Energy for Sustainable Development 74 (2023) 66–78

Contents lists available at ScienceDirect

Energy for Sustainable Development

journal homepage: www.journals.elsevier.com/energy-for-sustainable-development

Protecting avian wildlife for wind farm siting: The Screening Tool Proof of Concept

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ARTICLE INFO

Keywords:
Bird collisions
Wind energy
Bird conservation
Avoidance
Environmental Impact Assessment
Siting

ABSTRACT

Bird collisions with wind turbines continue to be a major problem within the wind industry. Developing scarecrow technologies and other, more advanced, multi-sensory bird monitoring systems on the market are paving the way to resolving this perplex dilemma. Environmental Impact Assessments are required by regulatory bodies to prove that a wind farm will not cause adverse impacts to vulnerable avian populations. The Screening Tool Proof of Concept is intended to help with permitting, and to reduce seasonal curtailment events resulting from annual migration. It revealed a positive correlation between bird activity hotspots for Pink-footed geese species and distance to crops. The most favorable crops were winter and spring cereals located at Klim Fjordholme Wind Farm in Northern Denmark. The 2 km test radius around the turbine revealed direct impacts of surrounding land use, however, for future developments, increasing the radius will provide further geospatially relevant information across a broader area. Avoidance through initial risk screening is arguably the most effective way to reduce impacts to biodiversity and ensure successful operation via coexistence with avian wildlife.

Introduction

Achieving a symbiotic relationship between wind turbines and avian wildlife conservation remains a challenging task, especially due to now larger turbines occupying available land, water, and free airspace. The Paris Agreement tells us that its goal is to limit global warming to well below 2, preferably 1.5 °C, compared to pre-industrial levels (Barston, 2019) via reducing global carbon emissions. Nevertheless, preserving the balance of ecosystems is an integral part of sustainability, if we are to achieve sustainability in its highest sense of the word. Moreover, a crucial element that contributes to the success of a wind farm includes the Environmental Impact Assessment (EIA) and thereby granting consent approval by the relevant regional authorities. However, before an EIA takes place, risk-screening surveys are carried out before a wind energy project is further developed. More specifically, this involves a desk-based process for identifying any potential biodiversity and ecosystem service risks and opportunities related to an(y) area(s) of interest. Normally, this is performed at the early project planning stage (IUCN & TBC, 2021). This can include, for instance, an avoidance by site-selection approach, where wind turbines are not situated along high biodiversity sensitivity areas (such as along migratory flyways). In this way, alternative sites are identified in which wind turbines are least likely to incur a negative environmental impact. Considerations for project development may include aspects such as spatial planning and/or sensitivity mapping information, to avoid developments taking place in sensitive areas (IUCN & TBC, 2021). Any such impacts to biodiversity—be it cumulative, direct or indirect—should be accounted for at this time.

Thus, the purpose of an EIA is to enable relevant authorities and/or governmental advisors to determine whether applicants can demonstrate that their development does not impose any adverse impact on the environment. It helps to reveal both the benefits and the downfalls that wind turbine projects introduce to local habitats. By applying processes, such as the Mitigation Hierarchy, in an iterative manner, it can help to reduce or mitigate any impacts to wildlife while also determining any residual impacts (IUCN & TBC, 2021).

On the other hand, if a wind farm project is refused planning consent, it can mean one of two things: there was either insufficient scientific data collected through the undergone bird or bat surveys, or that survey findings actually revealed projections of more damage done to a specific species and/or habitat than what was permitted. An example of this occurred in the UK, where the Docking Shoal Offshore Wind Farm was refused planning consent over the estimate numbers of Sandwich terns *Thalasseus sandvicensis* predicted to be killed (Cook et al., 2018). Because

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https://doi.org/10.1016/j.esd.2023.03.002
Received 13 August 2022; Received in revised form 22 December 2022; Accepted 2 March 2023
Available online 24 March 2023

wind farms are also the cause for disturbance and displacement from feeding areas, this makes some larger bird species particularly susceptible to population-level impacts (Broadbent & Nixon, 2019), inhibiting their chances of survival. Additionally it can be unfavorable to both developers and other relevant stakeholders that the consenting process can be lengthy and costly; where, in some cases, it calls for several years of scoping, site characterization, and environmental data collection (Broadbent & Nixon, 2019). Therefore, it is crucial that a thorough and detailed investigation on avian wildlife impacts is done first-hand. This will help all involved parties, including the developer and other regulatory bodies, make a scientifically based decision for granting planning consent. In order to accomplish this, the appropriate tools must be used which can collect sufficient amounts of data in order to predetermine any impacts to biodiversity.

Although current tools which are available for measuring avian biodiversity impacts in the wind industry have come a long way, knowledge gaps still remain, rendering wind energy coexistence with avifauna a challenge. First and foremost, human observation of birds around a wind farm via the human eye is an unreliable method of reporting bird counts and for identifying species. With increasing distance, detection rate and accuracy decrease (McClure et al., 2018) as the clear image of the bird diminishes the further way it flies. While this is an unreliable method onshore, it is impossible offshore due to the marine environment and logistics. Next, radar technologies alone are not enough for species identification, as they primarily provide information on movements of birds including their trajectory and altitude. That is why some bird monitoring systems such as TADS and MUSE (Dirksen, 2017; Tjørnløv et al., 2021) pair their radar with a camera to help with the species identification component. This is further improved using thermal camera's for night-time species detection. However, in addition to thermal camera's being expensive, the dynamic marine offshore conditions can cause the applied clutter filtration method to erase an increasing proportion of bird echoes, leading to significant false negative bird detection rates (Tjørnløv et al., 2021). This can paint an unrealistic picture of bird densities. Other camera-based technologies such as DTBird, and IdentiFlight do not show the size of bird activity occurring around a wind farm site, only the species identified and detected. Moreover, by combining accelerometers with camera's, such as in the WT-Bird system, this is limited by bird size in order to document a bird collision event (Wiggelinkhuizen et al., 2006) which can lead to misinformation on impacts. Systems pairing camera's with microphones, such as ATOM, combines thermal imaging with acoustic and ultrasound sensors to continuously monitor bird and bat abundance, flight height, direction, and speed (Willmott et al., 2015). However, its monitoring data is not delivered in real-time, adding a time delay for analysis (Willmott et al., 2015). The above-mentioned technologies do not provide any information on correlations between bird activity levels at potential wind farm sites and surrounding environmental features such as water bodies and crops, which can influence bird behavior. Furthermore, another tool available is shut down on demand, albeit this is an approach used already post-operation, it merely mitigates the avian collision problem. Technologies such as ROBIN Radar, DTBird, IdentiFlight, and MERLIN SCADA apply a curtailment module during calculated high-collision risk situations (Collier et al., 2012; H.T. Harvey & Associates, 2018; McClure et al., 2018; Niemi & Tanttu, 2020). Although effective, stopping the turbine equates to lost energy production, therefore reducing Annual Energy Production (AEP) targets. This, however, negates the entire purpose of carbon emission reduction efforts through renewable energy generation. Using the Mitigation Hierarchy as the guide, the author aimed to explore reducing impacts to avifauna at the first and most effective stage – avoidance.

In order to not only prevent bird populations from dwindling, but also to not further delay a wind farm project from going online, avian wildlife forecasting provided by the novel Screening Tool software can help mitigate these problem areas. For projects in the pre-construction and siting phase, the Screening Tool software will be applied. Its primary purpose is to forecast and identify all high-to-low density bird-activity areas including migration flyways, as well as to pinpoint hotspots for flock formations where habitat suitability is ranked the highest for the local species of interest. This is accomplished through the assessment of local environmental parameters onshore, which may influence bird activity. For already operating wind farms, the Screening Tool also has the potential to act as a non-stop surveillance device scanning for bird activity and performing round-the-clock data collection. The various data streams used to help identify bird activity areas and corridors will be stored year-round in order to prompt adjustments and fine-tune future curtailment. More specifically, reducing the curtailment period for seasonal migration down to a period where it is deemed absolutely necessary. This ensures avoiding the excess onset of curtailment, which would otherwise lose the industry money and lead to more wear and tear on the turbine. With that said, this style of biodiversity mapping may help all interested parties more effectively and scientifically site future wind turbines and resort to curtailing them less. Through successful implementation for an EIA, the Screening Tool Proof of Concept (PoC) has the potential to help warrant that AEP targets are met via reduced automated shutdown events. This is thanks to the combined approaches of biodiversity-friendly siting and real-time data analysis via spatial and temporal data streams. With a central, web-based platform housing the necessary environmental information related to wind farm siting and avifauna activity, it provides developers with an easy-to-use in-house tool, which can save time and reduce costs related to outsourcing for expert help. Finally, The Screening Tool provides a novel means of biodiversity screening whose purpose and application is becoming increasingly relevant as biodiversity-related issues become the center of attention for the success of future renewable energy projects.

