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Review of Available Models for Environmental Effects of Marine Renewable Energy

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Prepared for the U.S. Department of Energy
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Abstract

Development of marine renewable energy (MRE) has been hindered by the need for information about potential environmental effects. Monitoring of these effects, however, is expensive and it is not always clear how to efficiently collect data for a wide range of possible effects. Monitoring guidelines are needed for developers and regulators to use when planning and consenting MRE projects. Predictive modeling of environmental effects can help determine what needs to be monitored, while also estimating what effects might occur and their magnitude. Modeling for environmental effects of MRE is at different stages of maturity and applicability depending upon the type of impact being considered.

We reviewed models of six categories of stressors: collision risk, underwater noise, electromagnetic fields (EMFs), changes in habitat, displacement of marine species, and changes in oceanographic systems. Receptors were species or groups of species potentially affected by the stressors. Collision risk models are a developing field of modeling specific to MRE and are limited by insufficient data regarding avoidance or evasion and the outcomes of collisions, and by the challenges of monitoring animals very close to operating devices to derive such data. Underwater noise models are well-developed but applications to MRE remain few, with a limited understanding of the behavioral and long-term effects of noise on animals and populations. The physics of EMFs is well-understood, but we did not find any models for MRE or close analogs. As seen with the previously mentioned stressors, the effects of EMFs on physiology and behavior and how they affect populations over time are not well-understood.

Models of habitat changes have been developed for other purposes and can be used for MRE, but the few published studies are primarily theoretical, because of the lack of field testing and validation with MRE projects. Displacement of marine species has not yet been modeled. To model displacement, approaches used for the effects of underwater noise on populations and for changes in habitat could be adapted. This would require measuring the movement of animals relative to the presence of devices (for displacement) and distinguishing it from other drivers of behavior (noise, changes in habitat conditions). Hydrodynamic and wave models for predicting changes in oceanographic systems are well-developed, but their validation with data from active MRE projects is limited. These models frequently provide physical inputs to models of other stressors, so their accuracy is critical for overall estimates of stressor effects.

Most models require site-specific data for environmental parameters and species distribution. Physiological, behavioral or demographic data are best collected from the project site, but may be obtained from other sources when necessary. Monitoring of physical data is relatively straightforward, though consideration must be given to spatial coverage and time frames needed to adequately measure natural variability. Behavioral data for modeled species and linkages between stressors and effects on survival and reproduction present significant information gaps. Validation of MRE models is uncommon and mostly applied to baseline conditions because of the small number of operating MRE devices.

This review provides insight into the options available for modeling MRE-related stressors, the information needed to parameterize models, and development needs. The goal of strengthening the connection between models and monitoring is to work toward guidelines for effective and consistent monitoring, better use of monitoring data, and improved project evaluation. Common information needs among models for different stressors can strategically inform monitoring campaigns and create efficiencies for projects as a whole. Project characteristics should be compared to potential models because there is no universal set of models suitable for all MRE devices and locations. Modeling should be used iteratively with ongoing monitoring to characterize uncertainties and as a basis for consultation between developers and regulators.

Summary

The objective of the model review documented here was to identify models that have been applied to marine renewable energy (MRE) projects (i.e., tidal, wave, or current energy devices) and that can inform environmental risk assessments that are conducted as part of project planning and consenting. We describe how models have been applied, data requirements, strengths and weaknesses, and how monitoring can support model implementation, validation, and development. We also discuss how model approaches can be adapted to different environments and devices.

Models can be used to improve monitoring protocols by indicating what data are most important and the scale and resolution at which they should be collected. This report provides a starting point for a data identification process that would include site- and project-dependent considerations. We also describe the uncertainties and gaps in model development and where additional research would improve the ability to efficiently evaluate risk. We aimed to synthesize what is known about modeling approaches, rather than specific findings of modeling studies about environmental risk. The current state of knowledge about the environmental effects of MRE from field, laboratory, and modeling research is provided by Copping and Hemery (2020).

MRE projects can affect the environment through six main stressors, categorized as follows in this report: collision risk, underwater noise, electromagnetic fields (EMFs), changes in habitat, displacement of marine species, and changes in oceanographic systems. The stressors affect receptors, defined in this report as the organisms (typically animals) and their habitats . Most receptors are species or groups of species that are of interest because they are ecologically important and/or protected (e.g., marine mammals, seabirds) or because they are of commercial and/or recreational value (e.g., fish, shellfish).

Models are tools for focusing monitoring because they synthesize the data that are collected and help the user quantify the remaining uncertainties and their impacts on decisions. Numerical models can also be used directly for environmental assessment of planned devices and evaluation of their operation. Along with predicting the likelihood of outcomes that have not yet occurred, they can be used to identify and streamline what field data are needed and how they should be collected.

The range of potential stressors and receptors related to MRE calls for diverse modeling approaches, many having physical and biological components. The level of development of available models and their application to MRE varies among stressors, as does the availability of information and how site-specific it must be. Understanding the range of models currently available and how to use them would benefit from a thorough review of information requirements, the relationship between modeling and monitoring, model development needs, and commonalities among models and stressors that can improve monitoring efficiency.

For each stressor, we identified the model approaches and software that have been used, the attributes and applications of the models, and their strengths and weaknesses. We compiled information about parameters and inputs with a focus on their applicability to devices, receptors, and environments, and the extent to which the models and parameters were general or site-specific. We also described the use of field data for parameterization and/or validation. After reviewing stressors, we identified commonalities in information needs to inform cost-effective monitoring and we synthesized gaps and uncertainties in the models and monitoring approaches.

Below, we summarize each stressor and key findings of the review.

Collison Risk

The collision risk stressor refers to the likelihood of animals coming into contact with MRE devices, particularly tidal turbines or kites. The risk of interaction with devices has been modeled from two perspectives: the risk of individuals encountering or colliding with devices, and the rate of mortality from collisions that would harm the overall population.

Encounter rate models determine how often the animal comes close enough to the device that it may collide with the device if it does not take evasive action, whereas collision risk models determine the probability of the animal actually coming into contact with the device. Both the collision risk and encounter rate models use information about the structure of the device, the shape of the animal, and its swimming and diving behavior. Collision risk models can include the ability of the animal to avoid (from a longer distance) or evade (from immediately near) a turbine, but realistic estimates of these parameters are generally not available. Information about whether a collision would cause injury or death is also scarce. Observation of behaviors near turbines and collision outcomes is difficult but critical for improving these models.

Population-centric approaches work backward from species demographics to determine rates of fatal collisions that would still allow the population to sustain a particular abundance or growth rate. These models require survival and reproductive parameters. Estimating these parameters requires extended population surveys, but published values and demographic models may be available for well-studied species.

No reviewed collision risk studies included model validation; monitoring of the behavior of animals near MRE devices and the outcomes of collisions are necessary for predicting both the immediate and long-term risks of interactions with devices.

Underwater Noise

The underwater noise stressor includes the effects of noise produced by devices on species' health or behavior. Underwater acoustic modeling is well-developed for diverse applications, but relatively few studies have involved MRE devices. Noise produced by pile driving during offshore wind turbine construction has been modeled more frequently, but the differing nature of the noise and deployment locations limits the relevance of pile driving models to MRE. Acoustic models can estimate transmission loss of sound by distance or directly estimate sound propagation through water and sediment over short (nearfield) or long (farfield) distances. No single noise model is appropriate for every situation. Noise frequency, spatial scale, environmental complexity, and information availability should guide model selection. Models can be used to estimate the effects on species using maps of sound pressure or sound threshold distances, species distribution in response to noise, or the population effects if survival or reproduction might be affected by noise.

Nearly all propagation models require some level of spatial data about the seabed and water properties, which may be provided by a hydrodynamic model. Transmission loss models require field measurements of the noise at different distances for parameterization, but most propagation models do not. Sound levels at the source may be empirically measured or modeled. Modeling biological effects requires auditory thresholds for behavior or injury and may also require movement and demographic rates, which can be derived from monitoring or, in some cases, literature.

Field validation of noise models for MRE has been limited, and is complicated by spatial and temporal variability. Measurements taken regularly at multiple observation points for operating devices could greatly improve the process of choosing models and accurately predicting noise levels for a particular type of device. Noise that is not intense enough to harm animals may have longer-term effects on behaviors like foraging and breeding, but behavioral responses need further study to improve predictions on population-level effects.

Electromagnetic Fields

EMFs generated by MRE devices or cables have the potential to affect the physiology or behavior of species that are sensitive to them, but these responses and their long-term effects are not well-understood. The physics of EMFs are established and simplified conditions are straightforward to model, but there are only a few examples of models in real-world conditions like submarine cables buried in heterogeneous sediments. No models have been applied to MRE projects, either for transmission cables or for the MRE generators themselves. Field measurements of marine EMFs for model validation and for measuring animal responses are also very limited. Effects on animal movement and consequences for health or reproduction are not well-understood and have not been modeled. Overall, EMF models for MRE are in nascent stages and require more modeling of complex layouts, field validation, and species-response data from controlled laboratory studies and field observations in order to develop MRE-specific models that address the potential for long-term effects.

Changes in Habitat

The physical and biotic components of habitat can be altered directly by the presence of devices and their foundations or anchors and by indirect effects on benthic or pelagic conditions. Species and habitat distribution models are covered extensively in the literature, but only a few studies have addressed MRE, primarily tidal turbines that were planned or had been previously tested (none actually operational devices).

Several statistical methods have been used to estimate the importance of physical characteristics such as substrate, shear stress, currents, and water properties on species distribution, based on observations without devices present. They then predict the effects of MRE devices on those physical characteristics using hydrodynamic and sediment models. With that output, the statistical model results can be used to estimate any alterations to species distribution. These statistical methods vary by technique, but all require physical data from surveys or modeling before and after device deployment and some metrics of species distribution before deployment for prediction and after deployment for model validation.

Changes in food webs, such as those caused by the formation of artificial reefs, can also be assessed using ecosystem models; however, these models can become highly complex and require extensive biological information. Ecosystem models have been used to estimate the effects of hypothetical MRE devices acting as artificial reefs. Biophysical models have also been used to study the effects of devices as stepping stones for larval dispersal or the effects of changes in currents on plankton-based food webs.

The accuracy of habitat change models depends on the quality of the species occurrence or abundance surveys and having informative physical data at sufficiently high resolution. Ecosystem and food web models also require many parameters for the physiology of each species. The accuracy of the physical models used to predict changes in the substrate and water column will affect the predictive capabilities of the habitat models.

Displacement of Marine Animals

Marine species can be displaced when their movements and ranges change because of the presence of MRE devices, even if suitable habitat is still present. Displacement due solely to device presence (rather than other stressors, like noise) has not been modeled in any available studies. These effects can be addressed using an approach similar to the models for predicting noise effects on populations: models of individual movement that include behavioral responses to devices, at scales larger than those considered by collision risk models. This approach requires individual-based models that may use hydrodynamic model output to describe the physical conditions. The models can include other influences on behavior, such as prey distribution. As with models for other stressors, the lack of behavioral data and limited ability to separate the effects of multiple stressors on changes in species distribution are obstacles for displacement modeling. Statistical approaches, like those used in habitat change models, could also be adapted for displacement modeling if distances and/or directions from devices were used as predictor variables, but similar observational data needs apply.

Changes in Oceanographic Systems

MRE devices inherently alter the flow of water, waves, and energy in the surrounding environment and have the potential for both direct effects on species from these physical changes and indirect effects on other stressors such as habitat change and noise. Consequently, accurately modeling these effects is fundamental to the accuracy of many other models.

Software for modeling water and sediment dynamics in marine environments is well-established. Coastal hydrodynamic model software packages such as FVCOM, Delft3D, MIKE 3, TELEMAC 2D and Fluidity are used to predict the spatiotemporal dynamics of water surface elevation, currents, temperature, salinity, and other constituents like nutrients or chlorophyll. Wave models such as SWAN predict wave dynamics in shallow and deep water, and are often coupled with hydrodynamic models.

Placing an MRE device or array in the hydrodynamic model domain allows estimation of the effects on the energy and physical qualities of the system. Different models use different scales, resolutions, and dimensionalities, and strengths and weaknesses for different modeling situations based on the simplifying assumptions they make to reduce computing time. Computational fluid dynamic models and certain wave models are specialized for smaller scales and fine resolutions to model in detail the areas or volumes near devices. All require spatial data about bathymetry, substrates, tides, and other physical characteristics. Some input data are available through national or international databases; other input data require site-specific data collection, which can be challenging and time-consuming for variables that change both spatially and temporally. Wave spectra inputs for wave models can be particularly challenging to collect, because they can vary considerably by location and weather condition.

Model validation requires time series of the data output by the model, and adequate coverage of the spatial domain to assure accuracy in areas of particular interest. Some routinely collected data can be used for model calibration and validation, but nearshore or constrained areas may not be routinely monitored.

Synthesis

Model availability and maturity vary by stressor. Most models have been developed for other applications, but all stressors have approaches that can be adapted and further developed to assess the effects of MRE devices. There are no single “right” models for use for any particular stressor and all have significant room for development. In most cases, there are multiple approaches to choose from based on device type, site characteristics, data availability, and any specific regulatory requirements or research objectives.

