```

```
l_", fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_preplanning
_order_6_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_preplan
ning_order_4)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_6_displ_", fb
, "_erased_takeaway4')){OWF_", bf, "km_buf_preplanning_order_6_disp
l_", fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_preplanning
_order_6_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_preplan
ning_order_3)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_6_displ_", fb
, "_erased_takeaway3')){OWF_", bf, "km_buf_preplanning_order_6_disp
l_", fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_preplanning
_order_6_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_preplan
ning_order_2)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_6_displ_", fb
, "_erased_takeaway2')){OWF_", bf, "km_buf_preplanning_order_6_disp
l_", fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_preplanning
_order_6_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_preplan
ning_order_1)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_6_displ_", fb
, "_erased_takeaway1')){OWF_", bf, "km_buf_preplanning_order_6_disp
l_", fb, "_erased <- OWF_", bf, "km_buf_preplanning_order_6_displ_"
, fb, "_erased_takeaway1}
      #Erase OWF 7
      if(gContainsProperly(OWF_", fb, "km_buf_preplanning_order_6,O
WF_", bf, "km_buf_preplanning_order_7)==FALSE){OWF_", bf, "km_buf_p
replanning_order_7_displ_", fb, "_erased_takeaway6 <- erase(OWF_",
bf, "km_buf_preplanning_order_7,OWF_", fb, "km_buf_preplanning_orde
r_6)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_7_displ_", fb
, "_erased_takeaway6')){OWF_", bf, "km_buf_preplanning_order_7_disp
l_", fb, "_erased_takeaway5 <- erase(OWF_", bf, "km_buf_preplanning
_order_7_displ_", fb, "_erased_takeaway6,OWF_", fb, "km_buf_preplan
ning_order_5)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_7_displ_", fb
, "_erased_takeaway5')){OWF_", bf, "km_buf_preplanning_order_7_disp
l_", fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_preplanning
_order_7_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_preplan
ning_order_4)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_7_displ_", fb
, "_erased_takeaway4')){OWF_", bf, "km_buf_preplanning_order_7_disp
l_", fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_preplanning
_order_7_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_preplan
ning_order_3)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_7_displ_", fb
, "_erased_takeaway3')){OWF_", bf, "km_buf_preplanning_order_7_disp
l_", fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_preplanning
_order_7_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_preplan
ning_order_2)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_7_displ_", fb
, "_erased_takeaway2')){OWF_", bf, "km_buf_preplanning_order_7_disp
l_", fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_preplanning
_order_7_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_preplan
```

```
ning_order_1)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_7_displ_", fb
, "_erased_takeaway1')){OWF_", bf, "km_buf_preplanning_order_7_disp
l_", fb, "_erased <- OWF_", bf, "km_buf_preplanning_order_7_displ_"
, fb, "_erased_takeaway1}"))))
  }
}
#Erase 8
for(fb in buffer){
  for(bf in buffer){
    try(eval(parse(text = paste0("
      #Erase OWF 8
      if(gContainsProperly(OWF_", fb, "km_buf_preplanning_order_7,O
WF_", bf, "km_buf_preplanning_order_8)==FALSE){OWF_", bf, "km_buf_p
replanning_order_8_displ_", fb, "_erased_takeaway7 <- erase(OWF_",
bf, "km_buf_preplanning_order_8,OWF_", fb, "km_buf_preplanning_orde
r_7)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_8_displ_", fb
, "_erased_takeaway7')){OWF_", bf, "km_buf_preplanning_order_8_disp
l_", fb, "_erased_takeaway6 <- erase(OWF_", bf, "km_buf_preplanning
_order_8_displ_", fb, "_erased_takeaway7,OWF_", fb, "km_buf_preplan
ning_order_6)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_8_displ_", fb
, "_erased_takeaway6')){OWF_", bf, "km_buf_preplanning_order_8_disp
l_", fb, "_erased_takeaway5 <- erase(OWF_", bf, "km_buf_preplanning
_order_8_displ_", fb, "_erased_takeaway6,OWF_", fb, "km_buf_preplan
ning_order_5)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_8_displ_", fb
, "_erased_takeaway5')){OWF_", bf, "km_buf_preplanning_order_8_disp
l_", fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_preplanning
_order_8_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_preplan
ning_order_4)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_8_displ_", fb
, "_erased_takeaway4')){OWF_", bf, "km_buf_preplanning_order_8_disp
l_", fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_preplanning
_order_8_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_preplan
ning_order_3)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_8_displ_", fb
, "_erased_takeaway3')){OWF_", bf, "km_buf_preplanning_order_8_disp
l_", fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_preplanning
_order_8_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_preplan
ning_order_2)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_8_displ_", fb
, "_erased_takeaway2')){OWF_", bf, "km_buf_preplanning_order_8_disp
l_", fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_preplanning
_order_8_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_preplan
ning_order_1)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_8_displ_", fb
, "_erased_takeaway1')){OWF_", bf, "km_buf_preplanning_order_8_disp
l_", fb, "_erased <- OWF_", bf, "km_buf_preplanning_order_8_displ_"
, fb, "_erased_takeaway1}
      ")))
```

```
    )
  }
}
#Erase 9
for(fb in buffer){
  for(bf in buffer){
    try(
      eval(parse(text = paste0("
      #Erase OWF 9
      if(gContainsProperly(OWF_", fb, "km_buf_preplanning_order_8,O
WF_", bf, "km_buf_preplanning_order_9)==FALSE){OWF_", bf, "km_buf_p
replanning_order_9_displ_", fb, "_erased_takeaway8 <- erase(OWF_",
bf, "km_buf_preplanning_order_9,OWF_", fb, "km_buf_preplanning_orde
r_8)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_9_displ_", fb
, "_erased_takeaway8')){OWF_", bf, "km_buf_preplanning_order_9_disp
l_", fb, "_erased_takeaway7 <- erase(OWF_", bf, "km_buf_preplanning
_order_9_displ_", fb, "_erased_takeaway8,OWF_", fb, "km_buf_preplan
ning_order_7)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_9_displ_", fb
, "_erased_takeaway7')){OWF_", bf, "km_buf_preplanning_order_9_disp
l_", fb, "_erased_takeaway6 <- erase(OWF_", bf, "km_buf_preplanning
_order_9_displ_", fb, "_erased_takeaway7,OWF_", fb, "km_buf_preplan
ning_order_6)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_9_displ_", fb
, "_erased_takeaway6')){OWF_", bf, "km_buf_preplanning_order_9_disp
l_", fb, "_erased_takeaway5 <- erase(OWF_", bf, "km_buf_preplanning
_order_9_displ_", fb, "_erased_takeaway6,OWF_", fb, "km_buf_preplan
ning_order_5)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_9_displ_", fb
, "_erased_takeaway5')){OWF_", bf, "km_buf_preplanning_order_9_disp
l_", fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_preplanning
_order_9_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_preplan
ning_order_4)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_9_displ_", fb
, "_erased_takeaway4')){OWF_", bf, "km_buf_preplanning_order_9_disp
l_", fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_preplanning
_order_9_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_preplan
ning_order_3)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_9_displ_", fb
, "_erased_takeaway3')){OWF_", bf, "km_buf_preplanning_order_9_disp
l_", fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_preplanning
_order_9_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_preplan
ning_order_2)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_9_displ_", fb
, "_erased_takeaway2')){OWF_", bf, "km_buf_preplanning_order_9_disp
l_", fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_preplanning
_order_9_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_preplan
ning_order_1)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_9_displ_", fb
, "_erased_takeaway1')){OWF_", bf, "km_buf_preplanning_order_9_disp
l_", fb, "_erased <- OWF_", bf, "km_buf_preplanning_order_9_displ_"
```