Methods and materials

This case study took place at Klim Fjordholme Wind Farm, located in the Northern Jutland region of Denmark, in Jammerbugt Municipality. Klim Wind Farm was a repowering project that originally consisted of 35 Vestas V44 turbines and covered 111.5 ha. The repowering led to what is now a wind farm consisting of 22 Siemens 3.2 MW turbines with a hub height of 93 m and a rotor diameter of 113 m, giving a blade tip height of 149.5 m (Drachmann et al., 2020; Kahlert et al., 2012) (Fig. 1).

This wind farm is situated nearby an international NATURA-2000 bird protection area number 16 (known as Vejlerne), which consists of 5 EU bird protection areas (Kahlert et al., 2012):

(1) The coast from Aggersund to Bygholm Vejle (EU-8)
(2) Løgstor Bredning, Livø, Feggesund and Skarrehage (EU-12)
(3) Eastern Vejler (EU-13)
(4) Lønnerup Fjord (EU-19)
(5) Western Vejler, Arup Holme and Hovsør Røn (EU-20).

Fig. 3 is an image of the entire wind farm. From the image, one can see that it is surrounded by agricultural fields on all sides. Fig. 2 is another map showing the study area in more detail, particularly in terms of its location to nearby habitat (denoted by a yellow outline color) and bird protection areas (denoted by blue stripes). Due to the wind farm's unique location, each day thousands of birds leave their roosting areas in Vejlerne and fly out to the nearby fields to find food, with many passing the wind farm (Vattenfall Press Office, 2020). In this special bird protection area, 20–30,000 Pink-footed geese and several hundred cranes are found roosting (Vattenfall Press Office, 2020).

Two Furuno FAR – 2127 x-band magnetron marine radars (horizontal and vertical) were installed about 10 m distance South-east of wind turbine #223. A radar trailer housing the PC, laptop, security camera, solid-state radar, and HD Motion Camera was situated approximately 5 m south of the turbine tower. The two magnetron radars were installed and operational between May 2020 and August

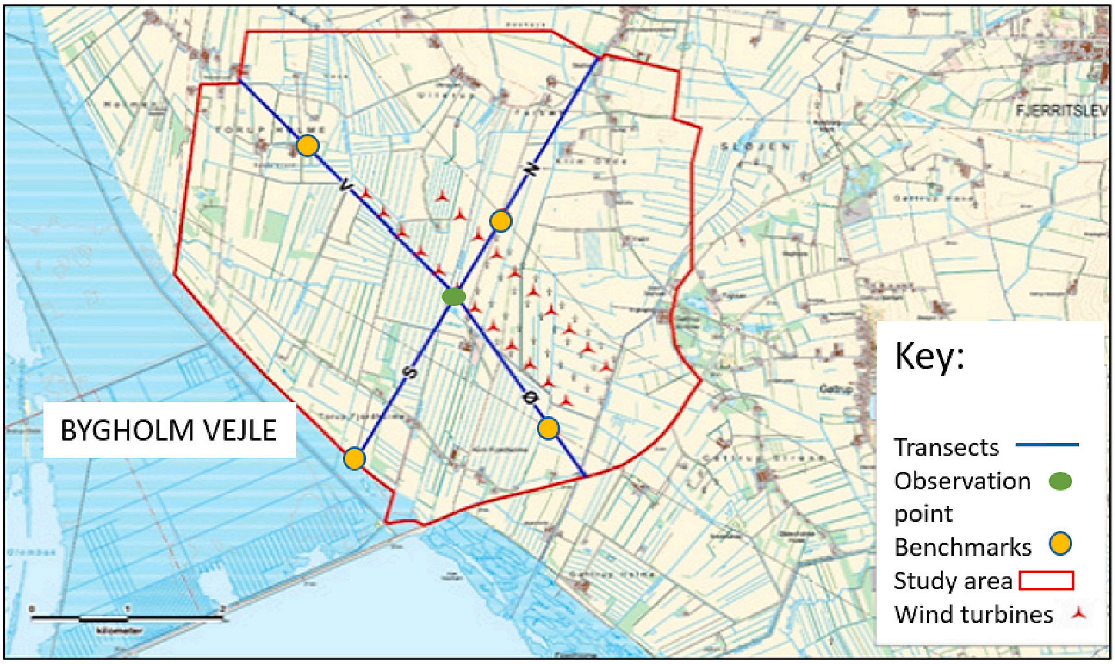

Fig. 1. Klim Fjordholme Wind Farm project area post-repowering.
(Adapted from Drachmann et al. (2020).)

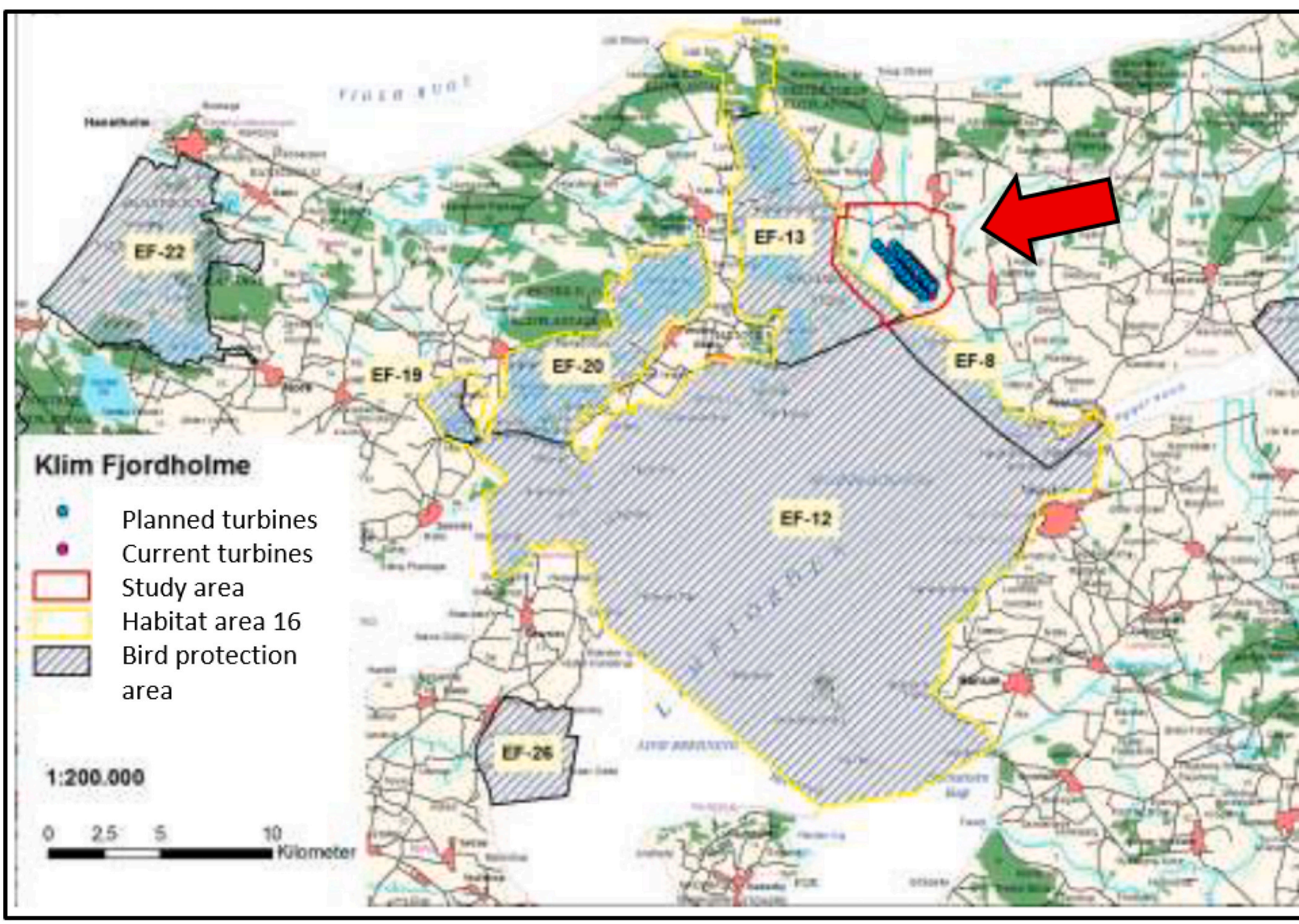

Fig. 2. Map of northern Thy and Vester Han Herred, including the study area for birds at Klim Fjordholme farm as well as nearby habitat and bird protection areas.
(Adapted from Kahlert et al. (2012).)