Some models can be applied to multiple stressors. For example, species distribution models can be used to assess changes in habitat (physical characteristics of the environment, distribution of other biota) and species displacement (distribution of the focal species based on device presence). Hydrodynamic models can be integrated with or provide time-series input data for a number of models for other stressors, so model choice, accuracy of input data, and validation are especially important.

There are commonalities in data needs across models. Information about the physical setting—bathymetry, sediment type, water properties—is required for most models. Models for collision risk, species displacement, and population effects of noise require some combination of information about swimming/diving behavior and species distribution and dispersal. Any model estimating population-level effects will at minimum require survival and reproductive parameters. Some data can be collected once for a site or for a short period of time, while other data may require ongoing monitoring for model parameterization and validation. Monitoring should consider the natural variation in physical parameters like water properties and seasonal behavior or changes in species distribution to assure variability is adequately characterized.

Obtaining species data is a common challenge for modeling studies because only a few highly studied species are sufficiently described in the literature. Site-specific data about species demographics are ideal but not required, because they require potentially high-effort monitoring for extended time periods.

Most of the models in this review have been used in theoretical studies or in environmental assessments prior to installation of MRE devices. Modeling studies of operating devices are rare, in part because of the limited number of operational devices. Model validation varies from extensive, especially for physical models, to none for models incorporating behavior, in accordance with the degree of difficulty inherent in collecting the necessary data. The limited testing and deployment of MRE devices to date is also an obstacle to collecting data for validation. Model validation with monitoring data from operational devices remains a significant task.

Next Steps

One or more models may be suitable for a project depending on the type of device, the characteristics of the site, existing information about the project and any previous deployments of the device, and whether there are receptors of particular interest (e.g., protected species.) To apply this review to field testing, the first steps would be to describe the site, device, expected nature of stressors, and potential receptors. That information should then be aligned with modeling approaches reviewed herein to identify the most suitable approaches to modeling and the degree of adaptation that may be necessary. In some cases, software may be available to apply existing models. In other cases, particularly for less-studied stressors or devices, additional model development may be needed.

After selecting an approach, existing information can be compared to data needs for the model to determine what data need to be collected and at what spatial and temporal resolution (fineness, frequency) and scale (total area, length of time). Modeling should be an iterative process in accordance with monitoring to update assessments of remaining uncertainties and future monitoring needs and priorities.

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Acronyms and Abbreviations

1D	one-dimensional
2D	two-dimensional
3D	three-dimensional
AcTUP	Acoustic Toolbox User-interface and Post-processor
AC	alternating current
AI	aggregation index
AUV	autonomous underwater vehicle
BRT	Boosted Regression Tree
CAD	computer-aided design
CFD	computation fluid dynamics (model)
CHD	coastal hydrodynamic (model)
CRM	collision risk model
DC	direct current
DEPONS	Disturbance Effect on the Harbour Porpoise in the North Sea
EIA	environmental impact assessment
EMF	electromagnetic field
ENFA	ecological niche factor analysis
ERM	encounter rate model
ETPM	exposure time population model
EwE	Ecopath with Ecosim
FEM	finite element model/finite element method
FVCOM	Finite Volume Coastal Ocean Model
GAM	generalized additive model
GAMM	generalized additive mixed model
GLM	generalized linear model
GLMM	generalized linear mixed-effect model
GPS	Global Positioning System
GSM	Global System for Mobile Communication
HAMMER	Hydro-Acoustic Model for Mitigation and Ecological Response
HVDC	high-voltage direct current
IBM	individual-based model
KHPS	Kinetic Hydropower System
MaxEnt	Maximum Entropy
MRE	marine renewable energy
MRED	marine renewable energy device
OES	Ocean Energy Systems

PCoD	population consequence of disturbance
PE	parabolic equation
PNNL	Pacific Northwest National Laboratory
PTS	permanent threshold shift
RF	Random Forest
ROV	remotely operated vehicle
SDM	species distribution modeling
SEL	sound exposure level
SEMLA	Swedish Electromagnetic Low-noise Apparatus
SPL	sound pressure level
SSM	state-space model
SVR	support vector regression
SWAN	Simulating WAves Nearshore
TFiT	Triton Field Trials
TL	transmission loss
TTS	temporary threshold shift
VOWTAP	Virginia Offshore Wind Technology Advancement Project
WAMIT	Wave Analysis Massachusetts Institute of Technology
WEC	wave energy converter
WI	wavenumber integration
WSE	water surface elevation

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1.0 Introduction

This report is part of the Triton Initiative at the Pacific Northwest National Laboratory (PNNL), and the Triton Field Trials (TFiT) project. The objective of Triton is to support development of environmental monitoring technologies for marine renewable energy (MRE) and quantification of environmental impacts of MRE devices. This model review advances the TFiT goal of developing monitoring and data analysis guidelines for marine energy deployment. It describes the current state of development of models for quantifying environmental effects of MRE, the data requirements for the models, and how models can be used together with monitoring to improve efficiency and effectiveness of data collection and analysis.

1.1 Issue

Development of MRE (energy extracted from tides, waves, or currents) has been hindered by uncertainty about the effects of MRE devices on the local ecosystem. Estimation of the environmental effects of devices prior to their deployment is a legal requirement in many countries. Assessments of new technologies are challenging because of the lack of existing or analogous devices. Similarly, regulators have found it difficult to establish assessment guidelines and standard monitoring protocols for MRE developers. Environmental monitoring and data analysis can be resource-intensive and deter the advancement of MRE projects and technologies, especially if unnecessary data are collected or useful data are not analyzed. Commitments to monitoring operating devices can reduce uncertainty for future development, but monitoring must be strategic to be cost-effective. The MRE industry needs systematic monitoring protocols that are agreed upon by the regulatory and research and development communities (Mendoza et al. 2019).

One approach to addressing uncertainty in the shortage or absence of empirical data is to apply numerical models to estimate outcomes and quantify information needs. The development of quantitative models includes identifying the states and processes that must be understood to describe a system and make predictions. Models synthesize existing information by using empirical data to parameterize and validate model functions. In doing so, information gaps become evident and the model can inform the user about the effects of those uncertainties and the importance of having additional data.

Applying models to evaluate MRE is challenging because the potential stressors on the environment encompass multiple scientific disciplines, from physics to population biology. The stressors require very different modeling approaches, some of which require specialized software or expertise. Most model approaches in this review were not originally developed to assess the effects of MRE devices, but they have been, or could be, adapted for MRE use. Additional changes may be necessary for different types of devices.

Models can be used while planning MRE projects for environmental effects assessments. They can also be used for operating devices to estimate hard-to-measure environmental effects using data that are easier to collect. Models can be informed by information specific to the project or adapt data collected for similar projects. Linking models and monitoring programs increases monitoring efficiency and effectiveness while also improving the models (Cleasby et al. 2020; Goh et al. 2020; Shabtay et al. 2018).

Models that can be readily adapted to new locations or devices facilitate further development by reducing up-front research and data collection costs and time. Most models are transferrable to different locations if enough site-specific information is available (e.g., bathymetry, water and substrate properties, species distribution). However, some locations or spatial scales may require a different modeling approach. For example, models developed for open, deeper water, and a relatively flat seabed could be unsuitable for nearshore locations that have complex bathymetries. Higher model resolutions may be needed to model complex environments or arrays of devices that may have interacting environmental effects. Simpler models trade ease of use and fewer parameters for more realistic model processes.

Species models and their demographic and behavioral parameters are more readily transferred to new locations, but with consideration of possible local effects on behaviors or demographics. Model research and validation at existing or test sites can be used to develop guidelines for how models can be transferred to new locations, information requirements for the site, and ongoing monitoring needs for model validation.

Development of improved, standardized monitoring protocols and modeling approaches for MRE should be approached comprehensively, rather than by individual stressors, because there are potential efficiencies to be gained by aligning data requirements. Identifying overlapping needs and focusing on the value of the necessary monitoring will provide the greatest amount of information from limited data sets and improve the efficiency of monitoring and reporting. A holistic assessment of modeling for MRE will determine which models are available, what information they use, and what work needs to be done to assure models adequately address stressors and are accessible to end users.

1.2 Background

Models of MRE environmental effects have been reviewed briefly (e.g., Bender et al. 2017) or as part of a broader review with a focus on their scientific conclusions (Copping et al. 2016; Copping and Hemery 2020). A thorough evaluation of model approaches, structures and techniques with an emphasis on data requirements has not previously been completed.

The number of peer-reviewed model studies specific to MRE remains small. A portion of the studies focused on theory (i.e., used simplified or abstracted devices and/or environments) and thus did not consider monitoring requirements. Other studies were conducted for environmental assessment as a planning requirement and were not developed to complement monitoring for operating devices. Environmental assessments conducted to meet regulatory requirements for proposed MRE devices often use overly simple models because of insufficient data, time, or resources. There is a shortage of readily available alternative modeling approaches or consistent guidelines for the minimum level of monitoring and modeling necessary to adequately assess the planned project.

A larger number of published studies have addressed the construction and/or operation of wind turbines and arrays because they are more prevalent than MRE devices. Offshore wind installations introduce some stressors to the environment that may have relevance to MRE projects such as habitat changes near foundations and the possibility of underwater noise. However, although wind farms may cover large areas, wind turbines interact with the underwater environment far less directly and extensively than tidal, wave, or current devices and may be sited in less complex physical environments (i.e., farther offshore). Noise impacts of wind turbines are primarily associated with pile driving during construction rather than operations.

Overall, MRE projects have unique interactions with the environment that don't have clear analogs to learn from. There are also fewer models of the high-energy and complex environments in which MRE devices would be sited for optimal power generation. These locations may not be adequately addressed by models that have only been developed in theoretical studies or low-complexity environments.

This review is part of the TFiT project, which seeks to develop improved guidelines for monitoring and estimation of device-animal interactions with field testing of devices. A project objective is to contribute to improved guidance regarding data collection for MRE developers and regulators. This model review explains available modeling approaches and their strengths and weaknesses, with particular focus on the data needs of the models, how the models can direct monitoring efforts, and the uncertainties and gaps in model development that can be addressed with further research. For that reason, this review goes beyond identifying models that can be used for specific TFiT test devices to cover a broader set of conditions that may be relevant to potential MRE development efforts.

1.3 Report Purpose, Scope, and Organization

The objective of the review documented here is to identify existing models of the environmental effects of MRE and evaluate how they can inform monitoring protocols. We have identified models for a number of stressors, receptors, and devices. Stressors are the ways in which the installation, presence, and/or operation of MRE devices affect the surrounding environment and ecosystem (Boehlert and Gill 2010). We evaluated the following stressors defined by Copping and Hemery (2020):

- collision risk
- underwater noise
- EMFs
- changes in habitats
- displacement of marine animals
- changes in oceanographic systems.

We focused on models that included stressors and biological receptors (i.e., species or groups). Receptors are ecosystem components (primarily biological) that may be altered by the stressor either directly or through changes in the environment. The most common receptors were marine mammals and fish. Seabirds, sea turtles, and a few invertebrate taxa were occasionally included in studies. In a few cases, receptors were functional groups or trophic levels within an ecosystem rather than individual species. When models including species were limited or not available, we also reviewed models of stressor effects on the physical environment that could be linked to biological receptors with additional model development.

Models of environmental changes could be used to estimate the effects on ecosystem function and/or services, but a focus on animal species as receptors was far more common in the literature because of the prevalence of regulatory requirements focused on protected or commercially important species. In a few cases, devices were evaluated for their effects on sedimentation or shoreline erosion, which could be considered physical, rather than biological, aspects of ecosystem functions.

The report is organized by stressor category. For each stressor, we first provide its definition and scope. We describe the types of models that have been applied for that stressor, example applications, their spatial and temporal scales, and the information required to parameterize and initialize the models. We specifically note whether studies used monitoring data and any model validation that was performed. We focus on MRE-specific models but because they were usually limited in number, we also review similar models for the stressor to provide insight into a broader range of approaches. We then summarize the relationship between the models for that stressor and monitoring needs, and then the information and modeling gaps, uncertainties, and research and development needs.

The review concludes with a synthesis that discusses model approaches, the types of devices that have been included, and model applications. We evaluate the level of development of models, how specialized they are to particular environments or devices, and what would be required to apply them to new devices and locations. We also summarize model parameters and inputs, identifying the most common and most critical information needs for the broadest range of modeling applications. These information needs can be a guide for monitoring, research to fill data gaps in existing models, and model validation.

This review is not intended to duplicate the thorough science summaries provided in the OES-Environmental 2020 State of the Science Report: Environmental Effects of Marine Renewable Energy Development Around the World (Copping and Hemery 2020). The State of the Science report describes and synthesizes the science findings of modeling studies, along with experimental and observational studies, as components of the full scope of research that has been conducted for each stressor. Our focus was not on what the conclusions of modeling studies have contributed to the overall understanding of MRE effects, but rather on the modeling techniques and their past and potential applications.

2.0 Methods

Published models were identified in four main ways:

- Searches of the Tethys Knowledge Base (Whiting et al. 2019)
- Keyword searches on the Web of Knowledge database (Clarivate)
- Models reviewed in the State of the Science reports (Copping et al. 2016; Copping and Hemery 2020)
- Literature cited in other reviewed papers.

We did not attempt to identify every applicable model study in the literature, but rather as many representative examples as we could locate. We attempted to identify all MRE-specific studies, but not all potentially relevant analogous cases were reviewed. Reports that were not part of peer-reviewed journals were used when they were the best examples of a model. If a report led to a journal publication, information from both may have been used to obtain model details. Books were used for background material about stressors and general modeling theory and approaches.