```
, fb, "_erased_takeaway1}"))))
  }
}
#Erase 10
for(fb in buffer){
  for(bf in buffer){
    try(eval(parse(text = paste0("
      #Erase OWF 10
      if(gContainsProperly(OWF_", fb, "km_buf_preplanning_order_9,O
WF_", bf, "km_buf_preplanning_order_10)==FALSE){OWF_", bf, "km_buf_
preplanning_order_10_displ_", fb, "_erased_takeaway9 <- erase(OWF_"
, bf, "km_buf_preplanning_order_10,OWF_", fb, "km_buf_preplanning_o
rder_9)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_10_displ_", f
b, "_erased_takeaway9')){OWF_", bf, "km_buf_preplanning_order_10_di
spl_", fb, "_erased_takeaway8 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_10_displ_", fb, "_erased_takeaway9,OWF_", fb, "km_buf_prep
lanning_order_8)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_10_displ_", f
b, "_erased_takeaway8')){OWF_", bf, "km_buf_preplanning_order_10_di
spl_", fb, "_erased_takeaway7 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_10_displ_", fb, "_erased_takeaway8,OWF_", fb, "km_buf_prep
lanning_order_7)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_10_displ_", f
b, "_erased_takeaway7')){OWF_", bf, "km_buf_preplanning_order_10_di
spl_", fb, "_erased_takeaway6 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_10_displ_", fb, "_erased_takeaway7,OWF_", fb, "km_buf_prep
lanning_order_6)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_10_displ_", f
b, "_erased_takeaway6')){OWF_", bf, "km_buf_preplanning_order_10_di
spl_", fb, "_erased_takeaway5 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_10_displ_", fb, "_erased_takeaway6,OWF_", fb, "km_buf_prep
lanning_order_5)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_10_displ_", f
b, "_erased_takeaway5')){OWF_", bf, "km_buf_preplanning_order_10_di
spl_", fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_10_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_prep
lanning_order_4)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_10_displ_", f
b, "_erased_takeaway4')){OWF_", bf, "km_buf_preplanning_order_10_di
spl_", fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_10_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_prep
lanning_order_3)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_10_displ_", f
b, "_erased_takeaway3')){OWF_", bf, "km_buf_preplanning_order_10_di
spl_", fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_10_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_prep
lanning_order_2)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_10_displ_", f
b, "_erased_takeaway2')){OWF_", bf, "km_buf_preplanning_order_10_di
spl_", fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_10_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_prep
```

```
lanning_order_1)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_10_displ_", f
b, "_erased_takeaway1')){OWF_", bf, "km_buf_preplanning_order_10_di
spl_", fb, "_erased <- OWF_", bf, "km_buf_preplanning_order_10_disp
l_", fb, "_erased_takeaway1}"))))
  }
}
#Erase 11
for(fb in buffer){
  for(bf in buffer){
    try(eval(parse(text = paste0("
      #Erase OWF 11
      if(gContainsProperly(OWF_", fb, "km_buf_preplanning_order_10,
OWF_", bf, "km_buf_preplanning_order_11)==FALSE){OWF_", bf, "km_buf
_preplanning_order_11_displ_", fb, "_erased_takeaway10 <- erase(OWF
_", bf, "km_buf_preplanning_order_11,OWF_", fb, "km_buf_preplanning
_order_10)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_11_displ_", f
b, "_erased_takeaway10')){OWF_", bf, "km_buf_preplanning_order_11_d
ispl_", fb, "_erased_takeaway9 <- erase(OWF_", bf, "km_buf_preplann
ing_order_11_displ_", fb, "_erased_takeaway10,OWF_", fb, "km_buf_pr
eplanning_order_9)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_11_displ_", f
b, "_erased_takeaway9')){OWF_", bf, "km_buf_preplanning_order_11_di
spl_", fb, "_erased_takeaway8 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_11_displ_", fb, "_erased_takeaway9,OWF_", fb, "km_buf_prep
lanning_order_8)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_11_displ_", f
b, "_erased_takeaway8')){OWF_", bf, "km_buf_preplanning_order_11_di
spl_", fb, "_erased_takeaway7 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_11_displ_", fb, "_erased_takeaway8,OWF_", fb, "km_buf_prep
lanning_order_7)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_11_displ_", f
b, "_erased_takeaway7')){OWF_", bf, "km_buf_preplanning_order_11_di
spl_", fb, "_erased_takeaway6 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_11_displ_", fb, "_erased_takeaway7,OWF_", fb, "km_buf_prep
lanning_order_6)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_11_displ_", f
b, "_erased_takeaway6')){OWF_", bf, "km_buf_preplanning_order_11_di
spl_", fb, "_erased_takeaway5 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_11_displ_", fb, "_erased_takeaway6,OWF_", fb, "km_buf_prep
lanning_order_5)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_11_displ_", f
b, "_erased_takeaway5')){OWF_", bf, "km_buf_preplanning_order_11_di
spl_", fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_11_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_prep
lanning_order_4)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_11_displ_", f
b, "_erased_takeaway4')){OWF_", bf, "km_buf_preplanning_order_11_di
spl_", fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_11_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_prep
lanning_order_3)}
```

```
      if(exists('OWF_", bf, "km_buf_preplanning_order_11_displ_", f
b, "_erased_takeaway3')){OWF_", bf, "km_buf_preplanning_order_11_di
spl_", fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_11_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_prep
lanning_order_2)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_11_displ_", f
b, "_erased_takeaway2')){OWF_", bf, "km_buf_preplanning_order_11_di
spl_", fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_11_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_prep
lanning_order_1)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_11_displ_", f
b, "_erased_takeaway1')){OWF_", bf, "km_buf_preplanning_order_11_di
spl_", fb, "_erased <- OWF_", bf, "km_buf_preplanning_order_11_disp
l_", fb, "_erased_takeaway1}"))))
  }
}
#Erase 12
for(fb in buffer){
  for(bf in buffer){
    try(eval(parse(text = paste0("
      #Erase OWF 12
      if(gContainsProperly(OWF_", fb, "km_buf_preplanning_order_11,
OWF_", bf, "km_buf_preplanning_order_12)==FALSE){OWF_", bf, "km_buf
_preplanning_order_12_displ_", fb, "_erased_takeaway11 <- erase(OWF
_", bf, "km_buf_preplanning_order_12,OWF_", fb, "km_buf_preplanning
_order_11)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_12_displ_", f
b, "_erased_takeaway11')){OWF_", bf, "km_buf_preplanning_order_12_d
ispl_", fb, "_erased_takeaway10 <- erase(OWF_", bf, "km_buf_preplan
ning_order_12_displ_", fb, "_erased_takeaway11,OWF_", fb, "km_buf_p
replanning_order_10)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_12_displ_", f
b, "_erased_takeaway10')){OWF_", bf, "km_buf_preplanning_order_12_d
ispl_", fb, "_erased_takeaway9 <- erase(OWF_", bf, "km_buf_preplann
ing_order_12_displ_", fb, "_erased_takeaway10,OWF_", fb, "km_buf_pr
eplanning_order_9)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_12_displ_", f
b, "_erased_takeaway9')){OWF_", bf, "km_buf_preplanning_order_12_di
spl_", fb, "_erased_takeaway8 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_12_displ_", fb, "_erased_takeaway9,OWF_", fb, "km_buf_prep
lanning_order_8)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_12_displ_", f
b, "_erased_takeaway8')){OWF_", bf, "km_buf_preplanning_order_12_di
spl_", fb, "_erased_takeaway7 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_12_displ_", fb, "_erased_takeaway8,OWF_", fb, "km_buf_prep
lanning_order_7)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_12_displ_", f
b, "_erased_takeaway7')){OWF_", bf, "km_buf_preplanning_order_12_di
spl_", fb, "_erased_takeaway6 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_12_displ_", fb, "_erased_takeaway7,OWF_", fb, "km_buf_prep
lanning_order_6)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_12_displ_", f
```