Fig. 3. Image of Klim Fjordholme Wind Farm (taken 16 January 2021) capturing migrating geese above the rotating turbine blades and operating radar and camera (indicated by the white radar trailer, located at the base of the right-most turbine).

Fig. 4. Image of data collection site at base of turbine #223. On the right are the two Furuno FAR-2127 x-band marine radars (horizontal & vertical); on top of the trailer is the solid-state Furuno DRS25A-NXT radar.

2021, whereas the newer solid-state radar was installed in February 2021 and operational until August 2021. This was due to the risk of the magnetron radars deteriorating over time (six months) and a more reliable radar was needed to continue data collection. The area where the trailer and radar were placed and operational was covered in gravel pavement. Due to the inherent presence of the turbine tower and the

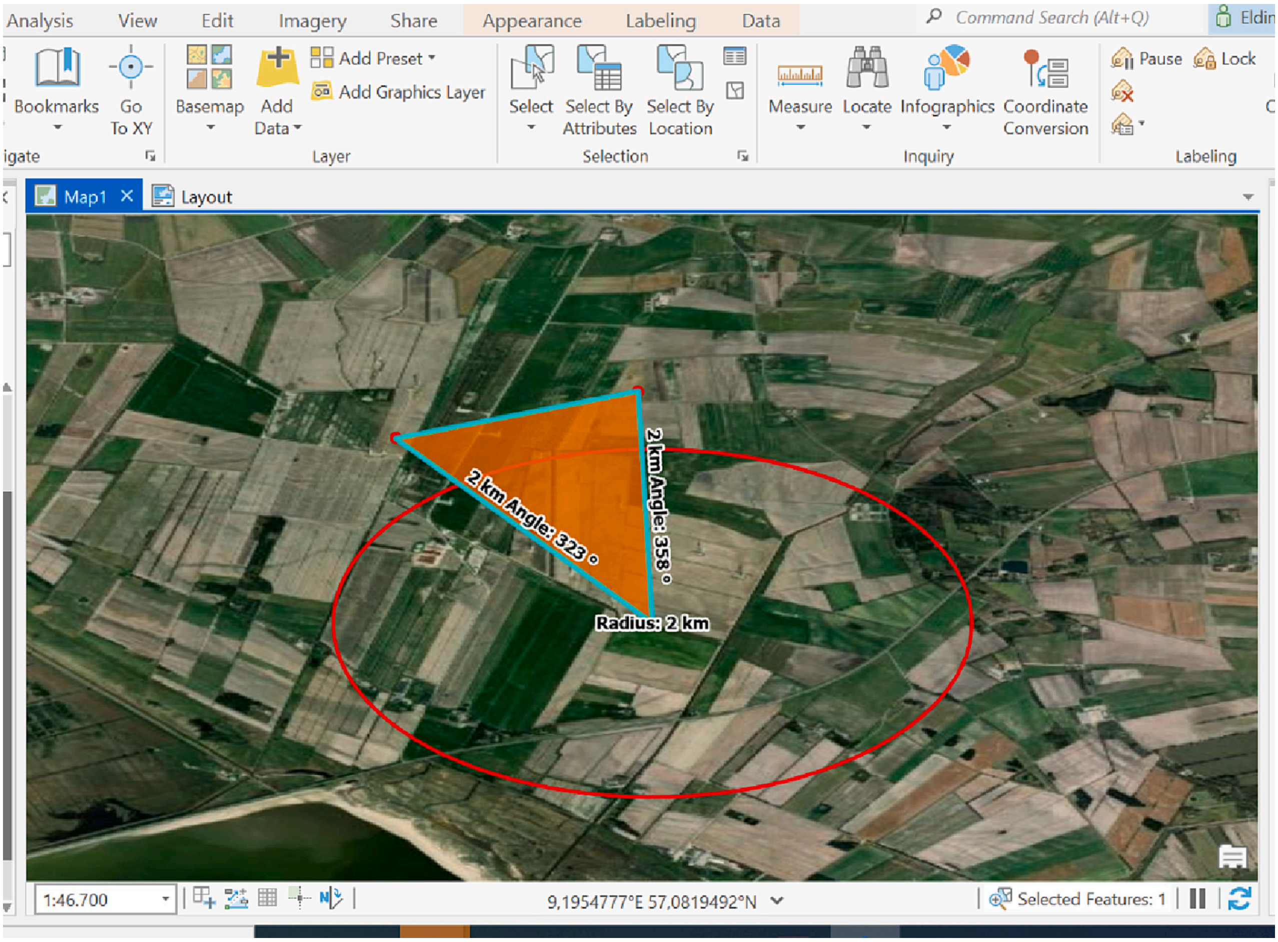

Fig. 5. Two blind sectors within 2 km radius delineated in study area due to presence of radar trailer and nearby turbine tower in the form of a GIS layer via ArcGIS Pro.

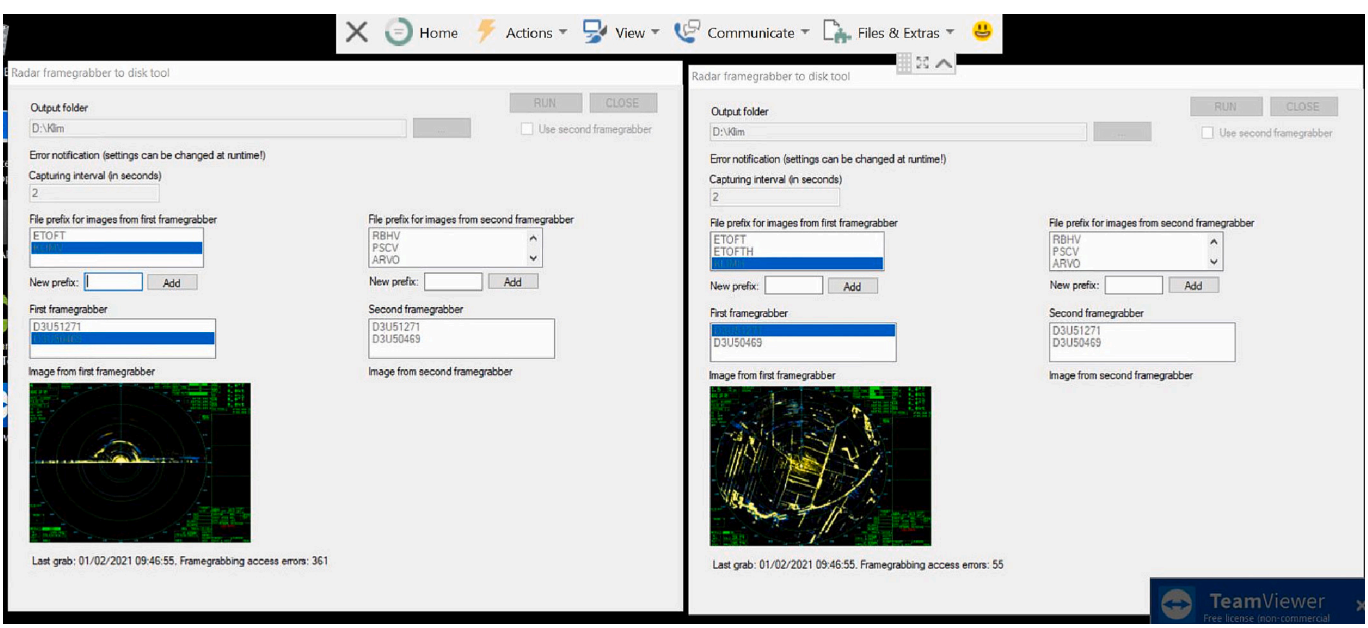

Fig. 6. TeamViewer screenshot showing the vertical and horizontal radar frame grabs via the local Windows image and video capturing software, Epiphan VGA/DVI Capture Tool.