Information about each model study was collected in tables and organized by stressor. The tables included information about the following:

- category: broad category of model type (if needed)
- model name/lineage: for any model given a name, and/or if it was based on previous publications
- type of model: modeling approach
- affiliation: institutional affiliation of authors
- reference: author(s) and date of study
- location: what area was modeled, if specified
- type of stress: type of device, presence vs. operation, etc.
- receptor group: species/taxa affected by the stressor
- spatial scale: area or volume covered in the model
- temporal scale: duration and time step
- general inputs: categories of information required for parameterization, specification of the domain, initial conditions, time-series inputs, and sources
- site-specific inputs: information used in specific published model applications and sources
- outputs: information generated by the model
- limits/constraints: situations or conditions that the model does not accommodate by design or because of lack of information
- uncertainties: parts of the model or inputs that are included but informed by limited data; particularly uncertainties identified by the study author(s)
- findings relevant to monitoring, verifying, and improving models: use of monitoring data in the model, model verification, or validation; uncertainties associated with monitoring

- applied to MRE: whether or not the study included MRE devices
- sensors: sensors or other monitoring equipment identified in study, if any.

Summaries of reviewed models are included in the Results section below. The complete tables are included in a supplement to this report.

3.0 Results

The results of the review of models presented for each stressor category include the stressor definition and scope, model types and approaches, the relationship of the models to monitoring, and associated gaps and uncertainties.

3.1 Collision Risk

This section describes models of how likely animals are to encounter or collide with MRE devices, based on the characteristics of the device and the animal. Some models also estimate collision risk based on animal behavior, or estimate the effects of collision mortality on populations.

3.1.1 Definition and Scope

Any device or technology that moves has the potential to interact with organisms living in or moving through the area where the device is installed. After the installation of a turbine, animals have some probability of (1) encountering the turbine, which means they are close enough to need to quickly evade the turbine; (2) colliding with the turbine by making physical contact; and (3) being injured or killed by the turbine strike. These probabilities depend upon the size and shape of the device and animal and the animal's behavior. Most of the studies reviewed for the collision risk stressor have involved tidal turbines and focused on identifying the proportion of organisms in an area that are at risk for collision. Few models assessed whether the collision would cause injury or mortality, and studies involving longer time scales or comparing risks of resident vs. migratory populations have not been conducted. The receptor groups covered for the collision risk stressor were seabirds (e.g., common murre, Atlantic puffin, northern gannet), marine mammals (e.g., killer whale, harbor seal, harbor porpoise), and fish (e.g., herring, salmon, sturgeon).

3.1.2 Model Types and Approaches

The types of models used to study collision risk include the following:

- Collision risk models (CRMs) estimate the potential collision rate of individuals based upon the number of passages of an animal through a device. This is the likelihood of the animal having direct contact with part of the device.
- Encounter rate models (ERMs) estimate the potential encounter rate of individuals with a device based upon the movement paths of animals and the volume swept by the device. An encounter is defined as being near the device but not yet in contact with it; if no evasive action is taken a collision may result.
- Exposure time population models (ETPMs) assess the mortality rate due to collisions that can affect a population.

Both CRMs and ERMs include characteristics of the species (e.g., size, behavior) and the physical characteristics of the device (Band 2016). The injury or mortality potentially caused by the collision has not been included in most CRMs and ERM studies. ETPMs focus on the effects of mortality caused by collisions at the population scale and do not include sublethal effects.

3.1.2.1 Collision Risk Models

CRMs have commonly been used to study the risk of birds colliding with wind turbines (Band 2012, 2016). They are now also applied to evaluate the collision probability of marine species with tidal turbines. The spatial scale for the collision rate estimate is usually in meters, immediately around the device of interest. To be able to estimate the probability of collision, the behavior of animals around devices should be included in CRMs. However, information about the avoidance and attraction of animals is rarely available and most of the models reviewed did not include such information.

Most of the CRMs reviewed were applied to marine mammals. Thompson et al. (2016) estimated the number of harbor seals that would collide with a rotating tidal turbine in a hypothetical array in one year. The model included the characteristics and locations of the turbines and the swimming and diving behavior of the seals as estimated from telemetry data. It was assumed that the animal behaviors were not influenced by the presence of the turbines (i.e., avoidance and evasion were not included in the model) and that collisions were fatal.

Wood et al. (2016) developed a CRM based on Band's wind turbine model (Band 2012) and applied it to harbor porpoises at the Strangford Lough SeaGen turbine (Ireland). The model included avoidance, defined as the animal deliberately moving away from the turbine after detecting it, and estimated the number of collisions per year. Copping and Grear (2018) modeled killer whale, harbor seal, and harbor porpoise at three locations favorable for the installation of tidal turbines (Admiralty Inlet, United States; Lashy Sound, Scotland; and Minas Passage, Canada, respectively). Three identical turbines in an array were simulated at each location. Their model assessed the risk of injury by determining the part of the animal's body that would be impacted.

CRMs were also used to calculate the potential collision rate of fish with turbines. Hammar et al. (2015) modeled the fish brassy trevally in a hypothetical one-turbine deployment. The model included fish behavior and predicted a low collision risk for smaller fish. Larger fish able to swim in faster currents were more likely to be at ideal turbine locations and so had a higher risk of collision. In another study, different numbers of turbines, numbers of blades per turbine, and avoidance rates were simulated to predict collision risk for Atlantic salmon (Xodus Group 2016). Collision risk was predicted to increase with the number of turbines and blades per turbine.

Other models described as probabilistic models also estimated the probability of collision. Those models have structures similar to CRMs. The model developed by Schmitt et al. (2017), implemented in the open-source freeCAD (Computer-Aided Design) software, predicted collision probability distributions in three dimensions. It was applied to a seal encountering a subsurface tidal kite, a simplification of the Deep Green subsea tidal kite developed by Minesto. No reaction of the animal to the kite was included. A similar three-dimensional (3D) model simulating movements of animals around the Deep Green tidal kite was the Hazard Zone 4D model (Kregting et al. 2016). It provided confidence intervals for collision probabilities that can be incorporated into a CRM. Another probabilistic model developed for the Verdant Kinetic Hydropower System (KHPS) turbines, named KHPS-Fish, was used to simulate the risk of fish striking turbines (Bevelhimer et al. 2016; Tomichek et al. 2015). The probability of blade strike was predicted from the model using information about fish distribution and behavior.

All models reviewed included, as inputs, the configuration of the operating device and behavioral parameters of the species of interest. Environmental characteristics including channel width and depth (or area) and current velocity are also included in some models. The device model for turbines includes information such as the number of blades, rotation time, blade width, blade speed, and the layout of turbines in an array. For the models of tidal kites, the depth, height and width of trajectory, and time it takes to travel the length of the track are specified. Biological characteristics are species-specific and can include diving behavior (i.e., dive frequency, proportion of time foraging), swimming speed, and body length. The reviewed studies did not address differences in behavior between populations of the same species. The main output is the probability of collision with the device when an organism passes through it.

3.1.2.2 Encounter Rate Models

ERMs include an approach similar to that of CRMs and were developed to predict the likelihood of animals encountering a turbine. An encounter happens as an animal approaches a turbine but has not yet come into contact with it. Once the animal has encountered the turbine, the encounter may lead to a collision if the animal does not successfully evade the turbine (Wilson et al. 2007). ERMs reviewed estimated the probability of encounter based upon the density of the animals (as affected by their behavioral patterns), the velocities of the animals and the turbine blades, and the “encounter radii” of both based upon their dimensions. ERMs can be extended by adding probabilities of evasion to estimate the collision rate.

Wilson et al. (2007) developed an ERM for herring and harbor porpoise in a hypothetical tidal array. The model included a probability that the animals would be within the depth range of the turbine and the density of individuals for each species, and estimated the probability of encounter between a rotating turbine and the animals. The probability of encounter increases with the body size of the animal. The risk of encountering a single array was multiplied by the number of turbines to determine the total risk; the interacting effect of turbines or their arrangement were not considered.

Parameters included in an ERM are the rotating speed of the device, the rotor diameter and “encounter radius” (relative to its path through the water), and the depth of the device. The biological parameters include the density of animals per unit volume, their swimming behavior, and their length, from which the encounter radius for the animal is calculated. Behavior may vary by time of day and time of year. The output is the number of animals per time that would encounter a rotating turbine.

3.1.2.3 Exposure Time Population Model

The ETPM was developed by Grant et al. (2014) and applied to diving birds in a tidal environment. If information about population dynamics is available, the ETPM can also be applied to other marine species. When little information is available about the behavior of organisms near a rotating turbine, the ETPM allows for estimating the size of the population at risk and identifying the risk of collision that would negatively affect the population. Essentially, this approach works backward to determine an acceptable collision risk as a function of the population size, the maximum rate of additional mortality that would not adversely affect the population, and the time the organism is exposed to the device(s). The definition of “adversely affect” may vary by application, ultimately depending upon project objectives or regulatory guidelines. A straightforward example would be: given a growing population, the increase in mortality that is less than that which would cause the population to decline.

The ETPM framework contains three steps (Band 2016; Grant et al. 2014):

1. Develop a population model to estimate the level of additional mortality that allows the population or population growth rate to remain above the specified threshold.

2. Quantify the exposure time based upon the amount of time the animal spends at the appropriate depth range and the proportion of water at that depth range swept by the device.
3. Estimate the rate of collision resulting in mortality, per unit of time, from the two first steps that will induce a decline or other undesirable change in the population.

The process does not require a specific type of population model, as long as it can be used to calculate the effects of different levels of mortality on the population. Age-structured matrix models or any other population viability modeling approach would be appropriate. These models do not generally account for sublethal effects of a collision, though this could be accommodated if the population model had a mechanism for sublethal effects on population dynamics (e.g., reduced breeding propensity if injured). The models also do not explicitly account for avoidance behavior. Conceptually, avoidance could be incorporated in the calculation of exposure time; e.g., if individuals avoid turbines 50% of the time, that would reduce the exposure time by 50%.

Inputs required for the population model are the number of individuals in the population, reproductive rate, survival rate (either of which could depend upon age or stage), and age at maturity. Estimating the exposure time requires the number of dives per unit of time, the total number of dives for each individual in the area, the mean time spent at the depth of the device, and the volume swept by rotors. The exposure time may be calculated differently depending on life stage (e.g., adult vs. juvenile behavior during the breeding season). The “acceptable” collision rate per individual is estimated using the number of individuals in the population, the threshold mortality rate, and the exposure time, all previously calculated.

3.1.3 Relationship of Models to Monitoring

In the models reviewed for collision risk, the characteristics of the organisms (e.g., swimming/diving behavior, size) and behavior around devices were obtained from literature review (e.g., Copping and Grear 2018; Grant et al. 2014) or from monitoring data (e.g., Hammar et al. 2015; Thompson et al. 2016). Most monitoring of fish behavior has used video cameras if the water clarity and light levels are sufficient (e.g., Hammar et al. 2015). If light levels are low, artificial light can be added but with the risk of confounding the data by repelling or attracting animals.

When light is insufficient for video capture, active acoustics are often used. For ranges less than 20 m, acoustic cameras (aka imaging sonar) are suitable. Bevelhimer et al. (2016) used a multibeam hydroacoustic system to track fish near a turbine to assess their spatial distribution, velocities, and response to the turbine when present. The study was performed without a turbine, with an operating turbine, and with a non-operating turbine. Although hydroacoustics cannot be used to identify species, it is a powerful tool for characterizing the behavior of taxonomic groups and measuring the size and range of detected targets. However, the water surface, seabed, and other boundaries can reflect sound, affecting data quality. Operational devices can also reflect sound. Dynamic components (e.g., turbine blades) can create a “blind area” close to the device where detection of a target is impossible because of turbulence and irregular reflections. For instance, acoustic camera data may clearly show a fish approaching an operational turbine, but when the fish is close to a moving blade, the strike, near-miss, or evasion behavior is obscured.

Some applications have combined video cameras and active acoustic devices to complement the advantages and disadvantages of each technology. For example, the range and size of targets are difficult to estimate with video cameras unless using expensive and complicated stereo configurations. Adding an acoustic camera can provide the range and size of targets when the target is in both sensors' fields of view. Such a method could be applied to all the monitoring locations proposed in the TFiT project to both detect the presence of marine organisms and describe their behavior.

Longer ranges (>20 m) can be acoustically monitored using echosounders. Animal distributions, densities, and large-scale movements can be produced from echosounder data streams. These data can provide inputs for ERMs and abundance estimates for a group of animals moving toward a device. Identifying species is usually not possible.

General behavioral data are important for knowing how much time animals might spend in the vicinity of turbines. Thompson et al. (2016) used telemetry data to include diving and swimming behavior of harbor seals in their model. Harbor seals were tagged with Global Positioning System and Global System for Mobile Communication (GPS/GSM) phone tags to provide locations and records of dives (including duration and depth) and haulouts. This method provides behavioral information at small spatial scales. High-resolution 3D acoustic telemetry tags can also be used to track detailed fish movements. Their utility is limited by the cost of tags and the hydrophone arrays that must be installed and calibrated in an energetic environment. Fish telemetry requires surgical implantation of tags, whose effects are uncertain. Overall, in telemetry studies, acquiring enough individuals of particular species can be difficult unless they are easily captured or procured from a rearing facility (in the case of fish).