```
b, "_erased_takeaway6')){OWF_", bf, "km_buf_preplanning_order_12_di
spl_", fb, "_erased_takeaway5 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_12_displ_", fb, "_erased_takeaway6,OWF_", fb, "km_buf_prep
lanning_order_5)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_12_displ_", f
b, "_erased_takeaway5')){OWF_", bf, "km_buf_preplanning_order_12_di
spl_", fb, "_erased_takeaway4 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_12_displ_", fb, "_erased_takeaway5,OWF_", fb, "km_buf_prep
lanning_order_4)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_12_displ_", f
b, "_erased_takeaway4')){OWF_", bf, "km_buf_preplanning_order_12_di
spl_", fb, "_erased_takeaway3 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_12_displ_", fb, "_erased_takeaway4,OWF_", fb, "km_buf_prep
lanning_order_3)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_12_displ_", f
b, "_erased_takeaway3')){OWF_", bf, "km_buf_preplanning_order_12_di
spl_", fb, "_erased_takeaway2 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_12_displ_", fb, "_erased_takeaway3,OWF_", fb, "km_buf_prep
lanning_order_2)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_12_displ_", f
b, "_erased_takeaway2')){OWF_", bf, "km_buf_preplanning_order_12_di
spl_", fb, "_erased_takeaway1 <- erase(OWF_", bf, "km_buf_preplanni
ng_order_12_displ_", fb, "_erased_takeaway2,OWF_", fb, "km_buf_prep
lanning_order_1)}
      if(exists('OWF_", bf, "km_buf_preplanning_order_12_displ_", f
b, "_erased_takeaway1')){OWF_", bf, "km_buf_preplanning_order_12_di
spl_", fb, "_erased <- OWF_", bf, "km_buf_preplanning_order_12_disp
l_", fb, "_erased_takeaway1}"))))
  }
}
```

Make rings

```
#Create rings from buffers
for(fb in buffer){
  for(ip in preplanning_OWFs){
    try(eval(parse(text = paste0("
      OWF_0km_ring_preplanning_order_", ip, "_displ_", fb, "_erased
<- OWF_0km_buf_preplanning_order_", ip, "_displ_", fb, "_erased
      OWF_1km_ring_preplanning_order_", ip, "_displ_", fb, "_erased
<- erase(OWF_1km_buf_preplanning_order_", ip, "_displ_", fb, "_eras
ed, OWF_0km_buf_preplanning_order_", ip, "_displ_", fb, "_erased)")
)))
    for (bf in buffer[3:17]) {
      try(eval(parse(text = paste0("OWF_", bf, "km_ring_preplanning
_order_", ip, "_displ_", fb, "_erased <- erase(OWF_", bf, "km_buf_p
replanning_order_", ip, "_displ_", fb, "_erased, OWF_", bf -1, "km_
buf_preplanning_order_", ip, "_displ_", fb, "_erased)"))))
    }
  }
}
```

Calculate area of rings

```
#Calculate area
preplanning_order_area <- data.frame(OWF=NA, Ring=NA, Area=NA)
a<-1
for(ip in preplanning_OWFs){
  b<-1
  for(fb in buffer){
    try(eval(parse(text = paste0("
        preplanning_order_area[((a-1)*length(buffer))+b,1] <- ip
        preplanning_order_area[((a-1)*length(buffer))+b,2] <- fb
        preplanning_order_area[((a-1)*length(buffer))+b,3] <- area(
OWF_", fb, "km_ring_preplanning_order_", ip, "_displ_16_erased)/100
0000"))))
    b<-b+1
  }
  a<-a+1
}
#Save
setwd("Y:/Marine Species/Rebecca Hall/Laptop files/PhD work/Future
cumulative displ/Results tables")
write.csv(preplanning_order_area,"preplanning_order_area.csv")
#Crop to SPA
for(ip in preplanning_OWFs){
  for(bf in buffer){
    for(fb in buffer){
      try(eval(parse(text = paste0("OWF_", fb, "km_ring_preplanning
_order_", ip, "_displ_", bf, "_erased_OTESPA <- raster::intersect(O
uter_Thames_Estuary_SPA, OWF_", fb, "km_ring_preplanning_order_", i
p, "_displ_", bf, "_erased)"))))
    }
  }
}
#Table
preplanning_order_area_OTESPA <- data.frame(MaxDispl=NA, OWF=NA, Ri
ng=NA, Area=NA)
a<-1
for(bf in buffer){
  b<-1
  for(ip in preplanning_OWFs){
    c<-1
    for(fb in buffer){
      try(eval(parse(text = paste0("
          preplanning_order_area_OTESPA[((a-1)*length(buffer)*lengt
h(preplanning_OWFs))+((b-1)*length(buffer))+c,1] <- bf
          preplanning_order_area_OTESPA[((a-1)*length(buffer)*lengt
h(preplanning_OWFs))+((b-1)*length(buffer))+c,2] <- ip
          preplanning_order_area_OTESPA[((a-1)*length(buffer)*lengt
h(preplanning_OWFs))+((b-1)*length(buffer))+c,3] <- fb
          preplanning_order_area_OTESPA[((a-1)*length(buffer)*lengt
h(preplanning_OWFs))+((b-1)*length(buffer))+c,4] <- area(OWF_", fb,
"km_ring_preplanning_order_", ip, "_displ_", bf, "_erased_OTESPA)/1
000000"))))
      c<-c+1
```

```
    }
    b<-b+1
  }
  a<-a+1
}
#Save
setwd("Y:/Marine Species/Rebecca Hall/Laptop files/PhD work/Future cumulative displ/Results tables")
write.csv(preplanning_order_area_OTESPA,"preplanning_order_area_OTESPA_Two_first.csv")
```

Crop density to OWFs & rings

```
#Crop density
for(fb in buffer){
  for (ip in preplanning_OWFs) {
    for (bf in buffer) {
      try(eval(parse(text = paste0("RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "_erased <-raster::intersect(RTD_density_Outer_Thames_Estuary_SPA, OWF_", bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "_erased)"))))
    }
  }
}
```

Displace birds

```
#Displace birds using displacement gradient
for (ip in preplanning_OWFs) {
  for (fb in buffer){
    for(bf in buffer){
      eval(parse(text = paste0("if(exists('RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "_erased')){if(!is.null(RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "_erased)){RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "_erased@data$RH_D_MaxDispl",fb,"<- as.numeric(sapply((1-(Displ_together[(fb*17)+(bf+1),Displ_grad])/100),'*',RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "_erased@data$RH_D))}}")))
    }
  }
}
```

Calculate numbers of birds displaced and mortality and as proportion of SPA