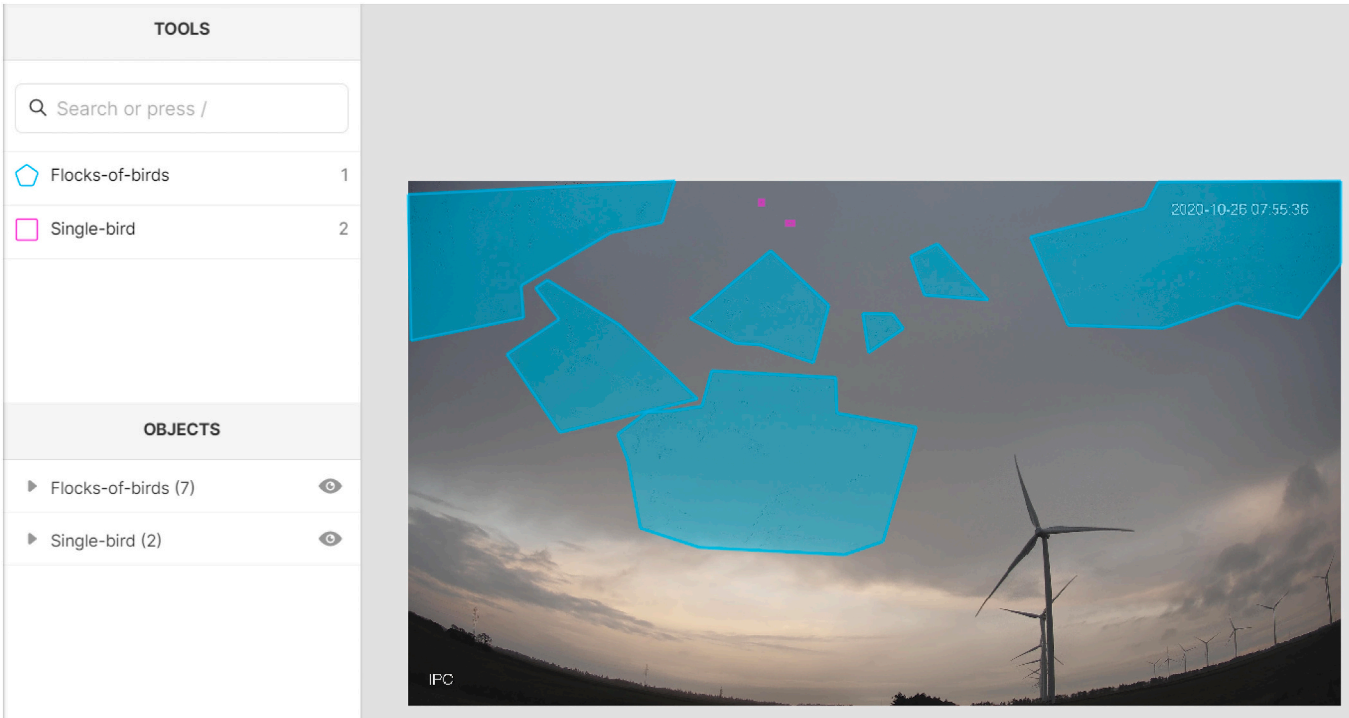

Fig. 7. Image annotation of single birds vs. flocks of birds via Labelbox.

Fig. 8. Prediction score generated by the YOLO model; score of 0.88 on a flock of birds.

trailer there were two blind spots to consider (given that azimuth North = 0, counting clock-wise). See Fig. 5 for details on:

(1) Blind sector due to trailer: from 323° to 337° and
(2) Blind sector due to the turbine tower: 344° to 358°.

In these blind sector angles, no bird tracking data was collected from the radars. These blind areas were delineated in the web tool, to avoid confusion for the end-user. The model of the HD motion camera was a Dahua 8MP Dome Camera IP ePoE 50M IR 2.8 mm Lens IPC-HDW4831EM-ASE. It was mounted onto the front side, top right corner of the radar trailer, facing the Eastern direction, as seen in Fig. 4. This IP camera allows the user to connect and configure online, by logging directly into the camera. Here it was possible to set up needed

Fig. 9. Prediction score generated by the YOLO model; score of 0.94 on a single bird.

criteria, such as 'Take a picture when moving - with the exception of these areas.' Once the camera took a picture, the image was automatically sent to the user's digital bucket, and later stored, making access to the images possible. Power cables for the radar, trailer PC's and camera were connected to the wind turbine, which was the main power source for all electronic devices. Vattenfall provided the power supply. After establishing a secure internet connection, TeamViewer was used for remote-control access to the local PC's so that data monitoring could be achieved. In Fig. 6, one can see what is displayed through TeamViewer via remote access. The Epiphan VGA/DVI Capture Tool is a local Windows software used to capture the live-stream frame-grab images collected from the horizontal and vertical Furuno Marine Radars. The frame grabs were saved onto an external hard disc. As both the horizontal and vertical radars were capable of collecting ca. 10 GB of data per day, this storage scheme was crucial for the storage of large amounts of data, which were later needed for image processing. Altogether, three external hard discs were used to manage all the radar data that was collected.

Bird tracking model

Next came the filtering process through a set of camera images collected between the months of September–November 2020. The images were extracted from the image folder bucket, uploaded via FileZilla software and then downloaded. Filtering was done based on the presence or absence of birds in the photos. If there were no birds captured within a specific image frame it was deleted. In contrast, those images with a bird visible in the frame were kept. This filtering was done for each time stamp, coming down to the date and time. After the filtering process was completed, the next step was annotating the saved images for single birds vs. flocks of birds (defined as a group of birds traveling together in cohesion with one another). In Fig. 7 a screenshot of the image annotation process is shown. The saved images were uploaded onto Labelbox in a designated folder and assigned two different types of classifiers: a polygon representing flocks of birds (blue color) and a square for a single bird (pink color). The classifiers are listed under the "tools" heading on the left-hand sidebar, while the number of each classifier found in the present image is listed under the heading "objects." In this example, one can see that there are seven blue polygons in the image indicating flocks, and two squares indicating single birds. Altogether, there were 337 images that were submitted; with 25 images being skipped after a re-evaluation of each image was done, concluding that there were no birds present. Of these 337 images, there were 658 flocks of birds, and 120 single birds identified. This led to a total of 778 annotations. Based upon the object counts listed in Table 1 the images primarily contained flocks of birds (85 %) in comparison to single birds (15 %).

Following the image annotation process, a YOLO ("You Only Look Once") model was trained on the annotated images to recognize birds in images from the motion camera. The researcher used the YOLO v5 for object detection. With the current algorithm, detection accuracy reached 68 %. Due to some operational malfunctioning of the camera, it had to be reset. From January the HD camera became unusable as it was no longer working properly. The cause of the malfunction is unknown. Nevertheless, to further optimize the detection accuracy, the same set of images were used to re-train the algorithm. Images were already categorized with birds and their detection scores; however, in some images, the wind turbine blades or even airplanes flying in the sky were classified as birds and this was obviously incorrect. Images with false-positives (false detection of birds) were separated into a separate folder named "No Bird." This is important because the "No Bird" classified images were used in the algorithm to teach it that objects such as moving blades, power lines, and airplanes are not birds. From Figs. 8 and 9, the prediction scores generated by the automated Machine Learning (ML) model are displayed.

After the training of the YOLO model was finished, sequences of the radar frame-grab images corresponding to bird sightings from the motion camera were extracted. Everything in the radar image first had to be removed, except for the radar signals represented by the yellow colors in the image. As can be seen in Fig. 10, there are grid lines and a lot of green text that needed to be removed from the standard radar frame grab. Removing these extras allowed for clearer depiction of bird tracks.