No reviewed studies performed validation of model outputs. When applied to a specific location, observations of collision rate for the species of interest and rates of injury or mortality following the collision are necessary to compare with the predictions. These data have, generally, not yet been collected, because of the limited number of turbines and the regulations requiring turbines to be shut down when marine mammals are present. Also needed for validation are more models designed for specific test sites rather than hypothetical turbines or arrays. If collision rates and outcome data are collected as part of a testing and/or required monitoring process for a device, the information will be useful to the models. The physical technologies for turbines vary considerably. Until one or a few designs become predominant, site-specific sensors and monitoring methods are likely to continue to be needed. This need creates challenges for developing models and parameters that can be generalized to new installations.

3.1.4 Gaps and Uncertainties

While the estimation of the collision risk probability using CRMs should include the behavioral response (i.e., avoidance, evasion, or attraction) of the animals toward the device of interest, it was rarely considered in the reviewed studies because of the lack of observations of animals behaving around and at different distances from devices. For the vast majority of species and devices, CRMs must make significant behavioral assumptions to predict the actual collision, or simplify the model by assuming no behavioral response.

Models addressed turbine arrays in terms of the total area/cross section of the channel that would be blocked (Thompson et al. 2016; Copping and Grear 2018), but did not incorporate avoidance or evasion in their models and consequently the potential for behavior to be affected by multiple devices encountered in sequence. This would require another layer of behavioral information that may not be possible to obtain without test arrays and intensive monitoring. It would be possible to explore possible effects of arrays using models with assumptions about behavior of individuals after they evade one turbine and approach another. This approach can be used to estimate how important such behaviors may be.

Only one model (Copping and Grear 2018) estimated the potential outcomes of a collision in terms of injury or mortality. Doing so requires additional information about the physiology of the organism and the effects of strikes by various-sized turbine blades, moving at various speeds, with an animal that is also in motion. Some information may be available from studies of collisions with other objects, such as ship propellers, but there are key differences in the physics and velocities involved that would limit extrapolation (Wilson et al. 2007).

CRMs and ERMs are focused on the individual scale and no effect on the population is predicted from these models. Only ETPMs address the effects of (hypothetical) collisions on the entire population, based on the assumption that collision results in mortality. Estimation of the population-level effects of fatal versus non-fatal collisions is also lacking in all the models reviewed. In most of the studies reviewed, assumptions were made about species behavior such as swimming speeds and diving depth or frequency. Differences in behavior among populations has not been addressed because of the lack of data, nor have the effects on migratory populations been compared to those on resident populations.

Diving birds are more challenging to model for collision risk than fish or mammals, in part because their diving behavior would need to include the distribution and behavior of prey near the turbines because they are unlikely to dive in their absence.

3.2 Underwater Noise

This section describes models used to estimate how noise from MRE devices is transmitted through the marine environment and the potential effects of that noise on individual animals and populations.

3.2.1 Definition and Scope

Underwater noise models have been developed for the construction and operation of some MRE devices. More models have been developed for offshore wind. The greatest potential for harmful noise for wind or water energy usually occurs during construction rather than operation of devices due to the higher intensity of impulsive sound occurring during pile driving (Dahl et al. 2015). Consequently, pile driving, typically for wind turbine construction, is heavily represented in the energy-related underwater noise modeling literature. There is a smaller selection of models specific to wave or tidal devices that focus on their operation. These devices produce sound levels more likely to affect behavior than to cause physical harm.

Model scales ranged from meters to hundreds of kilometers. Models were either applied to the immediate vicinity of the sound source (nearfield) to characterize the generation of sound at the source, or at longer distances (farfield) to characterize the propagation of a prespecified sound source. No single model is both appropriate and practical for all distances, so some studies used two different models for the nearfield and farfield.

Studies assessed noise impacts from sound propagation on population dynamics. Some estimated sound pressure level (SPL) or sound exposure level (SEL) without a specific receptor. Others delineated the spatial extent of noise impacts relative to regulatory or biological sound thresholds. Another class of models estimated the physiological and behavioral responses of animal populations to received sound. Population models characterized spatial patterns of

species in response to noise and/or estimated the effects of noise on survival or reproduction (e.g., sound avoidance reducing access to prey and consequently the ability to reproduce). Seals and porpoises were the most common receptor species. Other marine mammals (dolphins, whales), fish (cod), and sea turtles were also included, though less audiogram and behavioral data exist for most non-mammalian species. Several studies evaluated noise relative to thresholds for a large number of species or taxonomic groups.
The number of MRE-specific models were limited, so models related to wind energy were included in this review if the associated studies evaluated species effects or used approaches not demonstrated elsewhere. Literature about other sources of underwater noise, such as seismic exploration and ship noise, were not included in this review.

3.2.2 Model Types and Approaches

Model applications assessing MRE sound propagation and/or its impact on marine animals can be categorized into four approaches:

1. Transmission loss (TL) models: theoretical or semi-empirical estimates of the weakening of sound resulting from spreading, attenuation, and other factors invariant with distance.
2. Nearfield propagation models: direct solutions to the wave equation for sound propagation computed at fine resolutions, used to estimate how a source produces sound and its propagation over short distances of meters to 10s of meters.
3. Farfield propagation models: approximations to the wave equation practical for estimation over longer distances (kilometers). Some of these models incorporate complex bathymetries and variability in sound velocity by depth and distance.
4. Species-effect models: estimated impacts of sound on the behavior of individual animals or groups of animals and/or the effects on demographic rates and subsequent population dynamics.

Most of the TL and propagation models are simplified by removing the time dimension and solving only in the frequency domain, producing static 1D, 2D, or 3D maps. Models of population-level effects include time and either a constant sound field (for estimating effects of operations) or pulses (construction) that occur during all or part of the behavioral or population simulation.

The remainder of this section summarizes the models reviewed in each of these categories.

3.2.2.1 Transmission Loss Models

TL models calculate attenuation rates and consequent sound levels by estimating the geometric spreading of sound waves and attenuation from absorption, scattering, and leakage from sound channels (Urick 1983). Spreading and attenuation are functions of distance from the source. Spherical spreading is appropriate for unobstructed deep water, while cylindrical spreading is appropriate for surface ducts or shallow water. Hybrid geometries have been applied to intermediate cases (e.g., Bailey et al. 2010). Attenuation may be empirically estimated from field sound measurements or calculated using material properties of the water and sediment.

The only identified study that applied TL models to MRE operations was that by Pine et al. (2014), which used field measurements of operating noise from a single or pair of tidal turbines (via underwater playback) to show that models of spreading only (no attenuation), often used in environmental assessments because of their simplicity, would underestimate sound levels. They showed that a model that included an empirically estimated spreading constant along with published attenuation and absorption constants (Richardson and Thomson 1995) was more accurate.

Three studies used TL models for pile driving. Middel and Verones (2017) used a spherical spreading model without attenuation[1] to demonstrate how noise could be included in life cycle assessment for wind farms. Bailey et al. (2010) measured pile driving noise from recordings to evaluate a spreading and attenuation model used in an environmental statement for wind turbine construction. The statement assumed a geometry intermediate between cylindrical and spherical spreading. The model best fit to the data showed that a spherical model more accurately described observed noise, which the authors attributed to the location of the wind farm in deeper waters (42 m) than those previously constructed. This is an example of the need for models to be appropriate to the geometry and bathymetry of a site.

Lippert et al. (2018) parameterized a TL model for pile driving using analytical calculations of the attenuation coefficient (Zampolli et al. 2013). Rather than measuring sound in the field, they estimated the material properties of the water and bottom sediment to calculate attenuation. They verified results with data from a benchmark model and three published field studies.

TL models are simple enough to be implemented in a spreadsheet and therefore have been relatively common in environmental assessments. In exchange for simplicity, they do not account for spatial variation in water properties or bathymetry. They are best suited for open water with a flat seabed, a setting more likely for wind turbines than tidal turbines or wave energy converters. Models should be parameterized with site-specific measurements. Heterogeneity in bathymetry, water, or sea floor properties at the site are not accommodated and can be a primary source of error for TL models (Lippert and Von Estorff 2014).

3.2.2.2 Nearfield Propagation Models

Sound-propagation models predict the movement of sound waves through water and other media. They model sound intensity (as opposed to TL) as the speed of sound changes with depth, salinity, or temperature. Changes in velocity concentrate or spread sound waves, which also reflect and scatter when encountering other sediment or other objects. Propagation models can either be direct solutions to the wave equation that describes sound propagation or a variety of simplifications.

Finite element, finite difference, and boundary element models are direct solutions. They allow sound waves to be reflected back toward the source and interact with the outgoing waves, which requires the 2-way wave equation. These models accurately model sound in complex environments such as near a coastline or other obstacles or a complex seabed. They are less necessary in more open environments where sound is less likely to reflect.

Finite element models (FEMs) are the most common nearfield models. They require the model space to be divided into elements that are a fraction of the wavelengths being studied, so they are most practical on the order of meters or 10s of meters (the nearfield). Larger areas are possible but require extensive computational resources, especially for high-frequency sound. In acoustic modeling, FEMs are used for (1) short-range modeling in complex spaces, (2)

[1] Such a model is known as a 20 log R model where R is the distance and 20 is the spreading coefficient. Cylindrical models are based on a 10 log R spreading function, and hybrid models have coefficients in between 10 and 20. This terminology can be used in environmental assessments.

estimating generation of sound from a source to use in a farfield propagation model, or (2) to serve as a benchmark for other models (e.g., Jensen et al. 2011). There is well-established software for implementing FEMs, as shown in the following examples.

Ikpekha et al. (2014) used an FEM (COMSOL Multiphysics) to show how the SPL from a wave energy device would be amplified by reverberation on a sand seabed for a range of 200 m. The model was an abstraction with a homogeneous environment.

Kim et al. (2013) and Marmo et al. (2013) illustrated the hybrid approach of first using FEMs to model sound generation from pile driving and wind turbine operation, respectively. The model results were then used in a second model to estimate long-distance propagation. These studies used Abaqus (Kim) and COMSOL Multiphysics (Marmo) to create a 3D model of the pile or turbine base. Using the material properties of the pile, base material (e.g., concrete), water, and seabed, the FEM calculates the pressure field created by the impacts or vibrations entering the structure estimates the sound produced by that pressure field. This approach requires detailed information about structural geometry and composition, as well as load patterns expected during pile driving or operation. Using those data, the models can estimate sound generation by structures that have been designed but not constructed.

All three studies used hypothetical structures rather than planned devices. They did not include spatial heterogeneity such as water surface or bottom roughness (though the models allow it). Applications for specific devices would require fine detail about the sites and devices being evaluated. Lippert and von Estorff (2014) verified a combined FEM and wavenumber integration model (described below) in the farfield but did not evaluate FEM performance alone in the nearfield. Otherwise, these studies did not verify the models with observations.

Hafla et al. (2018) used a finite difference model, Paracousti, to model three generic MRE sound sources. Paracousti solves velocity-pressure equations, which are an alternative to the more common wave equation; the inputs and outputs are similar to FEMs. Paracousti uses parallel processing to reduce computation time. The resulting model is well-suited for shallow water and complex bathymetries likely to be found at MRE installations. For low-frequency sound, common to MRE devices, Paracousti should be employed on the scale of kilometers rather than meters.

Overall, nearfield models are highly accurate, even for complex problems, but are usually only practical to implement at small spatial scales. They have been beneficial for estimating the sound produced by devices when it cannot be measured empirically. The results can be used in a long-range model to estimate the effects of sound on animals at longer distances. Conceptually, these models are well-suited to modeling environments in complex environments. The software can be used for many applications, but models must be designed specifically for individual devices and their locations. Real-world applications are limited. If the device or a close analog is already installed, it may be easier to collect recordings for use in long-range models.

3.2.2.3 Farfield Propagation Models

Approximations to the wave equation have been developed to make large-scale sound-propagation modeling feasible. These models are typically created by restricting the model to the frequency domain (e.g., removing the time element and producing a “snapshot” of the sound field). Additional simplifications have produced five types of models suitable for different conditions. Ray theory, normal mode, multipath expansion, fast field, and parabolic equation models can be categorized by their suitability for shallow or deep water, low or high frequencies, and range-independent or -dependent problems (Table 1). Range-dependent models allow the seabed or water properties to vary with distance, while range-independent models only allow vertical variation. Parabolic equations (PEs) were most common in reviewed papers, but beam trace (or ray theory), and fast field (or wave number integration) models were also identified.

The only MRE-specific model in this category was a fast field model (SCOOTER), implemented in the AcTUP interface (Maggi and Duncan 2005), to evaluate the propagation of sound from three adjacent turbines (Lloyd et al. 2011). This model application was not documented in adequate detail to fully inform this review. Fast field models, sometimes called wavenumber integration (WI) models, model sound propagation in stratified water and sediment (Jensen et al. 2011) but do not include variation with distance from the source. The model requires detailed information about the properties of multiple water and bottom layers. Error in data about bottom layers or the absence of data creates increasing error with distance from the source (Lippert and Von Estorff 2014).