```
#No. birds in SPA
RTD_density_Outer_Thames_Estuary_SPA_sum <- sum((area(RTD_density_Outer_Thames_Estuary_SPA)/1000000)*RTD_density_Outer_Thames_Estuary_SPA@data$RH_D)
for (ip in preplanning_OWFs) {
  for (fb in buffer){
    for(bf in 0:fb){
```

```
      try(eval(parse(text = paste0("
          RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_
preplanning_order_", ip, "_displ_", fb, "_erased_sum <- sum((area(R
TD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_preplanning
_order_", ip, "_displ_", fb, "_erased)/1000000)*RTD_density_Outer_T
hames_Estuary_SPA_OWF_", bf, "km_ring_preplanning_order_", ip, "_di
spl_", fb, "_erased@data$RH_D)
          RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_
preplanning_order_", ip, "_displ_", fb, "_erased_sum_", fb, " <-sum
((area(RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_pre
planning_order_", ip, "_displ_", fb, "_erased)/1000000)*RTD_density
_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_preplanning_order_",
ip, "_displ_", fb, "_erased@data$RH_D_MaxDispl", fb, ")
          RTD_percloss_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring
_preplanning_order_", ip, "_displ_", fb, "_erased <- ((RTD_density_
Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_preplanning_order_", i
p, "_displ_", fb, "_erased_sum - RTD_density_Outer_Thames_Estuary_S
PA_OWF_", bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "_er
ased_sum_", fb, ")/RTD_density_Outer_Thames_Estuary_SPA_sum)*100"))
))
    }
  }
}
#Calculate numbers of bird casualties and as proportion of SPA
Mortality_rate <- 1:10
#Put into table
for (ip in preplanning_OWFs) {
  eval(parse(text = paste0("RTD_percloss_Outer_Thames_Estuary_SPA_p
replanning_order_", ip, " <- data.frame(Max_displ_km=NA, Ring=NA, M
ortalityRate=NA, RingArea=NA, NoBirds=NA, NoBirdLoss=NA, SPAPercLos
s=NA, NoBirdMortality=NA, SPAPercMortality=NA)")))
  a<-1
  for (fb in buffer) {
    b<-1
    for (bf in 0:fb) {
      c<-1
      for (mt in Mortality_rate) {
        eval(parse(text = paste0("try(if(!is.null(RTD_density_Outer
_Thames_Estuary_SPA_OWF_", bf, "km_ring_preplanning_order_", ip, "_
displ_", fb, "_erased)){
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,1] <- fb
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,2] <- bf
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,3] <- mt
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,4] <-sum(area(RTD_density_Outer_Thames_Estuary_
```

```
SPA_OWF_", bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "_e
rased)/1000000)
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,5] <-RTD_density_Outer_Thames_Estuary_SPA_OWF_"
, bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "_erased_sum
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,6] <-RTD_density_Outer_Thames_Estuary_SPA_OWF_"
, bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "_erased_sum
- RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_preplann
ing_order_", ip, "_displ_", fb, "_erased_sum_", fb, "
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,7] <-RTD_percloss_Outer_Thames_Estuary_SPA_OWF_
", bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "_erased
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,8] <-(RTD_density_Outer_Thames_Estuary_SPA_OWF_
", bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "_erased_su
m - RTD_density_Outer_Thames_Estuary_SPA_OWF_", bf, "km_ring_prepla
nning_order_", ip, "_displ_", fb, "_erased_sum_", fb, ")/100*mt
          RTD_percloss_Outer_Thames_Estuary_SPA_preplanning_order_"
, ip, "[((a-1)*length(Mortality_rate)*length(buffer))+((b-1)*length
(Mortality_rate))+c,9] <-(RTD_percloss_Outer_Thames_Estuary_SPA_OWF
_", bf, "km_ring_preplanning_order_", ip, "_displ_", fb, "_erased)/
100*mt})")))
        c<-c+1
      }
      b<-b+1
    }
    a<-a+1
  }
}
#Remova NAs
for (ip in preplanning_OWFs) {
  eval(parse(text = paste0("RTD_percloss_Outer_Thames_Estuary_SPA_p
replanning_order_", ip, "<-na.omit(RTD_percloss_Outer_Thames_Estuar
y_SPA_preplanning_order_", ip, ")")))
}
#Sum % birds for each scenario
for (ip in preplanning_OWFs) {
  eval(parse(text = paste0("RTD_percloss_total_Outer_Thames_Estuary
_SPA_preplanning_order_", ip, " <- data.frame(OWF_num=NA, Max_displ
_km=NA, MortalityRate=NA, NoBirdLoss=NA, SPAPercLoss=NA, NoBirdMort
ality=NA, SPAPercMortality=NA, Area=NA)")))
  a<-1
  for (fb in buffer) {
    b<-1
    for (mt in Mortality_rate) {
      eval(parse(text = paste0("
        RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_ord
```

```
er_", ip, "[((a-1)*length(Mortality_rate))+b,1] <- ip
        RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_ord
er_", ip, "[((a-1)*length(Mortality_rate))+b,2] <- fb
        RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_ord
er_", ip, "[((a-1)*length(Mortality_rate))+b,3] <- mt
        try({RTD_percloss_total_Outer_Thames_Estuary_SPA_preplannin
g_order_", ip, "[((a-1)*length(Mortality_rate))+b,4] <-sum(subset(R
TD_percloss_Outer_Thames_Estuary_SPA_preplanning_order_", ip, ", Ma
x_displ_km==fb & MortalityRate==mt, select=NoBirdLoss), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_ord
er_", ip, "[((a-1)*length(Mortality_rate))+b,5] <-sum(subset(RTD_pe
rcloss_Outer_Thames_Estuary_SPA_preplanning_order_", ip, ", Max_dis
pl_km==fb & MortalityRate==mt, select=SPAPercLoss), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_ord
er_", ip, "[((a-1)*length(Mortality_rate))+b,6] <-sum(subset(RTD_pe
rcloss_Outer_Thames_Estuary_SPA_preplanning_order_", ip, ", Max_dis
pl_km==fb & MortalityRate==mt, select=NoBirdMortality), na.rm=TRUE)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_ord
er_", ip, "[((a-1)*length(Mortality_rate))+b,7] <-sum(subset(RTD_pe
rcloss_Outer_Thames_Estuary_SPA_preplanning_order_", ip, ", Max_dis
pl_km==fb & MortalityRate==mt, select=SPAPercMortality), na.rm=TRUE
)
        RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_ord
er_", ip, "[((a-1)*length(Mortality_rate))+b,8] <-sum(subset(RTD_pe
rcloss_Outer_Thames_Estuary_SPA_preplanning_order_", ip, ", Max_dis
pl_km==fb & SPAPercLoss>0, select=RingArea), na.rm=TRUE)}, silent=T
RUE)")))
      b<-b+1
    }
    a<-a+1
  }
}
#Sum all OWFs
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_sum <
- data.frame()
a<-1
for (ip in preplanning_OWFs) {
  eval(parse(text = paste0("RTD_percloss_total_Outer_Thames_Estuary
_SPA_preplanning_order_sum <- rbind(RTD_percloss_total_Outer_Thames
_Estuary_SPA_preplanning_order_sum, RTD_percloss_total_Outer_Thames
_Estuary_SPA_preplanning_order_", preplanning_OWFs[a], ")")))
  a<-a+1
}
#Save
setwd("c:/Users/44755/OneDrive - University of Strathclyde/1. Thesi
s/12. Thesis V2")
#If using hundred within displacement gradient, save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_o
rder_sum,"RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_o
rder_Two_first_sum_Hundred_Within.csv")
#If using basic displacement gradient, save this:
write.csv(RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_o
```