By means of a Gaussian mixture-based background/foreground segmentation algorithm, the researcher used one hundred previously

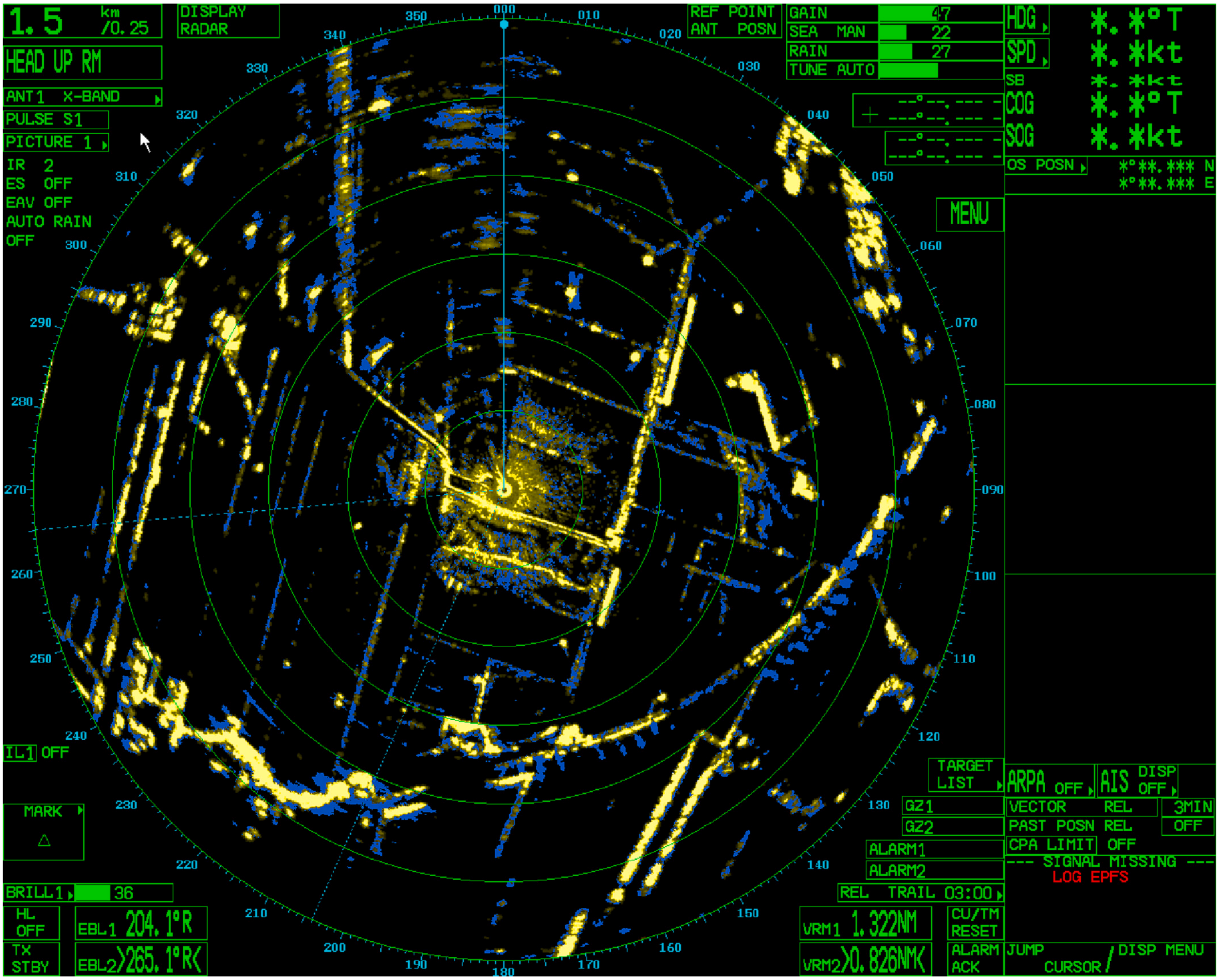

Fig. 10. Frame grab from the horizontal scanning FAR-2127 Furuno radar (pre-processed image).

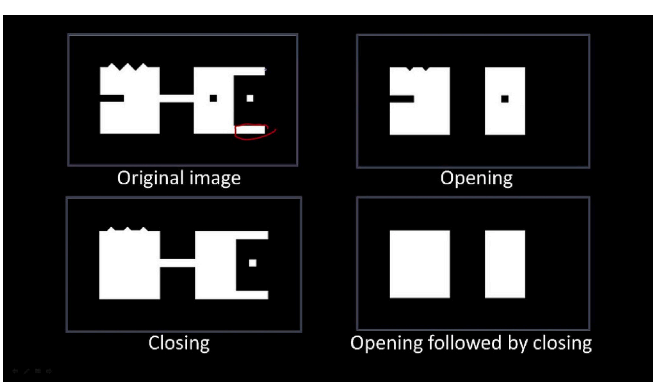

Fig. 11. Graphic showing the process of opening and closing in terms of morphological actions to reduce noise and fill in gaps.

saved radar images from the one hundred previous days as part of the background/foreground segmentation process. Following this, the color of these images was then converted to greyscale. A median filter was applied to reduce noise in the frame grabs. The total signal was then added up, and if it exceeded a threshold-value, it was considered to be raining and the image was disregarded. Afterwards, a couple of morphological actions were applied in order to piece everything together, such as opening (to reduce noise) and closing (to fill in the gaps). Morphological operations were done to make it easier to cluster objects together. Hence, these two actions taken together –opening and closing—helped to smoothen out the edges and fill in the gaps, as illustrated in Fig. 11.

Screening tool development

Data sources

Development of the Screening Tool software was done using a GIS approach. Various layers were selected and were based on the different environmental factors that may influence either attraction or repulsion by birds. GIS layers allow for flexibility for the end-user to select or de-select a particular parameter as a layer, and therefore draw conclusions on where siting future turbines would make the most sense, based on the spatial information provided. Table 2 provides more insight on the GIS layers used, as well as on the sources that provided the relevant shape files for the associated GIS layers. Moreover, all GIS layer data was derived from an open-source.

Crop favorability indices for 2019 and 2020 were generated based upon evaluating both the type of crop and the relative NDVI (Normalized Difference Vegetation Index) value, which was calculated by using

Fig. 12. BiCA Web homepage of Screening Tool.

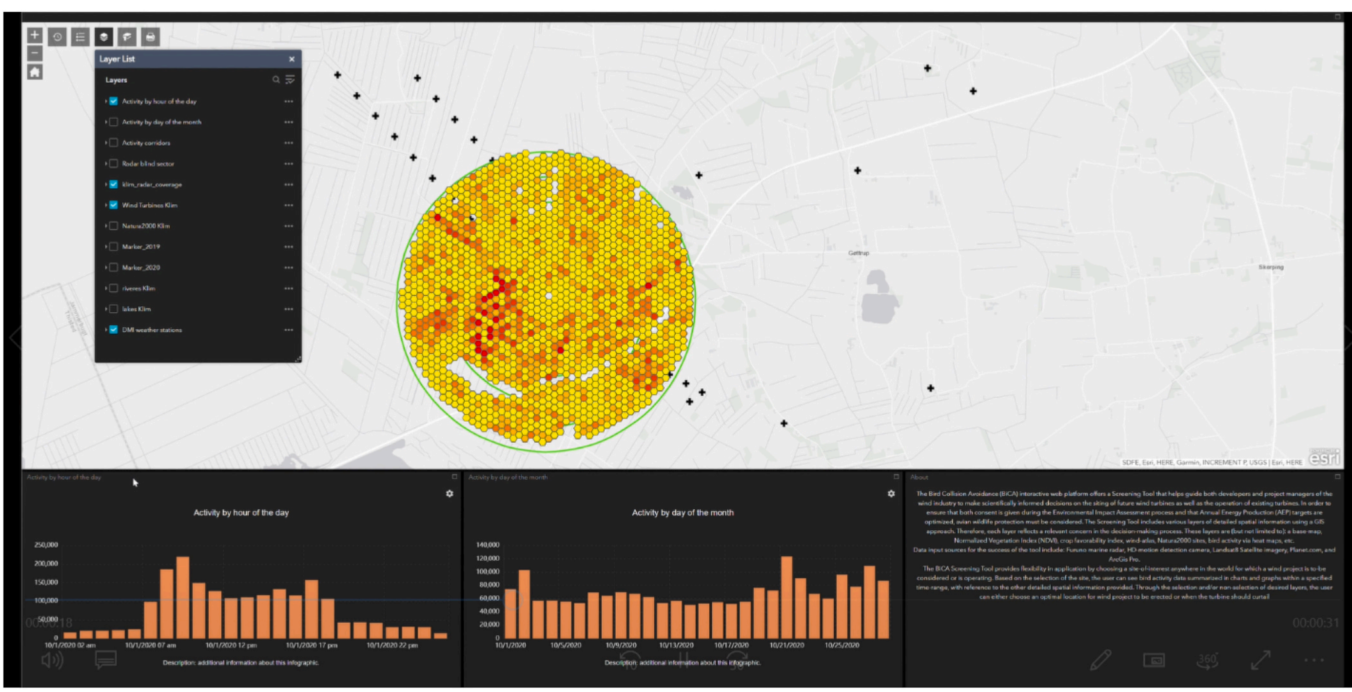

Fig. 13. Heat map of bird activity by hour of day; red hexagons indicate high activity levels, orange hexagons indicate medium activity levels, and yellow hexagons indicate low activity levels.