Table 1. Domains of frequently used farfield propagation models from Etter (2009). Filled circles indicate the model approach is applicable and practical in that domain; half-filled circles indicate limitations in accuracy or execution speed; and empty circles indicate the model is not applicable. Low frequency < 500 Hz, high frequencies > 500 Hz. RI = range-independent (environment does not change with distance from source); RD = range-dependent (heterogeneous environment).

Model type	Applications							
	Shallow water				Deep water			
	Low frequency		High frequency		Low frequency		High frequency	
	RI	RD	RI	RD	RI	RD	RI	RD
Ray theory	○	○	◐	●	◐	◐	●	●
Normal mode	●	◐	●	◐	●	◐	◐	○
Multipath expansion	○	○	◐	◐	◐	◐	●	◐
Fast field	●	◐	●	◐	●	◐	◐	◐
Parabolic equation	◐	●	○	○	◐	●	◐	◐

Parabolic equation models were the most common in this review and in many ocean acoustic applications because of their accuracy over long distances (Jensen et al. 2011). They are the most suitable range-dependent option for lower frequencies. Variations on the software RAM (Farcas et al. 2016) are commonly applied: RAMGeo for fluid seabeds (Tetra Tech 2013), RAMSGeo for elastic seabeds (Hastie et al. 2015), and HAMMER, which extends the 2D RAM output to an Nx2D model[1] (Rossington et al. 2013). All of these studies modeled pile driving. Tetra Tech (2013) also modeled wind farm operation. Lin et al. (2019) and Kim et al. (2013) modeled pile driving using PE models not based on RAM: an unnamed model (Lin et al. 2012) and the Monterey-Miami Parabolic Equation model (Smith 2001).

[1] Nx2D models use many 2D model output “slices” to construct a 3D result. Because there is no interaction in the third dimension these are not truly 3D models, but are more practical computationally.

The accuracy of PE models depends on the accuracy and spatial resolution of input data including bathymetry, sediment characteristics, and water properties. Water properties vary on short time scales, which can have a significant effect on sound propagation, for example by season (Farcas et al. 2016; Lin et al. 2019). Farcas et al. (2016) also broadly reviewed considerations related to input data, their availability, and consequences of uncertainty for several propagation models. They described model validation and steps to improve model predictions.

Lin et al. (2019) validated 2D and 3D PE models by comparing them to field data of recorded sound played from a moving source and recorded at a fixed vertical hydrophone array. They found good agreement except for late-arriving sound at longer distances. They ascribe this discrepancy to the assumption of constant acoustic properties for the seabed because of the lack of spatial data. While bathymetric and water property data are often accessible through large-scale, publicly available data sets, information about seabed composition is more likely to require site-specific data collection (Farcas et al. 2016). Hastie et al. (2015) also validated their model against field recordings up to 10 km and found a small (< 10 dB) positive bias in model predictions for most distances.

Ray models were not often used for MRE applications, in part because they are less accurate for lower frequencies. One exception was a Gaussian beam trace model implemented in AcTUP for wind farm operation (Marmo et al. 2013). A beam trace model adds random noise to the sound path to avoid artifacts common to ray models, like sound “shadows.” Small errors in the environmental domain create large impacts in longer-range predictions of ray or beam models. They are most valid at higher frequencies, in deep water (10–20x wavelength), and at shorter distances.

The long-range propagation models just described are well-studied and considered reliable if the correct model is chosen for the application. Spatial data for the site are very important: depth-based information for the water column and seabed layers for range-independent models, and bathymetry, water properties, and sediment characteristics for range-dependent models. Field-recorded sound at multiple distances is not required for model development, but is very useful for model validation (discussed further in the section about Relationship of Models to Monitoring below). Monitoring that accommodates spatial and temporal variability is important for validation, because it may be otherwise difficult to determine whether the model is “wrong” or the empirical data are not representative of the model domain.

3.2.2.4 Species-effects Models

The simplest estimate of the impacts of MRE noise on marine animals are the maximum distance(s) from the source at which sound would injure or affect the behavior of a species. More complex models predict changes in behavior and exposure based on sound avoidance. The most complex and data-intensive models also relate sound impacts to demographic rates and resulting population size and resilience. Output from any sound-propagation model can be used in species-effects models with static maps or time series of pulsed events.[1] Accuracy will partly depend on the reliability and resolution of the sound model and the availability of biological data.

[1] Because most acoustic models do not include time, time series of repetitive noises like pile driving would be created after modeling the spatial extent of the sound.

A number of reviewed models (Bailey et al. 2010; Ikpekha et al. 2014; Lloyd et al. 2011; Marmo et al. 2013; Tetra Tech 2013) estimated the maximum distances from the sound source(s) to regulatory and/or taxon-specific thresholds of audibility, behavioral response, or damage. Some studies used broadband sound levels (Bailey et al. 2010). Others compared multiple frequencies to taxon-specific audiograms to determine sound exposure based on hearing ability. They estimated distances for audibility (Ikpekha et al. 2014); audibility, behavioral response, and injury (Marmo et al. 2013); or permanent threshold shift (PTS; irreversible hearing loss) and temporary threshold shift (TTS; reversible hearing loss; Lloyd et al. 2011). Many studies rely on audiogram data from Southall et al. (2007), but sound sensitivity data are lacking for many species, especially non-mammals.

Hastie et al. (2015) used GPS tracking of harbor seals to estimate their sound exposure during pile driving. They used a model of TTS and recovery developed for California sea lions (Kastak et al. 2007) to estimate temporary auditory damage and used non-specific (m-weighted) audiograms[1] (Southall et al. 2007; Tougaard and Dähne 2017) to estimate PTS. This approach did not include a model to predict behavior, so it requires field data about animal movement. This and many other approaches are most effective with species-specific auditory damage models, which were unavailable in this instance.

Agent-based modeling allows behavior to be modeled rather than observed. Rossington et al. (2013) modeled cod behavior in response to pile driving sound and compared the resulting distribution with the same cod population but without a response to the noise. The model SAFESIMM (Donovan et al. 2017) consisted of superindividuals[2] following rules for swimming and diving behavior that change with sound disturbance, demonstrated for gray seals and harbor porpoises . As superindividuals moved, the model calculated the cumulative SEL weighted to their audiogram and the ensuing probability of TTS, PTS, or behavioral changes. As inputs, the model used baseline estimates of population density and distribution from survey data and/or environmental suitability models. The authors created a database of parameters for 115 species of marine mammal, with data from similar species used to fill gaps.[3] The quality of species-specific data was highly important, especially for longer model durations, and probabilistic approaches were recommended to address uncertainty. While observational movement data were not required at the specific site (e.g., as for Hastie et al. 2015), the models needed extensive behavioral information for the species of interest.

The long-term effects of sound on a population are of key interest, because TTS or behavioral changes may or may not have lasting effects over individual life spans or overall population dynamics. New et al. (2014) and Pirotta et al. (2018) described a Population Consequences of Disturbance (PCoD) model framework that can be used to evaluate the cumulative effects of sublethal disturbance on a population as mediated through behavioral changes or injuries that in turn affect health and then vital rates. King et al. (2015) demonstrated an “interim PCoD” application for a noise disturbance (pile driving) potentially affecting harbor porpoises. Information about the relationships between behavior or physiological changes and health and

[1] Frequency weighting is a process used to filter sound by frequency to the hearing capability of a species. M-weighting was designed as a generalized function for marine mammals that has equal weights for a broad range of moderate frequencies and tapers at low and high frequencies (Tougaard et al. 2017). It has been used when species-specific weighting information is not available.
[2] Superindividuals are multiple individuals modeled as one unit to simplify computation, which is particularly suitable for animals that move as groups.
[3] It was unclear whether this database was available for use by other researchers.

vital rates was not available, so the “interim” model used expert elicitation to parameterize the model.

Middel and Verones (2017) simplified the PCoD model for harbor porpoises by estimating “disturbance days” and “potentially disappeared fraction of species,” or the proportion of the species absent during pile driving. The sound-propagation model defined an area that the species would avoid during days during which pile driving occurred, resulting in temporary habitat loss which may affect foraging. This removes the need for estimating disturbance effects on health, but in doing so does not estimate cumulative effects on population survival or reproduction. Application of this approach to long-term/continuous sound sources that caused permanent habitat loss would have different implications.

Demographic models that incorporate sound predicted the effects of auditory injury or behavioral changes in reproduction and survival effects over multiple generations (Nabe-Nielsen et al. 2014; Thompson et al. 2013). Thompson et al. (2013) modeled decreased reproductive success for harbor seals that avoided foraging areas because of pile driving, and increased mortality by 25% for seals experiencing PTS. They projected the resulting population for 20 years with 4 years of construction. The study used a high-quality telemetry data set to determine seal habitat and initial distribution. They had to use behavioral data from porpoises as a proxy for seals and expert opinion for the relationships between noise impacts and vital rates.

Nabe-Nielsen et al. (2014) modeled the energetic consequences of sound disturbances on porpoises in the Inner Danish Waters. Individual behavior was a function of sound level and prey density, with disturbances (wind turbine operation and ship noise) reducing access to food patches and therefore affecting energy levels. The authors used the effects of stored energy on survival and reproduction to estimate the effects of noise on population dynamics. As with other models, this approach requires detailed information about species distribution and behavior and must also estimate prey availability and distribution. Nabe-Nielsen et al. (2014) had no prey data, so they assumed that prey was distributed according to the observed distribution of satellite-tracked porpoises.

The DEPONS model (Nabe-Nielsen et al. 2018; Van Beest et al. 2015) was the same model as Nabe-Nielsen et al. (2014) adapted to pile driving in the North Sea. It is also included in the displacement of marine animals section of this report. They used acoustic data loggers to record porpoise clicks in response to pile driving and tested multiple movement models to accommodate the lack of behavioral information. The authors also used porpoise density as a proxy for food availability. Prey distribution and its variability, other anthropogenic impacts, realistic movement behavior, and the details of the deterrence and return-time of the noise were all important gaps for further research. While this study focused on porpoises, these uncertainties apply to other species as well. Harbor porpoises are relatively well-studied for this and other stressors compared to other marine species.

Agent-based models can be applied to novel species and/or locations if behavior and distribution data are available. Behavioral data do not have to be collected at the study site, though doing so is beneficial. These models have high data requirements, especially if a more detailed sound-propagation model is used than the simple ones applied for these examples. Because of the uncertainty in most population and behavioral models, it is important to apply probabilistic approaches that allow parameter uncertainty to propagate through models.

3.2.3 Relationship of Models to Monitoring

Most underwater noise models reviewed here share common monitoring needs. Exceptions are the semi-empirical TL models that are parameterized using recorded sound, which is sufficient as long as the sound was recorded under similar environmental conditions. Analytical transmission models, nearfield models, and farfield propagation models require bathymetry, geophysical data, and water column data. Range-dependent models accommodate more complex environments but require a greater area and resolution of spatial data. Recorded sound can be used for model validation. Most information needs are site-specific, though the acoustic properties of many materials can be obtained in literature.

Field recordings of sound propagation require either the actual sound source (Bailey et al. 2010) or a nearfield recording of a similar source that can be played back at the same volume (Lin et al. 2019; Nabe-Nielsen et al. 2018; Robertson et al. 2018). Robertson et al. (2018) discussed the strengths and weaknesses of using recordings as a sound source. Measured sound propagation will vary with water temperature, salinity, and depth, while weather effects on surface roughness and other sources of background noise may interfere with or mask source noise (Urick 1983).

Most examples of field sound collection in this review consisted of single or few measurements and limited spatial extent, which are inadequate for understanding temporal variability. Ideally, sound data would be collected during different seasons and at multiple directions and distances from the source (Bailey et al. 2010; Farcas et al. 2016; Lin et al. 2019), but this level of data collection was rare. Fewer collections may be enough if sound production is limited to a specific time of year (e.g., a construction season) or the bathymetry is very simple. Insufficient sound data can introduce bias in semi-empirical models and erroneously indicate biases during validation of propagation models.

Nearfield models of sound sources are primarily concerned with the specifications of the structure and the water and sediment properties in the immediate vicinity, which are likely to be available from the planning and permitting process. At this scale, spatial heterogeneity is less of an issue and data needs are considerably fewer. Detailed information about water properties may only be needed for larger spatial scales.

Of the data requirements for farfield propagation models, bathymetric data are the most broadly available, though they may not be at fine enough resolutions. Data about seabed characteristics are rarely available, so data collection will likely be required. In most cases, only a single survey would be needed unless physical changes in the area during device operation are expected to be significant. Depth profiles of water properties are variable over time. They can be monitored, but higher spatial resolutions of data are easier to obtain using hydrodynamic models with less intensive monitoring for model validation.

For more information about input and validation data, Farcas et al. (2016) reviews considerations for collecting input data and calibrating and validating sound-propagation models. Key points include guidance for selecting models (similar to Table 1), considerations for data quality and resolution, estimation of source levels, examples of model validation and its interpretation, sources of real-world variability (e.g., tides and water temperature), the consequences of error in input data or parameters, and topics for further research.

Population models that include behavioral and demographic parameters are data-intensive. The studies reviewed above used satellite, aerial, and/or acoustic tracking of animals to determine distribution, general movement patterns, and responses to sound to inform model parameterization. Recordings of porpoise clicks have been used to evaluate avoidance of sound sources (Nabe-Nielsen et al. 2018; Williamson et al. 2016). Other models used behavioral data collected elsewhere and/or for other species. Behavioral parameters may be site-specific (Nabe-Nielsen et al. 2018) as well as species-specific, which introduces considerable uncertainty when data are lacking.