```
rder_sum,"RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_Two_first_sum_Gradient.csv")
```

~~~~~ PLOTS ~~~~~

From closest

```
#Load outputs
setwd("c:/Users/44755/OneDrive - University of Strathclyde/1. Thesis/12. Thesis V2/From closest")
#Hundred within
RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF_Hundred_Within <-read.csv(file ="RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF_Hundred_Within.csv")
RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF_Hundred_Within$Displacement <- "100% within"
#Basic gradient
RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF_Gradient <-read.csv(file ="RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF_Gradient.csv")
RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF_Gradient$Displacement <- "Basic gradient"
#Bind both displacement gradient types
RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF_both<-rbind(RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF_Hundred_Within,RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF_Gradient)
#Add columns of factors
RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF_both$Order <- 'Either first'
RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF_both$Scenario <- 'Impacted once from closest'
Displacement <- c('100% within','Basic gradient')
RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF_both$Displacement <- factor(as.character(RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF_both$Displacement), levels=Displacement)
Stage <- c('operational','consented','preplanning')
RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF_both$Stage <- factor(as.character(RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF_both$Stage), levels=Stage)
#Plot
ggplot(subset(RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF_both,MortalityRate==1), aes(x=Max_displ_km,y=NoBirdLoss, shape=Displacement))+geom_point(size=2)+geom_line(aes(linetype=Stage))+scale_color_manual(values = c("#DF0059","#D9DF63","#6C0091"))+theme_bw()+theme(panel.border = element_blank(), axis.line = element_line(colour = "black"),text=element_text(size=12,  family="Calibri"))+xlab("Maximum displacement distance (km)")+ylab("Number of birds displaced")+scale_x_continuous(limits=c(0, 16), breaks=seq(0, 16, 1))+scale_y_continuous(limits=c(0, 6500), breaks=seq(0, 6500, 1000))
```

Individual

```
#Load outputs
setwd("c:/Users/44755/OneDrive - University of Strathclyde/1. Thesi
s/12. Thesis V2/Individual")
#OPERATIONAL
#Hundred within
RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_sum_total_H
undred_Within <-read.csv(file ="RTD_percloss_total_Outer_Thames_Est
uary_SPA_operational_sum_total_Hundred_Within.csv")
RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_sum_total_H
undred_Within$Displacement <- "100% within"
RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_sum_total_H
undred_Within$Stage <- "operational"
#Basic gradient
RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_sum_total_G
radient <-read.csv(file ="RTD_percloss_total_Outer_Thames_Estuary_S
PA_operational_sum_total_Gradient.csv")
RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_sum_total_G
radient$Displacement <- "Basic gradient"
RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_sum_total_G
radient$Stage <- "operational"
#CONSENTED
#Hundred within
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_sum_total_Hun
dred_Within <-read.csv(file ="RTD_percloss_total_Outer_Thames_Estua
ry_SPA_consented_sum_total_Hundred_Within.csv")
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_sum_total_Hun
dred_Within$Displacement <- "100% within"
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_sum_total_Hun
dred_Within$Stage <- "consented"
#Basic gradient
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_sum_total_Gra
dient <-read.csv(file ="RTD_percloss_total_Outer_Thames_Estuary_SPA
_consented_sum_total_Gradient.csv")
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_sum_total_Gra
dient$Displacement <- "Basic gradient"
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_sum_total_Gra
dient$Stage <- "consented"
#PREPLANNING
#Hundred within
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_sum_total_H
undred_Within <-read.csv(file ="RTD_percloss_total_Outer_Thames_Est
uary_SPA_preplanning_sum_total_Hundred_Within.csv")
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_sum_total_H
undred_Within$Displacement <- "100% within"
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_sum_total_H
undred_Within$Stage <- "preplanning"
#Basic gradient
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_sum_total_G
radient <-read.csv(file ="RTD_percloss_total_Outer_Thames_Estuary_S
PA_preplanning_sum_total_Gradient.csv")
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_sum_total_G
radient$Displacement <- "Basic gradient"
```

```
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_sum_total_G
radient$Stage <- "preplanning"
#Bind tables
RTD_percloss_total_Outer_Thames_Estuary_SPA_multiple_allOWF_both<-r
bind(RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_sum_to
tal_Hundred_Within,RTD_percloss_total_Outer_Thames_Estuary_SPA_cons
ented_sum_total_Hundred_Within,RTD_percloss_total_Outer_Thames_Estu
ary_SPA_preplanning_sum_total_Hundred_Within,RTD_percloss_total_Out
er_Thames_Estuary_SPA_operational_sum_total_Gradient,RTD_percloss_t
otal_Outer_Thames_Estuary_SPA_consented_sum_total_Gradient,RTD_perc
loss_total_Outer_Thames_Estuary_SPA_preplanning_sum_total_Gradient)
RTD_percloss_total_Outer_Thames_Estuary_SPA_multiple_allOWF_both$Or
der <- 'Either first'
RTD_percloss_total_Outer_Thames_Estuary_SPA_multiple_allOWF_both$Sc
enario <- 'Impacted multiple times'
#Add columns of factors
Displacement <- c('100% within','Basic gradient')
RTD_percloss_total_Outer_Thames_Estuary_SPA_multiple_allOWF_both$Di
splacement <- factor(as.character(RTD_percloss_total_Outer_Thames_E
stuary_SPA_multiple_allOWF_both$Displacement), levels=Displacement)
Stage <- c('operational','consented','preplanning')
RTD_percloss_total_Outer_Thames_Estuary_SPA_multiple_allOWF_both$St
age <- factor(as.character(RTD_percloss_total_Outer_Thames_Estuary_
SPA_multiple_allOWF_both$Stage), levels=Stage)
#Plot
ggplot(subset(RTD_percloss_total_Outer_Thames_Estuary_SPA_multiple_
allOWF_both,MortalityRate==1), aes(x=Max_displ_km,y=NoBirdLoss, sha
pe=Displacement))+geom_point(size=2)+geom_line(aes(linetype=Stage))
+scale_color_manual(values = c("#DF0059","#D9DF63","#6C0091"))+them
e_bw()+theme(panel.border = element_blank(), axis.line = element_li
ne(colour = "black"),text=element_text(size=12,  family="Calibri"))
+xlab("Maximum displacement distance (km)")+ylab("Number of birds d
isplaced")+scale_x_continuous(limits=c(0, 16), breaks=seq(0, 16, 1)
)+scale_y_continuous(limits=c(0, 12000), breaks=seq(0, 12000, 1000)
)
```