both the shape files for crops planted/harvested provided by *Ministeriet for Fødevarer, Landbrug og Fiskeri: NaturErhvervstyrelsen* and Landsat8 imagery. Only years 2019 and 2020 were used in this study, due to the open-access limitation. Landsat8 imagery was downloaded from the USGS Global Visualization Viewer (GloVis) website. By setting the parameters for a given scene in GloVis (in our case, Klim Fjordholme), it was possible to deduce the correct satellite data needed to perform the remote sensing analysis. Thus, satellite imagery was compiled for the time period 4 April 2013–4 March 2021, as the earliest Landsat8 satellite imagery was recorded from April 2013 at the specific coordinates for Klim (57.053242, 9.158134 Decimal Degrees). Cloud cover was then set to the range 0–20 %, in order to reduce the impacts of cloud presence on

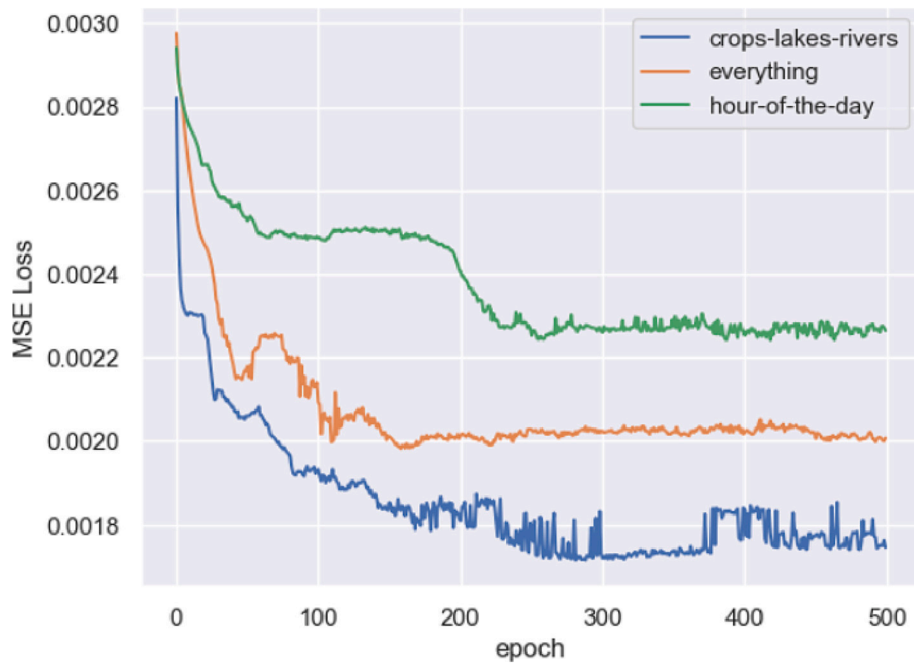

Fig. 14. Bird Tracking Model illustrating the validation losses for three models tested (blue model tests distances to crops, lakes, and rives; orange model tests distances to crops, lakes, rivers, wind–speed/-direction, and temperature; and the green model represents hour of the day).

Table 1
Total counts of each object and percentage share of all submitted images.

Object count		
Object	Count	Share
Flocks-of birds	658	85 %
Single-bird	120	15 %

the ArcGIS NDVI raster analysis calculator. Moreover, sifting through the remaining 0–20 % cloud cover images, some satellite scenes were additionally deleted from the final selection, as they included too much cloud cover, blocking the view of Earth's surface. This additional filtering step helped to ensure a more accurate vegetation analysis for the study site. The next step was the creation of a multispectral band through ArcGIS Pro, using all of the satellite images compiled for the given time period via GloVis. The NDVI calculator on ArcGIS Pro was then used to find the values for the study site area (radius 2 km from wind turbine).

The general formula for NDVI is as follows:

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{1}$$

where:

NIR = Near Infrared
$NDVI$ = Normalized Difference Vegetation Index.
Red = Red Spectral Band (Band 4 in Landsat8).

Since the images for Klim were collected using Landsat8 satellite imagery (with 30 m resolution), Bands 5 and 4 were therefore applied to the calculation. The NDVI calculation here was, however, performed using the raster calculator tool in ArcGIS Pro. The below equation illustrates the relevant bands for Landsat8 imagery data.

$$NDVI = \frac{Band\ 5 – Band\ 4}{Band\ 5 + Band\ 4} \tag{2}$$

Table 3 gives more details about the various bands, their wavelengths and their corresponding resolution.

A vegetation index is an indicator that describes the greenness (the relative density and health of vegetation) for each picture element, or

Table 2
List of GIS layers, their definitions and corresponding data source (italicized) that provided the open-access shape files.

GIS layer	Definition
Turbines	The wind turbine layer contains information about the position of the wind turbines in Denmark; *Energistyrelsen*
Rivers	A layer containing rivers in the area of Klim; *Styrelsen for Dataforsyning og Effektivisering*
Lakes	A layer containing lakes in the area of Klim; *Styrelsen for Dataforsyning og Effektivisering*
Natura 2000	The Natura 2000 layers is a network of nature protection areas in the European Union. The Natura 2000 areas are set aside to protect and preserve wild animals, plants and habitat types, which are endangered, rare, or characteristic for the countries within the European countries. The areas cover both land and at sea; *European Environmental Agency*
Fav. Crop Index 2019	A layer illustrating a gradient of low-high favorability to birds for feeding, based upon crops which were planted around Klim in 2019; *Ministeriet for Fødevarer, Landbrug og Fiskeri: NaturErhvervstyrelsen*
Fav. Crop Index 2020	A layer illustrating a gradient of low-high favorability to birds for feeding, based upon crops which were planted around Klim in 2020; *Ministeriet for Fødevarer, Landbrug og Fiskeri: NaturErhvervstyrelsen*
Radar Buffer	A multi-ring buffer around the position of the radar. There is a 250 m of distance between each ring; **Own creation*
Blind Sector	A layer indicating the blind sectors where the radar does not pick up any echoes. Blind sector due to trailer: from 323° to 337° (azimuth North = 0, counting clock-wise). Blind sector due to turbine shaft: 344° to 358°; **Own creation*
Weather Stations	Weather station locations found all across Denmark; *Danmarks Meteorologiske Institute (DMI)*

Table 3
Landsat8 Bands displayed as red, green, blue (RGB) taken from (Interior, 2014).

Bands	Wavelength (μm)	Resolution (m)
Band 1- Coastal aerosol	0.43–0.45	30
Band 2- Blue	0.45–0.51	30
Band 3- Green	0.53–0.59	30
Band 4- Red	0.64–0.67	30
Band 5- Near Infrared (NIR)	0.85–0.88	30
Band 6- SWIR 1	1.57–1.65	30
Band 7- SWIR 2	2.11–2.29	30
Band 8- Panchromatic	0.50–0.68	15
Band 9- Cirrus	1.36–1.38	30
Band 10- Thermal Infrared (TIRS) 1	10.6–11.19	100
Band 11- Thermal Infrared (TIRS) 2	11.50–12.51	100

pixel, in a satellite image (Brown, 2018). NDVI is one of the most commonly used vegetation indices researchers use to transform raw satellite data into NDVI values. Thus, these values (ranging from −1.0 to +1.0) can create images that give a rough measure of vegetation type, amount, and condition on land surfaces around the world (Brown, 2018). By extracting the NDVI values of each land parcel around the wind farm and correlating it with its crop type, the favorability indices (as seen in Table 4) were created as a means of illustrating the effect of favorable food attracting the Pink-footed geese around the wind farm. Further details on the NDVI values and their corresponding vegetation type are found in Table 4.

Results and discussion

BiCA Web

BiCA-Web was created to act as the private access web platform to test the Screening Tool PoC through. It was made possible thanks to the ESRI license provided by Aarhus University. The platform was only accessible to the researcher who had the link. Fig. 12 shows what the end-user encounters when first loading up the private access webpage.