Only six of the reviewed studies conducted model validation. In most cases, models were validated against sound levels recorded by stationary or towed hydrophones. Only one model validation was specific to MRE, but not an installed device: Pine et al. (2014) played back recordings of tidal turbines and measured sound levels up to 5 km away. They used the resulting data to show that simple spreading models were inadequate. The same data were used to fit a more complex model, which was not itself validated (which would have required a separate data set).

Lippert and von Estorff (2014) validated their coupled FEM and WI model using sound measurements from pile driving at 60 m and 750 m from the source. Hastie et al. (2015) used recordings taken from 1.0 to 9.5 km from pile driving activity and reported error statistics for the model predictions. However, they modeled sound 200 km from the source, so were unable to validate the majority of model predictions. Lin et al. (2019) used a stationary receiver and a towed speaker of recorded pile driving. They note that their single transect was on a path not as bathymetrically complex as some other parts of the study area, which limited their ability to validate the model and compare the accuracy of a 3D model with that of a N x 2D model.

Thompson et al. (2013) compared model predictions of species-specific sound thresholds for harbor seals with data previously collected at the same location (Bailey et al. 2010), which included measurements at multiple distances and directions from the pile driving source. Lippert et al. (2018) used published data from recordings of pile driving at three sites in the North Sea, consisting of transects of three to eight measurements ranging from ~200 m to 5 km. This strategy is efficient but requires previous work to have been done at the same or a similar location and to be sufficient for the new study. Lippert et al. (2018) also compared their model predictions to a generic benchmark model, COMPILE, which numerically solved a simple case study for use in verifying other models.

The reviewed population models used all of the available data to parameterize models and did not discuss validation. Behavior or movement models could be validated by reserving some empirical data from the initial collection or conducting additional monitoring, but limited sample sizes or resources (or lack of interest in validation) appears to have precluded this approach. Validation of predicted changes in vital rates or population responses could require tracking of animals over long time periods, a resource-intensive process with a multi-year time lag before validation would be possible. These time frames should be considered when deciding upon modeling approaches.

None of the studies reviewed appeared to be part of a longer-term monitoring effort. Modeling assessments were typically done during the pre-construction planning process (Tetra Tech 2013; Thompson et al. 2013) or during construction (Hastie et al. 2015). Some studies were conducted to demonstrate the inadequacy of common approaches to modeling for environmental assessment and/or suggest improved approaches (Lippert and Von Estorff 2014; Pine et al. 2014; Rossington et al. 2013).

3.2.4 Gaps, Limits, and Uncertainties

Models of underwater noise have received extensive research focus for other applications, and generally perform well if provided with adequate input data. Most sound-propagation questions related to MRE are not unique and can use existing models and software, but the choice of model is important. Far more models have been developed for pile driving (primarily for wind farms) than for the operation of MRE devices, because of the greater potential for auditory injury from impulsive noise. Less work has been done on the non-impulsive and generally quieter noise from operating devices, which are more likely to affect behavior than cause injury. Most models of MRE devices have been hypothetical or based on recordings rather than actual devices because of the small number of devices deployed. Modeling approaches vary among studies and the transferability of models between devices has not been addressed.

A primary limitation is the availability of spatial data (seabed material and water column properties) and its temporal variation. It has been common for environmental assessments to use simple TL models, which require limited data and development and do not require specialized software. However, multiple studies have shown that these models are prone to significant error without site-specific transmission data (Bailey et al. 2010; Pine et al. 2014). Even with site-specific data, TL models are not well-suited to areas with variable bathymetry or water properties, or over longer distances.

Range-dependent propagation models can handle spatial variability much more accurately, especially with high-resolution bathymetry and seabed composition data. Temporal variability in the water column remains a challenge. Because the output of most propagation models represents one point in time, additional data and modeling effort are required to represent temporal changes. A conservative approach to simplifying modeling for environmental assessments is to identify maximum ranges of auditory impacts (worst-case scenarios), which may overestimate risk at other times of the year. If noise models can be informed by reliable hydrodynamic models, spatiotemporal variability can be addressed more directly.

Examples of model validation are sparse, and usually limited to one or a few transects or point observations. Effective validation requires measurements of sound (with and without the source operating to control for ambient noise) at multiple angles and distances from the source and ideally under multiple weather conditions and/or seasons. Environmental complexity requires both a more complex model and a richer set of observations to assure that model validation is reflecting model skill and not a mismatch between modeled and empirical conditions. Modeling for environmental assessments done before a device is installed can be validated using sound source recordings if any are available (i.e., from previous installations of a device), but this, too, is challenging and has been done infrequently, and most assessments do not appear to have follow-up validation after installation.

Models of biological effects of underwater noise are highly uncertain for all but the most well-studied species, like harbor porpoises. Data are sparse for non-mammalian taxa. The population-level impacts of sound are of high interest, but complex. Existing examples have relied extensively on assumptions about behavior, resource availability, and the effects of noise on behavior and vital rates. Prey distribution, needed for understanding the effects of sound on foraging and therefore species distribution and movement, is identified as a critical information gap that has not been directly addressed by monitoring. Full population modeling also requires reproduction and survival rates and estimates of the effects of sound on those rates. This information is rarely available and resource- and time-intensive to collect. Identifying threshold distances and areas of impact is more straightforward than modeling populations, but still requires species-specific auditory impact data. Overall, biological models incorporating noise might have been parameterized with field data, but none have not been validated.

3.3 Electromagnetic Fields

This section describes models that estimate the extent of EMFs generated by objects that produce or carry electrical current, including MRE devices and transmission cables. Models that estimate the effects of EMF on animals and populations are still to be developed.

3.3.1 Definition and Scope

EMFs are generated by any electrical current-producing or carrying system, including the electricity generators on MRE devices that convert motion to electricity and the submarine cables that transmit electric current to land. The electric generator produces an EMF and drives the flow of current through one or more transmission cable(s). The flow of current through cables can either be direct current (DC) or alternating current (AC) and will generate a static or time-varying magnetic field, respectively, that can be detected outside the cable. The magnetic field strength depends primarily on the magnitude and direction of the electric current and the characteristics of the cable, and it attenuates with distance from the cable (Associates et al. 2011). While the electric fields produced by generators are constrained inside insulated inductors and cables, AC magnetic fields change rapidly and can induce a coupled electric field in the seawater around a conductor.

The generation and propagation of magnetic fields and electric fields are governed by Maxwell’s equations. These equations are used to generate models that can be applied to all sources of EMF, including generators and cables associated with MRE devices. Based on Maxwell’s equations, software has been developed to simulate the distribution of electric and magnetic fields surrounding a cable. The spatial scale of the models reviewed was generally the extent of the cable of interest, from meters to kilometers and the currents used were within an order of magnitude for underwater high power cables. No model applications for MRE were identified in this review. However, there are no unique characteristic of EMF generated by MRE devices that would change how it is modeled.

Some marine organisms are electro- and/or magneto-sensitive and their movement, behavior, and migration may be affected by the presence of EMFs generated by undersea cables or generators (Albert et al. 2020; Gill et al. 2014). Their physiological development may also be affected in the presence of high intensity EMF (Albert et al. 2020; Lee and Yang 2014; Scott et al. 2018). The majority of research has been on individuals in laboratory settings and responses to EMF in that context do not indicate significant effects on populations or species interactions; realistic field studies of individual or population effects are lacking. No models applied to study the effects of EMF on marine organisms were found in this review.

3.3.2 Model Types and Approaches

Models of EMF take two basic forms:

- Analytical models are the simplest, consisting of equations for simple cases that can be solved without specialized software.
- Simulation models are solved using numerical techniques such as FEM to accommodate greater complexity in the structure of the device or cable and the surrounding materials.

To date, there have been no published models of effects of EMF on species behavior or population dynamics. Species effects are limited to some laboratory and field observations for a limited number of species.

3.3.2.1 Mathematic Models for EMF

Several related analytical approaches can be used to model EMFs under simplified conditions. The law of Biot-Savart is an equation describing a magnetic field generated by a direct electric current. Kavet et al. (2016) used this equation to model the magnetic field from an electric DC cable 85 km long in San Francisco Bay (the Trans Bay Cable). Outputs of the model were compared with the measured magnetic field. Model parameters included information about cable location (buried depth, angle) its configuration (conductor separation, cable twist) and the north, east, and vertical components of the cable field and geomagnetic field. Dhanak et al. (2015) also used the Biot-Savart equation to estimate the magnetic field produced by a DC cable to compare it with empirical observations. Similarly, Ampere's law can be used to calculate the magnetic field when the field is constant in time (see Slater et al. 2010).

Lucca (2013) developed an analytical expression to model both the electric and magnetic fields outside an AC submarine cable. They compare a model that assumes the sea is infinitely deep and one that includes finite sea depth and the resistivity of the seabed and qualitatively validate the model against an FEM (Huang and Gloyne-Philips 2005) and a radial transmission line model (Slater et al. 2010). This model does not accommodate environmental variability along the cable.

3.3.2.2 Software for EMF

Two simulation software applications that model EMFs were reviewed. The Maxwell 2D software was developed to simulate EMF in 2D (i.e., the cross section of the cable is assumed to be uniform along its length) using the finite element method. It was used to model the EMF generated by a submarine cable with AC and to assess the effects of sediment type on the magnitude of the generated magnetic and electric fields (Center for Marine and Coastal Studies 2003). Gill et al. (2012) used Maxwell 2D to model the magnetic field and electric current density from a buried submarine AC cable at an offshore wind farm after determining that the real-world setting was too complex for an analytical approach. The parameters included in the model were the material characteristics of the cable, seawater, and sediment and the boundary conditions of the field (field behavior, sources and intensity of the current).

Hutchison et al. (2020) used the software package COMSOL to model the magnetic fields of two DC cables: the Cross-Sound Cable (40 km long, Long Island Sound) and the Neptune Regional Transmission System (105 km long, from New Jersey to Long Island). Like Maxwell 2D, COMSOL is a 2D multiphysics simulation software that can simulate the coupling effects of different fields using an FEM. It includes an AC/DC module to simulate EMF. The parameters required in the module are the shape and size of the cable (cable radius, armor thickness, lead sheath radius and thickness, conductor radius), the material properties, the distribution and number of cables, and the depth at which the cable is buried. The authors modeled multiple cross sections to account for varying depths. The outputs of the model are the electric potential distribution within the cable and the density of the magnetic flux. They compared model results to field measurements and found agreement with the magnetic flux predictions and observations. However, field measurements detected unexpected AC fields induced by the DC cables which were not predicted by the COMSOL module.

3.3.3 Relationship of Models to Monitoring

The production of EMFs can be modeled based upon the design of the cable or the generator on the MRE device. Modeling underground cables or other components requires information about the seabed composition. Data for validating EMF models for marine devices or cables have been limited until recently; while measuring EMFs is conceptually straightforward, it involves practical challenges in marine environments. Field measurements of species response to EMFs are even more challenging to collect. Most behavioral response data have been derived from highly controlled laboratory studies, and most often related to fish (Hutchinson et al. 2018).

Thomsen et al. (2016) used a custom-built platform (SEMLA) with a magnetometer and electricity incorporated into a sledge that was towed in the water or along the seabed to measure EMFs along an AC cable and near wind turbines. They demonstrated that empirical measurements for electric fields could be readily measured alongside magnetic fields, and therefore previous obstacles to model validation can be overcome (they did not evaluate a specific model). Hutchinson et al. (2020) used the same sensor platform to measure electrical and magnetic fields along both DC and AC cables and to validate the EMF simulation model described above for DC cables. They note that a remotely operated vehicle (ROV) equipped with a magnetometer could not produce satisfactory results. The sledge design was easier to control than the ROV, especially when used directly on the seabed, which also improved measurements by stabilizing the platform.

Dhanak et al. (2015) deployed an autonomous underwater vehicle (AUV) with electric sensors, towing a magnetometer, to measure EMF at both DC and AC cables. They visually compared the measurements for the DC cable with analytical model results. Kavet et al. (2016) measured magnetic fields along a high-voltage DC (HVDC) cable using a pair of magnetometers towed behind a vessel and compared the results with analytical estimates of the magnetic field and found a very close and statistically significant match. This was the only one of these studies to provide a direct comparison of observed and predicted magnetic fields and quantitative model validation.

Monitoring of EMF has been demonstrated at both DC and AC cables, but the additional complexity of the magnetic and electric fields of AC cables has so far precluded the type of modeling studies reported here for DC cables. Both Hutchinson et al. (2020) and Dhanak et al. (2015) measured EMF at both DC and AC cables, but only modeled DC cables; therefore model validation was only provided for the magnetic field and not the electric field.

Some studies of species responses, both behavioral (activity, attraction or repulsion) such as Hutchison et al. (2020) and physiological (cellular or developmental/reproductive), to EMF have been made in the field and laboratory as reviewed by Albert et al. (2020). These studies are short-term and do not evaluate effects over longer life cycles or on populations. The findings of the studies reviewed by Albert et al. (2020) have been varied and inconclusive as a whole. They recommend careful selection of study organisms, assuring that laboratory-generated EMFs match the temporal patterns expected in the field and that intensities and frequencies would match what an animal would experience, which differs by species habitat and behavior. More field measurements of EMFs consistent with marine devices and cables would be needed to adequately simulate these fields in the lab. Field and laboratory studies of behavior should assure adequate randomization and replication.