In order

```
#Load outputs
setwd("c:/Users/44755/OneDrive - University of Strathclyde/1. Thesi
s/12. Thesis V2/In order")
#Read in OneNorth first
#Hundred within
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_OneNo
rth_first_sum_Hundred_Within <-read.csv(file ="RTD_percloss_total_O
uter_Thames_Estuary_SPA_preplanning_order_OneNorth_first_sum_Hundre
d_Within.csv")
#Gradient
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_OneNo
rth_first_sum_Gradient <-read.csv(file ="RTD_percloss_total_Outer_T
hames_Estuary_SPA_preplanning_order_OneNorth_first_sum_Gradient.csv
")
```

```
#Read in Two first
#Hundred within
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_Two_f
irst_sum_Hundred_Within <- read.csv(file ="RTD_percloss_total_Outer
_Thames_Estuary_SPA_preplanning_order_Two_first_sum_Hundred_Within.
csv")
#Gradient
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_Two_f
irst_sum_Gradient <- read.csv(file ="RTD_percloss_total_Outer_Thame
s_Estuary_SPA_preplanning_order_Two_first_sum_Gradient.csv")
#Split out operational OWFs (OWFs 1 to 9)
#Hundred within
RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_order_sum_H
undred_Within <-subset(RTD_percloss_total_Outer_Thames_Estuary_SPA_
preplanning_order_OneNorth_first_sum_Hundred_Within, OWF_num>=1 & O
WF_num<=9)
RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_order_sum_H
undred_Within$Stage <- "operational"
#Gradient
RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_order_sum_G
radient <-subset(RTD_percloss_total_Outer_Thames_Estuary_SPA_prepla
nning_order_OneNorth_first_sum_Gradient, OWF_num>=1 & OWF_num<=9)
RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_order_sum_G
radient$Stage <- "operational"
#Split out consented OWFs (OWFs 1 to 9) OneNorth first
#Hundred within
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_OneNort
h_first_sum_Hundred_Within <-subset(RTD_percloss_total_Outer_Thames
_Estuary_SPA_preplanning_order_OneNorth_first_sum_Hundred_Within, O
WF_num>=10 & OWF_num<=11)
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_OneNort
h_first_sum_Hundred_Within$Stage <-"consented"
#Gradient
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_OneNort
h_first_sum_Gradient <-subset(RTD_percloss_total_Outer_Thames_Estua
ry_SPA_preplanning_order_OneNorth_first_sum_Gradient, OWF_num>=10 &
OWF_num<=11)
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_OneNort
h_first_sum_Gradient$Stage <-"consented"
#Split out consented OWFs (OWFs 1 to 9) Two first
#Hundred within
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_Two_fir
st_sum_Hundred_Within <-subset(RTD_percloss_total_Outer_Thames_Estu
ary_SPA_preplanning_order_Two_first_sum_Hundred_Within, OWF_num>=10
& OWF_num<=11)
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_Two_fir
st_sum_Hundred_Within$Stage <-"consented"
#Gradient
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_Two_fir
st_sum_Gradient <-subset(RTD_percloss_total_Outer_Thames_Estuary_SP
A_preplanning_order_Two_first_sum_Gradient, OWF_num>=10 & OWF_num<=
11)
```

```
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_Two_fir
st_sum_Gradient$Stage <-"consented"
#Split out preplanning OWFs (OWFs 1 to 9) OneNorth first
#Hundred within
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_OneNo
rth_first_sum_Hundred_Within <-subset(RTD_percloss_total_Outer_Tham
es_Estuary_SPA_preplanning_order_OneNorth_first_sum_Hundred_Within,
OWF_num>=12)
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_OneNo
rth_first_sum_Hundred_Within$Stage <- "preplanning"
#Gradient
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_OneNo
rth_first_sum_Gradient <-subset(RTD_percloss_total_Outer_Thames_Est
uary_SPA_preplanning_order_OneNorth_first_sum_Gradient, OWF_num>=12
)
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_OneNo
rth_first_sum_Gradient$Stage <- "preplanning"
#Split out preplanning OWFs (OWFs 1 to 9) Two first
#Hundred within
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_Two_f
irst_sum_Hundred_Within <-subset(RTD_percloss_total_Outer_Thames_Es
tuary_SPA_preplanning_order_Two_first_sum_Hundred_Within, OWF_num>=
12)
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_Two_f
irst_sum_Hundred_Within$Stage <- "preplanning"
#Gradient
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_Two_f
irst_sum_Gradient <-subset(RTD_percloss_total_Outer_Thames_Estuary_
SPA_preplanning_order_Two_first_sum_Gradient, OWF_num>=12)
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_Two_f
irst_sum_Gradient$Stage <- "preplanning"
#Add numbers from OWFs together
#Operational
#Hundred within
RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_order_sum_H
undred_Within_total <-aggregate(RTD_percloss_total_Outer_Thames_Est
uary_SPA_operational_order_sum_Hundred_Within[,5:9],by=list(Max_dis
pl_km = RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_ord
er_sum_Hundred_Within$Max_displ_km,MortalityRate = RTD_percloss_tot
al_Outer_Thames_Estuary_SPA_operational_order_sum_Hundred_Within$Mo
rtalityRate),sum)
RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_order_sum_H
undred_Within_total$Stage <- 'operational'
RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_order_sum_H
undred_Within_total$Displacement <- '100% within'
RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_order_sum_H
undred_Within_total$Order <- 'Either first'
#Gradient
RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_order_sum_G
radient_total <-aggregate(RTD_percloss_total_Outer_Thames_Estuary_S
PA_operational_order_sum_Gradient[,5:9],by=list(Max_displ_km = RTD_
percloss_total_Outer_Thames_Estuary_SPA_operational_order_sum_Gradi
```

```
ent$Max_displ_km,MortalityRate = RTD_percloss_total_Outer_Thames_Es
tuary_SPA_operational_order_sum_Gradient$MortalityRate),sum)
RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_order_sum_G
radient_total$Stage <- 'operational'
RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_order_sum_G
radient_total$Displacement <- 'Basic gradient'
RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_order_sum_G
radient_total$Order <- 'Either first'
#Consented One North first
#Hundred within
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_OneNort
h_first_sum_Hundred_Within_total <-aggregate(RTD_percloss_total_Out
er_Thames_Estuary_SPA_consented_order_OneNorth_first_sum_Hundred_Wi
thin[,5:9],by=list(Max_displ_km = RTD_percloss_total_Outer_Thames_E
stuary_SPA_consented_order_OneNorth_first_sum_Hundred_Within$Max_di
spl_km,MortalityRate = RTD_percloss_total_Outer_Thames_Estuary_SPA_
consented_order_OneNorth_first_sum_Hundred_Within$MortalityRate),su
m)
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_OneNort
h_first_sum_Hundred_Within_total$Stage <- 'consented'
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_OneNort
h_first_sum_Hundred_Within_total$Displacement <- '100% within'
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_OneNort
h_first_sum_Hundred_Within_total$Order <- 'East Anglia One North fi
rst'
#Gradient
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_OneNort
h_first_sum_Gradient_total <-aggregate(RTD_percloss_total_Outer_Tha
mes_Estuary_SPA_consented_order_OneNorth_first_sum_Gradient[,5:9],b