When first navigating the Screening Tool via BiCA Web, the end-user will come across a google-maps-based satellite image automatically zoomed into the projects study area in the Northern region of Denmark. Here, the wind turbines are automatically selected from the layer list to display the wind turbines from Klim Wind Farm, with black x's, displayed in two rows. Already from the first page, the end-user can find bird activity information displayed in the form of histograms on the bottom, along with an “About” section, describing the purpose of the Screening Tool. The bottom left histogram data displays the daily bird activity in October 2020 (1–28 October), in addition to hourly (24 h) bird activity data presented in the histogram to the right, for the same month. October 2020 was selected for the PoC because this was the month where data across all of the assessed parameters (represented in the form of layers) could be extracted. In this way, it was possible to set out finding relationships between these inputs for the same period. When the end-user moves the cursor along individual bars on the graphs, the highlighted bar will then display the level of bird activity with a set number in a pop-up. Moreover, when selecting the layer for bird activity levels either by day or by hour from the drop-down layer list (as seen in Fig. 13), a heat-map is generated displaying where bird activity hotspots are located. Such a map also helps delineate where potential migratory corridors fall along the wind farm. As Klim is situated between a nearby roosting site and nearby feeding sites, activity levels around the wind farm are prevalent. From Fig. 13, one can see that high levels of activity occurred in the Southwestern area of the wind turbine. This is indicated by the red hexagonal colors. Neighboring orange and yellow hexagons indicate either medium or low level of bird activity.

Table 4
NDVI Ranges and their corresponding vegetation type indicator (adapted from Brown, 2018).

NDVI range	Vegetation type
−1.0–0.1	Barren rock, sand, or snow
0.2–0.5	Shrubs, grasslands, or senescing crops
0.6–1.0	Dense vegetation (corresponding to temperate and tropical forests) or crops at their peak growth stage

As part of the ML component for this project, the researcher set out to combine various environmental parameters (distances to lakes/rivers, wind speed/direction, and distance to crops) to predict where bird tracks were most likely to occur (refer to Fig. 14, the Bird Tracking Model).

Distances to lakes/rivers and to crops were selected due to the attractive influence of birds to water-bodies and crop fields for preening, drinking and feeding. Wind speed and direction were tested due to the varying effects of wind on avian flight behavior and collision risk. While it was unsuccessful finding a correlation with these parameters to bird activity, our findings did reveal a positive correlation between the distance to crops present and where bird activity hotspots were highest. Fig. 14 illustrates at which Mean Squared Error (MSE) value the model converges – or rather, where the MSE value does not improve anymore. The blue model converged at a lower MSE value than both the orange and green models, and therefore this lower MSE value of the blue model is an indicator of the relationship. More specifically, the blue model converged at epoch 282, with an MSE loss of 0.00171, the orange model converged at epoch 159, with an MSE loss of 0.00198, and the third model converged at epoch 257, with an MSE loss of 0.00224. After these epoch values, however, the model starts overfitting the data. The model that performed best was the combination of distance to crops, lakes and rivers–disregarding wind speed, wind direction and temperature (blue model). For purposes of understanding, it is important to note here that a higher MSE value indicates the model performed poorly. In addition, neural networks were trained on combinations of these parameters in order to reveal any possible relationships, which may influence bird attraction around the wind farm at Klim Fjordholme.

With that said, the concentrated red/orange area seen in the heat-map includes crops such as Spring Wheat, Spring Barley, Winter Wheat, and Alfalfa. Corresponding to this, the NDVI values for this high bird activity area were primarily in the range of 0.1–0.3. Sparse vegetation such as shrubs and grasslands or senescing crops may result in moderate NDVI values (approximately 0.2 to 0.5) (Brown, 2018), and this was the overall case for the study site area. Through monthly field observations, the researcher primarily encountered shrub cover, amongst the surrounding agricultural fields. By using the tool, and after selecting Marker_2019 and/or Marker_2020 from the layer list, the end-user is able to click on each land parcel colored in the map image and retrieve further information such as what kind of crop, and the assigned favorability index. Additional information is also available in the pop-up; however, these were not particularly relevant for our assessment.

Limitations and future scope

At the initial start of the project, the intention of the HD motion camera was to be able to act as a second registration system, to ensure that we had another data collection source confirming a bird sighting. Moreover, it was also intended as a means of trying to capture the species-specific information about what kind of avian species was captured within the camera's field of view. However, after four months of the camera's operation, it was made apparent that the camera's capabilities were insufficient in capturing the species-specific data for bird activity. The researcher could identify the species type when the bird flew within at least 40 m of the camera. This was extremely limiting, particularly in terms of being able to capture the migratory species flying about the wind farm – it was too far away to perform any kind of valuable deduction. Moreover, the camera began to malfunction after six months of operation. The cause for its malfunction is unknown, but one possibility could be due to the heavy rains and water leaking into the hole, where the electrical wiring was fastened. Hence, the camera was discontinued, as its data inputs were no longer valid. For future developments of the Screening Tool, it would be extremely beneficial to have a camera of higher quality (i.e. durable and resistant to heavy rainfall depending on regional climate conditions) and with increased capability, allowing for recognition of a species from a further distance ($\geq$1 km). This would add onto further details of the kind of species within a particular area of interest, and further enhance awareness and knowledge on impacts to protected species of interest, or those covered under the EU Birds Directive. In essence, this would be added as an additional layer of information that the end-user could then select/deselect. Having a camera that has infrared capabilities for species-detection at nighttime would also be advantageous, allowing for a larger data collection range. As the hardware setup for the Screening Tool could theoretically be translated in an offshore context too, the camera would then need to be capable of handling marine-conditions and include a self-cleaning system for the lens. If the Screening Tool software were used in the offshore realm, instead of using crops as a data input for NDVI calculation and habitat suitability, more information on wind speeds, visibility conditions and weather patterns (such as storms) could be analyzed in order to identify correlations and changes in bird behavior around a site.

Furthermore, as part of the PoC, the radar range was set to cover only a 2 km radius from the radar trailer as the center point. While this helped us assess the direct impacts of nearby farmland, and other water bodies such as scattered streams, in order to gain a broader more comprehensive understanding of how particular environmental parameters (i.e. wind, water or crops) affects bird activity, it would have been beneficial to expand the coverage area of bird tracking. As for the Bird Tracking Model, increasing this range to landscape scale may better help identify migratory corridors and other patterns of bird behavior, which would otherwise be beneficial for the intended purpose of the Screening Tool for an EIA. Through the inclusion of more varying landscapes and land-use systems, the Screening Tool could potentially find more correlations between certain conditions and bird activity hotspots which would aid in decision-making during the siting phase. This additional range would also more likely include the other nearby feeding areas, which influenced geese flight behavior.

With that said, at the moment, the current YOLO model is limited to identifying single birds vs. flocks of birds, and the primary focal species at Klim Fjordholme were the Pink-footed geese. Further refinement of the model is needed through additional training data sets. This may lead to more accurate detection rates (>68 %) of birds. Additionally, expanding the focal species beyond the Pink-footed goose also would be beneficial. By collecting larger datasets from camera imagery and radar frame grabs, for more than a single year, there is opportunity for additional training of the model thereby improving the software's capabilities in terms of detection and tracking as well as expanding the software's application to different regions.

Notwithstanding, the Screening Tool PoC is currently focused on the siting of future wind farms, and it explores how, through avoidance, instances of wildlife interaction can be reduced. However, for the future development of the Screening Tool, it should also be able to assess the post-construction projects by utilizing the same multi-layer and multi-sensory approach, and therefore mitigate wildlife interactions. This would be, for example, through 24/7 active and passive data collection methods, which would be used to curb curtailment time, in order to both optimize on energy delivery and also on wildlife conservation. Particularly, looking at wind farms that are operating which have either excessive curtailment regiments or operating wind farms which are exploring a curtailment regime.

Other potentials of the Screening Tool PoC include that it is a software that is not spatially limited; meaning that it can be applied and used anywhere in the world and adapted to different avian species (birds and bats) and contexts (onshore and offshore). A Wind Resource Area Map, provided through the developer's company, could potentially also be integrated into this web-based platform, thereby not only housing environmental, geo-spatial, and bird activity data, but also crucial wind speed and location data which is key for optimal wind farm siting. This would make this PoC software a central hub for scientific data-driven decision-making. Limitations here could be, for example, that the Wind Resource Area Map may not be in a suitable format to begin with and will require extra time and work to merge formats so that it functions with the GIS-based application.

Last but not least, the crop favorability index as it currently stands, is merely a crude representation of how Pink-footed geese species are attracted to certain kinds of crops. A ranking of low-high favorability is over-simplified, and yet it highlights the importance of how plant stage growth and types of crops present attract varying species of birds. A crop index, which would otherwise be used as a type of bird-use scoring system, is an incredibly complex form of measurement to create. To create it is a study in itself, and would require much time spent out on the fields documenting which fields birds use the most (Wejdling, 2021). Hence, if a crop index *were* to be included as a form of measurement on how often a species exploits an area, documenting where such foraging occurs via time-lapse photography would be a good start; otherwise, it would be a massive undertaking (Wejdling, 2021). If the Screening Tool were to include a crop favorability index, methods that are more efficient would have to be explored.