3.3.4 Gaps and Uncertainties

A number of existing submarine HVDC cables are used to transfer megawatts of power tens of kilometers whose magnetic fields have been measured and used to validate physical models of EMF. MRE devices are more likely to generate AC power for transmission across several kilometers to shore-based facilities or be used in directly powering remote devices. As AC power applications, these MRE devices will involve a higher current-to-voltage ratio than HVDC power cables and will likely generate a stronger magnetic field for their size. In addition, studies efficiently measuring both electric and magnetic fields are very recent, and only the magnetic fields produced by DC cables have been modeled, and those models validated. Modeling the induced electric fields from AC cables is computationally more complex.

Most models are for idealized cables, perfectly straight, and in 2D cross section. While spatial variability in sediment can be accounted for by modeling multiple cross sections, the models of idealized cables do not accommodate cable curvature or interactions with other EMF-producing objects. The generators incorporated into MRE devices have not been sufficiently studied as EMF sources. Their effects will typically be located in the water column rather than buried in sediment, so they may affect different species. In some environments and device configurations this may merit further study of the generator fields, particularly for arrays of devices.

The effects of EMF on marine organisms are still being evaluated. The impact of DC and AC fields, intensity, frequency of oscillation and trends of repulsion and attraction have been documented for some species (Albert et al. 2020), but are not well-understood for many electro/magneto-sensitive species. The behavior of organisms when encountering EMF is poorly known.

To date, no models of EMF effects on species are available, either of short-term effects or of life cycle or population-level effects. Models will be important for evaluating whether any direct effects of EMFs on species, e.g., behavioral changes, would have population- or community-level effects. In these cases, the location of devices and cables will be important. For example, if EMFs generated by cables crossing the entrance to a bay reduced access to important foraging or breeding areas, greater effects on the population would be expected than if only part of the entrance or bay was affected. It is likely that data limitations will continue to limit modeling for some time, but modeling studies may be possible for some species that can help inform further data collection.

3.4 Changes in Habitat

This section describes modeling related to environmental conditions (seafloor, water column, other biota) required by species and their resulting distribution as affected by MRE installations.

3.4.1 Definition and Scope

Most MRE devices must be attached to the bottom by foundations or anchoring systems, which could alter sediment characteristics, species distributions (attraction or avoidance), and community composition. Changes in water properties, currents, and waves caused by river and tidal turbines and wave converters (see the section about Changes in Oceanographic Systems below) can also affect benthic and pelagic habitats. Specific survey designs, such as a before-after control impact study, may be able to document potential effects by monitoring changes in the area around a deployed device. Modeling can also be used to characterize habitat components and forecast changes. Changes can be modeled from a population to an ecosystem level, from a local to a global scale, and over various time periods. Changes induced by MRE may be combined with other sources including marine pollution, vessel traffic, and climate change, which together produce cumulative effects.

A great diversity of habitat models are used outside of the MRE field. Most of them could be applied in the MRE context, but few MRE-specific studies exist. Habitat models may focus on species distribution, habitat suitability, ecological niches, ecoregionalization of communities, trophic networks, animal (larval) dispersion, habitat connectivity, and other aspects of species-environment interactions (see comparative review in Drew et al. 2011; Elith et al. 2006; Franklin 2010; Norberg et al. 2019; Zhang et al. 2019). Most of these models were developed for terrestrial ecology before being adapted for the marine environment. The dynamic nature of currents, sediments, and water properties may create challenges in marine habitat characterization relative to terrestrial habitats that typically change at slower rates.

For the present review, most studies that applied one or more models to assess changes in habitats caused by MRE development involved tidal turbines. While no studies were directly related to specific existing MRE deployments, some of them were related to sites that either are currently being evaluated for deployment or had test deployments in the past decade. Other studies used theoretical cases to demonstrate concepts. The types of models reviewed here are not limited to tidal sites and can be broadly applied to MRE and other marine applications (e.g., conservation, resource management). Seven other studies, related to the offshore wind industry and to basic benthic ecology, were reviewed to broaden the search and bring in analogous models.

The receptors covered by these studies were diverse (e.g., crustaceans, sea stars, plankton, fish) and ranged from individual species to groups of related species, theoretical taxa, and functional groups. Neither spatial scale nor temporal scale are limited for any of these models and varied from very local (one sampling station) to several thousands of square kilometers (an ocean basin), and from a day to 30 year time periods.

3.4.2 Model Types and Approaches

Four classes of models that characterize and forecast changes in benthic and pelagic habitats are reviewed here. All four have statistical components, while the third also includes an option for simulating changes in food webs or changes in species dispersal. The fourth category primarily addresses the effect of devices as novel habitats to increase population connectivity and distribution.

- Species Distribution Modeling (SDM), also called habitat suitability modeling or ecological niche modeling, is used to estimate a species' distribution and suitable habitat, as well as its ecological requirements.
- Decision-tree ensemble models (e.g., Random Forest [RF], Boosted Regression Tree [BRT]) are compilations of multiple classification or regression models used for detecting, quantifying, or forecasting change in species distribution based on estimated relationships between observed habitat use and environmental characteristics.
- Trophic web and spatial ecosystem models focus on ensembles of organisms and functional groups to draw relationships within a food web and predict spatiotemporal changes in the ecosystem.
- Biophysical models are used to estimate the role of MRE devices as artificial reefs in the dispersal of larvae and resulting species distribution.

There is overlap in the application between SDM and decision-tree ensemble models. Both use species distribution observations to determine the importance of environmental parameters to the ability to predict species presence or presence/absence. The estimated relationships can then be used to predict species distributions when the environmental parameters are altered by the presence and/or operation of the device. The methods involved in estimating the relationships differ.

Several of these model categories overlap with models applicable to the displacement of marine animals; this section only addresses changes in distribution based on habitat alteration, as opposed to avoidance of devices.

3.4.2.1 Species Distribution Models

When evaluating changes in habitats, studies often focus on distributions of species and environmental conditions associated with those distributions. A wide range of modeling approaches is available for addressing these questions and can use abundance numbers, presence-absence, or presence-only data as response variables (Drew et al. 2011; Franklin 2010). These approaches are known as SDM, Habitat Suitability Modeling, or Ecological Niche Modeling. They estimate the probability of occurrence of the species in defined areas using correlations between species records and environmental data. Other outputs include characterization of habitat requirements and maps of habitat suitability. Such approaches can also be used to model the displacement of marine animals from areas targeted by MRE developments (see the Displacement section).

Reliable presence-absence data are rare, especially in the marine environment, and models able to deal with presence-only data have become highly popular over the past decade. Examples of such models are MaxEnt (Maximum Entropy; Phillips et al. 2006) and ENFA (Ecological Niche Factor Analysis; Hirzel et al. 2002). MaxEnt uses environmental data to model the probability of species occurrence in a way that agrees with everything known about its distribution without making any assumptions about what is not known (Phillips et al. 2006). Along with the species occurrence points, MaxEnt samples a random subset of background points in the study area that represent the overall distribution of environmental conditions, providing a comparison with conditions at the occurrence points (Elith et al. 2011; Phillips et al. 2006; Phillips and Dudík 2008). MaxEnt estimates the probability of each pixel of the study area to be a presence point rather than a background point and returns a map of the distribution probability of the species, a list of the percentage of contribution of each parameter to this distribution, and response curves of the species to the environmental variables. The user can supply a sample bias grid to account for uneven observations.

ENFA is a multidimensional factor analysis that uses occurrence points and environmental data to characterize the ecological niche of a species (Basille et al. 2008). The ecological space is a hyper-volume where each environmental variable defines a dimension, and a species' ecological niche is described by the distribution of its occurrences within the hyper-volume. In an ENFA, this model describes the "available habitat" (the quantity of environmental conditions accessible to the organisms) and the "used habitat" (the quantity of environmental conditions used by the organisms). The model returns a value of "marginality" of the habitat, which is the difference between the available and the used habitats and measures the eccentricity of the species' niche relative to the ecological space. It also returns multiple values of "specialization" of the habitat, which are ratios of the variance of the available habitat to the used habitat, and measure the narrowness of the niche (Basille et al. 2008). Pixels corresponding to the combination of environmental variables that define the ecological niche can be projected on a map to represent the suitable habitat distribution (Hirzel et al. 2002).

MaxEnt was the only SDM algorithm implemented in the MRE context, evaluating suitable habitats of the acorn barnacle (*Balanus crenatus*) and the brown crab (*Cancer pagurus*) and their responses to changes in bed-shear stress due to the presence of tidal turbine arrays (du Feu et al. 2019). This study relied on publicly available records (occurrence points for the species, depth and substrate types in the study area) and on outputs of a hydrographic model (bed-shear stress, distance to shore and flow velocity). The model was run independently for each species and did not include species interactions. MaxEnt produced species occurrence probability (habitat suitability) maps, environmental variable response curves, and the model features retained at the end of the modeling process. These outputs were provided to the software OpenTidalFarm. The authors then used scenarios of variation in bed-shear stress depending on different designs of tidal arrays to model changes in occurrence probability.

Combining results of SDM approaches, especially for species of concern, with algorithms to design wave and tidal arrays may prove efficient in reducing negative impacts of proposed arrays on habitats of interests. Other classes of models like generalized regression models (e.g., Generalized Additive Models [GAMs]) or decision-tree ensemble models (e.g., BRT, RF) may be used instead of MaxEnt or ENFA to generate species occurrence probability maps (Elith et al. 2006; Norberg et al. 2019).

3.4.2.2 Decision-tree Ensemble Models

A robust method for modeling spatiotemporal changes in habitats, either at a specific location over time or across a wide spatial area, is to use decision-tree ensemble models, which were developed for finding patterns and information within large and messy data sets. Decision-tree models, also known as Classification and Regression Trees, are sequences of branching operations based on comparisons of the dependent variables that split them into two or more homogeneous sets (Breiman et al. 1984). Using a set of training data, the algorithm identifies the most significant variable(s) and its values that give best homogeneous sets of data. For example, a subset of presence and absence data points for a species of interest could be used to predict its distribution based on the spatial variation in the environmental variables (temperature, current velocity, substrate, etc.) The remaining presence/absence data are used for validation. Changes in the environmental variables, e.g., changes in tidal currents and sediment distribution expected to follow installation of turbines, can then be used as inputs to predict the effect of the turbines on species distribution. These models can make very accurate predictions when trained on high-quality data (Kingsford and Salzberg 2008). The method is nonparametric, contains no assumptions about the model structure, and performance of the model is not affected by nonlinear relationships between variables; it will outperform classical linear or logistic regression models when complex relationships are involved (Breiman et al. 1984).

Decision-tree ensemble models, also called ensemble learning or machine learning, make predictions based on multiple decision trees and tend to be less sensitive to bias and variance than single models (Breiman 2001; Kingsford and Salzberg 2008). Because of their high accuracy, stability, and ease of interpretation, decision-tree ensemble models such as RF and BRT are widely used in a diversity of biological and social science applications. RF has been increasingly used for ecological applications since it was developed by Breiman (2001) and popularized by Cutler et al. (2007) . RF works as an ensemble of “weak learner” decision trees developed from random subsets of the dependent and independent variables in the data set

(Breiman 2001; Drew et al. 2011). The predictions from all the decision trees are then averaged to obtain the final prediction. The very high classification accuracy of RF and its ability to model complex interactions and to deal with missing values make this algorithm one of the most powerful statistical classifiers (Cutler et al. 2007).

RF was applied to MRE in one study characterizing nekton density and patchiness data in a tidal inlet under consideration for tidal energy generation. Multiple model approaches (Figure 1) were compared for their ability to detect changes in nekton distribution that an operating tidal turbine might cause (Linder et al. 2017). In these studies, independent variables were daily tidal range, tidal speed, Julian day, and time of day. Dependent variables were mean volume backscattering (for nekton density) and aggregation index (for nekton patchiness). In energy generation scenarios, tidal speed was changed to represent potential turbine array configurations. The models were run for 28-day time frames and assessed for effectiveness at detecting, quantifying, and forecasting change. RF was the best model for detecting changes in variance (Figure 1) and excellent for interpolating data although less suitable for baseline data characterization (e.g., data variability and trends). Other models that scored well in these comparative studies were support vector regressions (SVRs) and state-space models (SSMs).