y=list(Max_displ_km = RTD_percloss_total_Outer_Thames_Estuary_SPA_c
onsented_order_OneNorth_first_sum_Gradient$Max_displ_km,MortalityRa
te = RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_On
eNorth_first_sum_Gradient$MortalityRate),sum)
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_OneNort
h_first_sum_Gradient_total$Stage <- 'consented'
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_OneNort
h_first_sum_Gradient_total$Displacement <- 'Basic gradient'
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_OneNort
h_first_sum_Gradient_total$Order <- 'East Anglia One North first'
#Consented Two first
#Hundred within
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_Two_fir
st_sum_Hundred_Within_total <-aggregate(RTD_percloss_total_Outer_Th
ames_Estuary_SPA_consented_order_Two_first_sum_Hundred_Within[,5:9]
,by=list(Max_displ_km = RTD_percloss_total_Outer_Thames_Estuary_SPA
_consented_order_Two_first_sum_Hundred_Within$Max_displ_km,Mortalit
yRate = RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order
_Two_first_sum_Hundred_Within$MortalityRate),sum)
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_Two_fir
st_sum_Hundred_Within_total$Stage <- 'consented'
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_Two_fir
st_sum_Hundred_Within_total$Displacement <- '100% within'
```

```
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_Two_first_sum_Hundred_Within_total$Order <- 'East Anglia Two first'
#Gradient
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_Two_first_sum_Gradient_total <-aggregate(RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_Two_first_sum_Gradient[,5:9],by=list(Max_displ_km = RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_Two_first_sum_Gradient$Max_displ_km,MortalityRate = RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_Two_first_sum_Gradient$MortalityRate),sum)
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_Two_first_sum_Gradient_total$Stage <- 'consented'
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_Two_first_sum_Gradient_total$Displacement <- 'Basic gradient'
RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_Two_first_sum_Gradient_total$Order <- 'East Anglia Two first'
#Preplanning One North first
#Hundred within
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_OneNorth_first_sum_Hundred_Within_total <-aggregate(RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_OneNorth_first_sum_Hundred_Within[,5:9],by=list(Max_displ_km = RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_OneNorth_first_sum_Hundred_Within$Max_displ_km,MortalityRate = RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_OneNorth_first_sum_Hundred_Within$MortalityRate),sum)
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_OneNorth_first_sum_Hundred_Within_total$Stage <- 'preplanning'
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_OneNorth_first_sum_Hundred_Within_total$Displacement <- '100% within'
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_OneNorth_first_sum_Hundred_Within_total$Order <- 'East Anglia One North first'
#Gradient
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_OneNorth_first_sum_Gradient_total <-aggregate(RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_OneNorth_first_sum_Gradient[,5:9],by=list(Max_displ_km = RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_OneNorth_first_sum_Gradient$Max_displ_km,MortalityRate = RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_OneNorth_first_sum_Gradient$MortalityRate),sum)
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_OneNorth_first_sum_Gradient_total$Stage <- 'preplanning'
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_OneNorth_first_sum_Gradient_total$Displacement <- 'Basic gradient'
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_OneNorth_first_sum_Gradient_total$Order <- 'East Anglia One North first'
#preplanning Two first
#Hundred within
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_Two_first_sum_Hundred_Within_total <-aggregate(RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_Two_first_sum_Hundred_Within[,
```

```
5:9],by=list(Max_displ_km = RTD_percloss_total_Outer_Thames_Estuary
_SPA_preplanning_order_Two_first_sum_Hundred_Within$Max_displ_km,Mo
rtalityRate = RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanni
ng_order_Two_first_sum_Hundred_Within$MortalityRate),sum)
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_Two_f
irst_sum_Hundred_Within_total$Stage <- 'preplanning'
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_Two_f
irst_sum_Hundred_Within_total$Displacement <- '100% within'
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_Two_f
irst_sum_Hundred_Within_total$Order <- 'East Anglia Two first'
#Gradient
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_Two_f
irst_sum_Gradient_total <-aggregate(RTD_percloss_total_Outer_Thames
_Estuary_SPA_preplanning_order_Two_first_sum_Gradient[,5:9],by=list
(Max_displ_km = RTD_percloss_total_Outer_Thames_Estuary_SPA_preplan
ning_order_Two_first_sum_Gradient$Max_displ_km,MortalityRate = RTD_
percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_Two_first
_sum_Gradient$MortalityRate),sum)
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_Two_f
irst_sum_Gradient_total$Stage <- 'preplanning'
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_Two_f
irst_sum_Gradient_total$Displacement <- 'Basic gradient'
RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_order_Two_f
irst_sum_Gradient_total$Order <- 'East Anglia Two first'
#Put into one table
RTD_percloss_total_Outer_Thames_Estuary_SPA_order_allOWF_both <-rbi
nd(RTD_percloss_total_Outer_Thames_Estuary_SPA_operational_order_su
m_Hundred_Within_total,RTD_percloss_total_Outer_Thames_Estuary_SPA_
operational_order_sum_Gradient_total,RTD_percloss_total_Outer_Thame
s_Estuary_SPA_consented_order_OneNorth_first_sum_Hundred_Within_tot
al,RTD_percloss_total_Outer_Thames_Estuary_SPA_consented_order_OneN
orth_first_sum_Gradient_total,RTD_percloss_total_Outer_Thames_Estua
ry_SPA_consented_order_Two_first_sum_Hundred_Within_total,RTD_percl
oss_total_Outer_Thames_Estuary_SPA_consented_order_Two_first_sum_Gr
adient_total,RTD_percloss_total_Outer_Thames_Estuary_SPA_preplannin
g_order_OneNorth_first_sum_Gradient_total,RTD_percloss_total_Outer_
Thames_Estuary_SPA_preplanning_order_OneNorth_first_sum_Hundred_Wit
hin_total,RTD_percloss_total_Outer_Thames_Estuary_SPA_preplanning_o
rder_Two_first_sum_Gradient_total,RTD_percloss_total_Outer_Thames_E
stuary_SPA_preplanning_order_Two_first_sum_Hundred_Within_total)
RTD_percloss_total_Outer_Thames_Estuary_SPA_order_allOWF_both$Scena
rio <- 'Impacted once in order'
#Plot
ggplot(subset(RTD_percloss_total_Outer_Thames_Estuary_SPA_operation
al_order_sum_Hundred_Within_total,MortalityRate==1), aes(x=Max_disp
l_km,y=NoBirdLoss))+geom_point(size=2)+theme_bw()+theme(panel.borde
r = element_blank(), axis.line = element_line(colour = "black"),tex
t=element_text(size=12,  family="Calibri"))+xlab("Maximum displacem
ent distance (km)")+ylab("Number of birds displaced")+scale_x_conti
nuous(limits=c(0, 16), breaks=seq(0, 16, 1))+scale_y_continuous(lim
its=c(0, 6500), breaks=seq(0, 6500, 500))
```