Conclusion

As a result of future wind development projects, aiming to reduce global carbon dioxide emissions, these tall manmade structures are more frequently appearing across our horizons. With more businesses investing into the renewable energy agenda and more stakeholders expressing interest in transitioning to clean energy sources, fossil-fuel-free energy demands will continue to rise. In countries where good resources and cheap financing are available, wind and solar PV plants will challenge existing fossil fuel plants. Looking at the picture overall, renewables are to set to account for 95 % of the net increase in global power capacity through 2025 (Kent, 2018). In addition, the total installed wind and solar PV capacity is on course to surpass natural gas in 2023 and coal in 2024. Thanks to further cost declines, annual offshore wind additions are set to surge, accounting for one-fifth of the total wind annual market in 2025 (Kent, 2018).

Nevertheless, biodiversity interactions with the wind sector are bound to occur, and this is why it is ever so important to reiterate that either avoiding (via strategic siting and avoidance of sensitive areas) or mitigating (via scarecrow technologies) the adverse impacts to avian wildlife is essential, in order for the two worlds to coexist. Since there are eight migration flyways occurring worldwide, this leaves a high probability of migratory birds encountering wind turbine towers in their airspace environment. This can potentially lead to these long-distance travelers experiencing effects such as displacement, habitat disruption and/or flight behavior changes. Project developers will only face further delay in a project going online, if the demands and thresholds for wildlife impact surveys are not met. The best way to circumvent this problem is through addressing the problem at the earliest point possible, by using the relevant technology and data streams, and that can be best accomplished at the siting phase.

BiCA Web's Screening Tool PoC software solution illustrated that through understanding flight behavior influencers in a given area, one can better deduce which factors have a particularly strong effect, in comparison to others. Whereas most market solution's focus on mitigation measures to biodiversity impacts, this PoC illustrates how the approach to the avian collision dilemma may be more effectively resolved or reduced through avoidance – an approach that is arguably the most effective according to current scientific literature. The Screening Tool's flexibility in application allows it to be used in both the onshore and offshore contexts, giving it an added advantage in targeting a larger market. Furthermore, through the testing of the Bird Tracking Model, the researcher could see that distance to crops had a positive correlation to where bird activity hotspots occurred, in comparison to distance to water bodies and wind speed changes. This was primarily due to the type of crops present in the surrounding land parcels, which were winter and spring cereals—a type of food that Pink-footed Geese like. The generated heat-maps along with the bird activity statistics provided the end-user with an easy-to-understand visual representation as to the counts of corresponding bird activity areas. Moreover, using a layer-based approach like GIS allows the end-user to deduce which areas in a site of interest would theoretically make sense if wanting to site a wind farm project. The drop-down menu provided in the tool, which includes a number of environmental parameters, helps paint an overarching picture of what Klim has to offer in terms of habitat suitable areas. The use of the Furuno Marine Radars showed to be an effective way to not only track large numbers of birds, but also an efficient manner in which the researcher does not have to use traditional time-consuming methods, such as manual logging of individual bird sightings, to track bird trajectories.

For the future, wind developments must consider the associated risks to the continued delivery of ecosystem services, i.e. the benefits and values that people obtain from natural resources. If not carefully managed, such developments can change the supply of, or limit access to, ecosystem services, including provisioning services, such as food and water as well as recreational, cultural (including a sense of place and belonging) and other non-material benefits (IUCN & TBC, 2021). In markets like the United States, Denmark, and Germany, where cases of wind farms suffering from lack of consent approval or shutting down altogether as a result of documented kills to sensitive or protected avian species have resurfaced, the biodiversity issue is yet to be resolved. Hence, while the siting phase may not be the most favorable phase where developers in the industry have the opportunity to alter their approaches, it remains as *the* stage where impacts to wildlife and avian mortality may be greatly reduced, and for coexistence to be achieved.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

I would like to express my sincere thanks to Furuno Radar Denmark and Wind Power Lab for their time, efforts and assistance in this project. Moreover, a big thank you to Vattenfall for allowing the researcher to perform her data collection at one of their wind farms. This study was supported by The EU Regional Fund Denmark.

References

Barston, R. P. (2019). The Paris agreement. *Modern Diplomacy*. https://doi.org/10.4324/9781351270090-20

Broadbent, I. D., & Nixon, C. L. B. (2019). Refusal of planning consent for the Docking Shoal offshore wind farm: Stakeholder perspectives and lessons learned. *Marine Policy, 110*. https://doi.org/10.1016/j.marpol.2019.103529

Brown, J. (2018). *NDVI, the foundation for remote sensing phenology*. U.S. Geological Survey. Usgs. https://www.usgs.gov/special-topics/remote-sensing-phenology/science/ndvi-foundation-remote-sensing-phenology.

Collier, M. P., Dirksen, S., & Krijgsveld, K. L. (2012). A review of methods to monitor collisions or micro-avoidance of birds with offshore wind turbines - part 2: feasibility study of systems to monitor collisions. In *Report Commissioned by The Crown Estate Strategic Ornithological Support Services*, 30 pp.

Cook, A. S. C. P., Humphreys, E. M., Bennet, F., Masden, E. A., & Burton, N. H. K. (2018). Quantifying avian avoidance of offshore wind turbines: current evidence and key knowledge gaps. *Marine Environmental Research, 140*, 278–288. https://doi.org/10.1016/j.marenvres.2018.06.017

Dirksen, S. (2017). Review of methods and techniques for field validation of collision rates and avoidance amongst birds and bats at offshore wind turbines. In *Sjoerd Dirksen ecology report number SjDE 17-01*.

Drachmann, J., Waagner, S., & Nielsen, H. H. (2020). Klim Vindmøllepark Monitering af fuglekollisioner: Resumé. https://group.vattenfall.com/contentassets/36627206e80942949cf3f5e1ab2a7601/klim-vindmollepark_monitering-af-kollisioner_endelig-rapport_resume_160120.pdf.

Harvey, H. T., & Associates. (2018). *Evaluating a Commercial-ready Technology for Raptor Detection and Deterrence at a Wind Energy Facility in California*. www.awwi.org.

Interior, U. D.of the (2014). *What are the band designations for the Landsat satellites?* Usgs. http://landsat.usgs.gov/band_designations_landsat_satellites.php.

IUCN, & TBC. (2021). *Mitigating biodiversity impacts associated with solar and wind energy development*. IUCN. https://doi.org/10.2305/IUCN.CH.2021.04.en

Kahlert, J., Therkildsen, O. R., & Haugaard, L. (2012). *Konsekvensvurdering af effekten på fugle- og dyreliv ved ændring af en vindmøllepark ved Klim Fjordholme*. Nationalt Center for Miljø Og Energi.

Kent, R. (2018). Renewables. *Plastics Engineering, 74*(9). https://doi.org/10.1002/peng.20026

McClure, C. J. W., Martinson, L., & Allison, T. D. (2018). Automated monitoring for birds in flight: Proof of concept with eagles at a wind power facility. *Biological Conservation, 224*(May), 26–33. https://doi.org/10.1016/j.biocon.2018.04.041

Niemi, J., & Tanttu, J. T. (2020). *Deep learning-based automatic bird identification system for offshore wind farms*. https://doi.org/10.1002/we.2492

Tjørnløv, R. S., Skov, H., Armitage, M., Barker, M., Cuttat, F., & Thomas, K. (2021). *AOWFL resolving key uncertainties of seabird flight and avoidance behaviours at offshore wind farms*.

Vattenfall Press Office. (2020). Birds are good at avoiding wind turbine blades. https://group.vattenfall.com/press-and-media/newsroom/2020/birds-are-good-at-avoiding-wind-turbine-blades.

Wejdling, H. (2021). In *Personal communication* (p. 12).

Wiggelinkhuizen, E. J., Rademakers, L. W. M. M., Barhorst, S. A. M., Boon, & Den, H. J. (2006). *Bird collision monitoring system for multi-megawatt wind turbines WT-Bird ® Summary of prototype development and testing*.

Willmott, J. R., Forcey, G. M., & Hooton, L. A. (2015). Developing an automated risk management tool to minimize bird and bat mortality at wind facilities. *Ambio, 44* (Suppl. 4), S557–S571. https://doi.org/10.1007/s13280-015-0707-z