Put all together to plot

```
#Order columns the same
RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF_both <- RTD
_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF_both[,c(3,4,5,
6,7,8,2,9,11,10)]
RTD_percloss_total_Outer_Thames_Estuary_SPA_multiple_allOWF_both <-
RTD_percloss_total_Outer_Thames_Estuary_SPA_multiple_allOWF_both[,c
(2,3,4,5,6,7,9,8,11,10)]
RTD_percloss_total_Outer_Thames_Estuary_SPA_order_allOWF_both <-RTD
_percloss_total_Outer_Thames_Estuary_SPA_order_allOWF_both[,c(1,2,3
,4,5,6,8,9,11,10)]
#Bind all together into one final table
RTD_percloss_total_Outer_Thames_Estuary_SPA_ALL_allOWF_both <- rbin
d(RTD_percloss_total_Outer_Thames_Estuary_SPA_plus_allOWF_both,RTD_
percloss_total_Outer_Thames_Estuary_SPA_multiple_allOWF_both,RTD_pe
rcloss_total_Outer_Thames_Estuary_SPA_order_allOWF_both)
#Add column of factors
Stage <- c('operational','consented','preplanning')
Displacement <- c('100% within','Basic gradient')
Scenario <- c('Impacted once in order','Impacted once from closest'
,'Impacted multiple times')
Order <- c('East Anglia One North first','East Anglia Two first','E
ither first')
RTD_percloss_total_Outer_Thames_Estuary_SPA_ALL_allOWF_both$Stage <
- factor(as.character(RTD_percloss_total_Outer_Thames_Estuary_SPA_A
LL_allOWF_both$Stage), levels=Stage)
RTD_percloss_total_Outer_Thames_Estuary_SPA_ALL_allOWF_both$Displac
ement <- factor(as.character(RTD_percloss_total_Outer_Thames_Estuar
y_SPA_ALL_allOWF_both$Displacement), levels=Displacement)
RTD_percloss_total_Outer_Thames_Estuary_SPA_ALL_allOWF_both$Scenari
o <- factor(as.character(RTD_percloss_total_Outer_Thames_Estuary_SP
A_ALL_allOWF_both$Scenario), levels=Scenario)
RTD_percloss_total_Outer_Thames_Estuary_SPA_ALL_allOWF_both$Order <
- factor(as.character(RTD_percloss_total_Outer_Thames_Estuary_SPA_A
LL_allOWF_both$Order), levels=Order)
#Plot operational OWFs only
RTD_percloss_total_Outer_Thames_Estuary_SPA_ALL_allOWF_both_operati
onalPlot <-ggplot(subset(RTD_percloss_total_Outer_Thames_Estuary_SP
A_ALL_allOWF_both, MortalityRate==1 & Stage=='operational'), aes(x=
Max_displ_km, y=NoBirdLoss, shape=Displacement,colour=Scenario))+ge
om_point(size=2)+geom_line()+scale_color_manual(values = c("#DF0059
","#D9DF63","#6C0091"))+theme_bw()+theme(panel.border = element_bla
nk(), axis.line = element_line(colour = "black"),text=element_text(
size=12,  family="Calibri"))+xlab("Maximum displacement distance (k
m)")+ylab("Number of birds displaced")+scale_x_continuous(limits=c(
0, 16), breaks=seq(0, 16, 1))+scale_y_continuous(limits=c(0, 11500)
, breaks=seq(0, 11500, 1000))
#Save
setwd("c:/Users/44755/OneDrive - University of Strathclyde/1. Thesi
s/12. Thesis V2")
ggsave('RTD_percloss_total_Outer_Thames_Estuary_SPA_ALL_allOWF_both
```

```
_operationalPlot.png', RTD_percloss_total_Outer_Thames_Estuary_SPA_
ALL_allOWF_both_operationalPlot, height = 5, width = 6)
#Plot consented OWFs only
RTD_percloss_total_Outer_Thames_Estuary_SPA_ALL_allOWF_both_consent
edPlot <-ggplot(subset(RTD_percloss_total_Outer_Thames_Estuary_SPA_
ALL_allOWF_both, MortalityRate==1 & Stage=='consented'), aes(x=Max_
displ_km, y=NoBirdLoss, shape=Displacement,colour=Scenario))+geom_p
oint(size=2)+geom_line(aes(linetype=Order))+scale_linetype_manual(v
alues=c("dashed", "dotted","solid"))+scale_color_manual(values = c(
"#DF0059","#D9DF63","#6C0091"))+theme_bw()+theme(panel.border = ele
ment_blank(), axis.line = element_line(colour = "black"),text=eleme
nt_text(size=12,  family="Calibri"))+xlab("Maximum displacement dis
tance (km)")+ylab("Number of birds displaced")+scale_x_continuous(l
imits=c(0, 16), breaks=seq(0, 16, 1))+scale_y_continuous(limits=c(0
, 450), breaks=seq(0, 450, 50))
#Save
setwd("c:/Users/44755/OneDrive - University of Strathclyde/1. Thesi
s/12. Thesis V2")
ggsave('RTD_percloss_total_Outer_Thames_Estuary_SPA_ALL_allOWF_both
_consentedPlot.png', RTD_percloss_total_Outer_Thames_Estuary_SPA_AL
L_allOWF_both_consentedPlot, height = 5, width = 6)
#Plot consented OWFs only between 15km and 16km
RTD_percloss_total_Outer_Thames_Estuary_SPA_ALL_allOWF_both_consent
ed15to16kmPlot <-ggplot(subset(RTD_percloss_total_Outer_Thames_Estu
ary_SPA_ALL_allOWF_both, MortalityRate==1 & Stage=='consented'), ae
s(x=Max_displ_km, y=NoBirdLoss, shape=Displacement,colour=Scenario)
)+geom_point(size=2)+geom_line(aes(linetype=Order))+scale_linetype_
manual(values=c("dashed", "dotted","solid"))+scale_color_manual(val
ues = c("#DF0059","#D9DF63","#6C0091"))+theme_bw()+theme(panel.bord
er = element_blank(), axis.line = element_line(colour = "black"),te
xt=element_text(size=12,  family="Calibri"))+xlab("Maximum displace
ment distance (km)")+ylab("Number of birds displaced")+scale_x_cont
inuous(limits=c(15, 16), breaks=seq(15, 16, 1))+scale_y_continuous(
limits=c(0, 450), breaks=seq(0, 450, 50))
#Save
setwd("c:/Users/44755/OneDrive - University of Strathclyde/1. Thesi
s/12. Thesis V2")
ggsave('RTD_percloss_total_Outer_Thames_Estuary_SPA_ALL_allOWF_both
_consented15to16kmPlot.png', RTD_percloss_total_Outer_Thames_Estuar
y_SPA_ALL_allOWF_both_consented15to16kmPlot, height = 5, width = 6)
#Plot preplanning OWFs only
RTD_percloss_total_Outer_Thames_Estuary_SPA_ALL_allOWF_both_preplan
ningPlot <-ggplot(subset(RTD_percloss_total_Outer_Thames_Estuary_SP
A_ALL_allOWF_both, MortalityRate==1 & Stage=='preplanning'), aes(x=
Max_displ_km, y=NoBirdLoss, shape=Displacement,colour=Scenario))+ge
om_point(size=2)+geom_line()+scale_linetype_manual(values=c("dashed
", "dotted","solid"))+scale_color_manual(values = c("#DF0059","#D9D
F63","#6C0091"))+theme_bw()+theme(panel.border = element_blank(), a
xis.line = element_line(colour = "black"),text=element_text(size=12
,  family="Calibri"))+xlab("Maximum displacement distance (km)")+yl
ab("Number of birds displaced")+scale_x_continuous(limits=c(0, 16),
breaks=seq(0, 16, 1))+scale_y_continuous(limits=c(0, 1200), breaks=
```

```
seq(0, 1200, 100))
#Save
setwd("c:/Users/44755/OneDrive - University of Strathclyde/1. Thesi
s/12. Thesis V2")
ggsave('RTD_percloss_total_Outer_Thames_Estuary_SPA_ALL_allOWF_both
_preplanningPlot.png', RTD_percloss_total_Outer_Thames_Estuary_SPA_
ALL_allOWF_both_preplanningPlot, height = 5, width = 6)
```