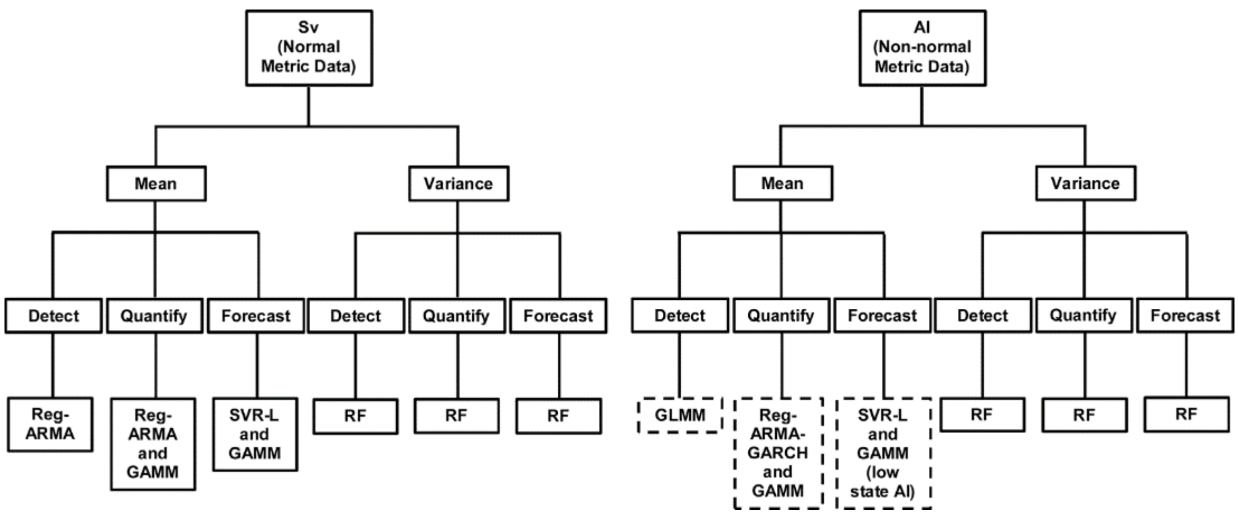

Figure 1. Recommended models for detecting, quantifying, and forecasting changes in density (mean volume backscattering strength [Sv]; representative of normally distributed data) and patchiness (aggregation index [AI]; representative of non-normally distributed data) of nekton organisms in MRE monitoring data. For more details, see Linder and Horne (2018). Evaluated models included regression—autoregressive moving average (Reg-ARMA), autoregressive moving average—generalized autoregressive conditional heteroscedasticity model (Reg-ARMA-GARCH), generalized additive mixed model (GAMM), support vector regression (SVR-L), and Random Forest (RF).

The example presented here was very specific to one site with the purpose of comparing multiple models. However, RF could be applied to other circumstances in the MRE context, like SDM, especially when forecasting changes in distribution due to changes in the physical system or cumulative effects with climate change. BRTs would be another efficient decision-tree ensemble model to consider for this aspect.

3.4.2.3 Trophic Web and Spatial Ecosystem Models

Organisms in an ecosystem are connected through food webs, networks of trophic (feeding) relationships among species. Any habitat change has the potential to alter food webs and ecosystem structures. Because characterizing dynamic trophic interactions and their changes through field observations and measurements is a complex task, many have turned to modeling approaches to assess and quantify direct and indirect changes in an ecosystem network (Brose and Dunne 2009). The diversity of trophic web models is broad, and the range of applications is even broader (see review in Belgrano et al. 2005). A popular algorithm within the marine ecology community is Ecopath, a mass-balanced, carbon-budget trophic model (Christensen and Pauly 1992).

Ecopath is an open-source ecological modeling software that allows users to characterize trophic webs and ecological relationships within an ecosystem (Christensen and Pauly 1992). The model applies a type of statistics called "path analysis" to estimate the direction and strength of all factors influencing the functioning of a system. Ecopath comes with several variants, among them Ecosim and Ecospace (Pauly et al. 2000). Because Ecopath is often used paired with the Ecosim variant, the model is usually referred to as EwE (for Ecopath with Ecosim). Ecopath provides a mass-balanced snapshot of the ecosystem functioning; Ecosim is usually implemented to simulate the ecosystem's evolution through time; and Ecospace adds spatiotemporal dynamics to explore cumulative effects and changing environmental conditions (Pauly et al. 2000). The EwE package addresses marine policy issues such as the general functioning of an ecosystem, ecosystem effects of fishing, effects of management, impact and placement of conservation areas, or effects of global environmental changes (Heymans et al. 2016).

The EwE modeling approach was implemented by Alexander et al. (2016) for MRE and offshore wind and by Raoux et al. (2017) for offshore wind. Both studies used EwE to assess the artificial reef effect (i.e., the aggregation of benthic and pelagic organisms around manmade structures) of hypothetical MRE and wind turbine arrays. Alexander et al. (2016) also modeled the exclusion zone effect and the benefits or drawbacks for the fishing industry. Both studies used as receptor groups a combination of individual species (e.g., grey seals, king scallops), higher-level taxonomic groups (e.g., sharks, crustaceans), and functional groups (e.g., diving seabirds, phytoplankton). For each receptor group, the model required a variety of physiological parameters such as feeding/growth rate, survival rate, dispersal rate, production over biomass ratio, and so on. Sources for all these empirical data were described in the studies. Many were available from literature, but others were estimated by the model according to the mass balance equations. Parameters for the spatial simulations used by Alexander et al. (2016) came from a combination of literature values and "logic" (expert opinion). Alexander et al. (2016) also assigned habitats to each receptor group. The models simulated 25 and 30 years, respectively, and projected the final changes in biomass per grid cell. In the first study, changes in catch value per fishery also projected. These two studies illustrate the interest in using modeling approaches like EwE to predict ecosystem-wide changes in trophic relationships and biomass over long periods of time caused by the presence of ocean renewable energy devices. They also illustrate the complexity of such models and the difficulty of generalizing without good knowledge of eco-physiological processes.

3.4.2.4 Biophysical Models

Biophysical models (described in more detail in the Displacement section below) can also be used to simulate the effects of changes in currents caused by MRE devices, such as the effect of tidal turbines on plankton dynamics and connectivity (Schuchert et al. 2018). The physical component of these models comes from a 2D or 3D hydrodynamic model that includes current velocity, heat balance, river runoff, and other oceanographic variables. The biological component can be a biogeochemical flux model describing physiological processes, such as a nutrient-phytoplankton-zooplankton-detritus model used by Schuchert et al. (2018) to estimate the differences in plankton concentrations with and without an array of tidal turbines. Biophysical models have also been used to study how offshore structures acting as artificial reefs facilitate the dispersal of larvae across larger geographic areas (Adams et al. 2014; Bray et al. 2017; van der Molen et al. 2018). Structures become stepping stones allowing for dispersal over longer distances than larval durations would otherwise allow. Studies used oil/gas infrastructure (van der Molen et al. 2018), offshore wind farms (Bray et al. 2017) or unspecified “offshore renewable energy devices” (Adams et al. 2014) as the artificial reefs. Some MRE devices could act in a similar manner and be modeled using the same approach. Biophysical models use information from hydrodynamic models and physiological/behavioral characteristics of the organisms to estimate how individuals might move throughout the landscape. For the larval dispersal studies, the length of time larvae spent in the water column before becoming competent to settle was the key biological parameter; the hydrodynamic model determined how far the larvae were transported and whether they had access to suitable substrate once they were competent to settle.

3.4.3 Relationship of Models to Monitoring

Each of the habitat modeling approaches requires site-specific input data such as occurrence/abundance data for the focal organisms, water column data (e.g., bathymetry, water temperature and salinity, current velocity), and seabed characteristics (e.g., substrate types, bed-shear stress). Unless a site favored for an MRE deployment has already been surveyed for other reasons (e.g., fish-stock assessments, installation of other infrastructure), it is unlikely that these data will already be (freely) available to modelers, and specific sampling will be required during environmental impact assessment and monitoring surveys. Other site-specific inputs, such as bathymetry and water properties, may be obtained from large-scale models or databases but local measurements may be needed for sufficient spatial resolution.

Species occurrence may also be available from existing databases, but baseline data collection is recommended. Occurrence data collection methods depend on the species, but may include aerial or boat-based visual or photo/video surveys, underwater camera or dive transects, mark-recapture, or sampling with nets. For early life stages, data from sampling are useful but resource-intensive to collect and analyze. An alternative to sampling is the use of underwater cameras to capture images of small organisms from micron to millimeter size (Luo et al. 2018; Nayak et al. 2018).

The trophic web and spatial ecosystem models usually require physiological parameters for the focal species (e.g., feeding, growth, movement, survival, vulnerability to predation). Biomass, diet, and survival data appeared to be available for many species, especially fish. Data availability may depend upon region (northern European waters are well-studied in this regard) and the taxa being modeled (heavily represented in the EwE literature), and protected and commercially valuable species have more data reported in literature. Behavioral data are less available and may require assumptions for modeling. Monitoring surveys are rarely designed for characterizing such parameters, which can take years to collect for longer-lived species. Some physiological parameters required for habitat change modeling are also needed for some model approaches for other stressors, creating potential efficiencies for species-specific data collection.

The studies reviewed here were for fundamental research purposes only, using data from specific MRE sites as case studies. None of the model outputs from these studies were used in planning and/or monitoring any project, nor were they validated with field monitoring. Validation would require the collection of additional species occurrence/abundance data beyond what are used to develop the model or evaluate the predicted habitat suitability. In some cases, input data limitations made models sufficiently abstract that field validation would not be possible. For example, for Alexander et al. (2016), limited fishery data and reliance on modeled environmental parameters meant that validation could not be performed.

Collecting data about benthic/pelagic species diversity, occurrences and abundance, as well as seabed characteristics and water properties during the TFiT field campaigns will provide input data to develop such models for the sites targeted under the TFiT project. However, a trophic web model like EwE may be difficult to implement if inputs such as consumption, growth, and mortality rates are not available for the local species (see next point).

3.4.4 Gaps, Limits, and Uncertainties

Several predominant constraints are common to models used to assess changes in benthic and pelagic habitats. Most models (e.g., BRT, ENFA, GAM, MaxEnt, and RF) rely on species occurrence and/or abundance data, usually as response variables. Poor availability or quality will impede the strength of the model and reliability of the outputs. Models like BRT, GAM and RF require presence/absence data; however, absence data are particularly difficult to reliably obtain in the marine environment without extensive sampling. Availability of relevant and uncorrelated environmental parameters to serve as predictor variables is another limiting factor. A crucial limit for most of these models is the spatial extent and resolution of environmental data like seabed characteristics or water properties. In some instances, it may be possible to use as input the results from other models (e.g., regional ocean circulation models as used in Hemery et al. 2011; Hemery et al. 2016), with the inherent uncertainty of using model outputs to inform another model.

Any trophic web and spatial ecosystem model will require inputs on species' (or functional groups') growth rate, survival (or mortality) rate, excretion rate, reproduction success rate, and/or dispersion rate. These various rates may be difficult to obtain for all but the most well-studied organisms, requiring repeated monitoring over multiple generations. They may have to be estimated from distantly related species. Species-specific data may require adjustments for the targeted location (e.g., an enclosed bay may have a higher larval retention rate than a nearby open shore).

Model-specific limitations include the following:

- EwE needs species or functional groups to be assigned to particular types of habitat, which can be difficult without explicit knowledge (Alexander et al. 2016).
- Generalized regression models such as GAM and the generalized additive mixed model (GAMM) can be prone to overfitting and convergence issues, often due to a high "predictor to response variable" ratio that would be alleviated with a greater coverage of occurrence data (Coolen et al. 2016; Linder and Horne 2018).

- Nonparametric models like RF and SVR are excellent models for interpolating data, for forecasting, but less so for data characterization to identify variability and trends (Linder et al. 2017).
- Time-series models like SSM are excellent in fitting change scenarios but poor in forecasting trended change (Linder et al. 2017).
- 2D and 3D biogeochemical models can be limited by a lack of data and by the inherent complexity of the system, which compel the user to simplify or omit processes or variables and reduce the resolution of the model such that the natural variability is not represented adequately. Overcoming these limitations requires extensive data collection and increased computing capabilities (Schuchert et al. 2018; van der Molen et al. 2018; van der Molen et al. 2016).

Models to detect, quantify, and forecast changes in benthic and pelagic habitats are numerous and adapted to all sorts of scientific problems. The shortcomings of a model in a specific situation could be strengths in a different situation. Many of these models have been applied to contexts other than MRE and the MRE community would benefit from implementing them. For instance, some models such as BRT and MaxEnt are particularly interesting for hindcasting and forecasting species distributions due to climate change (e.g., Freer et al. 2019; Guillaumot et al. 2019) and could be more widely applied in conjunction with oceanographic models (see the section about Changes in Oceanographic Systems) to forecast changes in species distributions due to the operation of MRE arrays (du Feu et al. 2019).

3.5 Displacement of Marine Animals

This section describes models related to the temporary or permanent change in species distribution caused by behavioral responses to the presence of an MRE device, even if physical habitat remains suitable.

3.5.1 Definition and Scope

Species are displaced when MRE devices or arrays induce a partial or complete loss of habitat or changes in migratory routes because of the presence of the device or array (as opposed to noise or EMF emitted from the device). The development of anthropogenic structures can cause a temporary change in the habitat of marine species (i.e., disturbance) or create a barrier disturbing the movement of animals (i.e., barrier effects). Physical characteristics of the habitat may still be suitable, but the animals cannot or are unwilling to access it. Displacement is described as movement of species from their habitat at a larger temporal and spatial scales than considered for collision avoidance. Consequences include the loss of access to resources and the energetic costs of longer dispersal or migration routes. Impacts may also arise from increased intra- and interspecific competition for prey or exposure to predators. The models reviewed for this stressor were mainly applied to tidal environments but can be applied elsewhere. The receptor groups covered by these studies were seabirds, marine mammals, and fish.

No models were identified for this review that directly addressed displacement in the absence of (or not considering) other stressors, such as noise. There is also limited empirical data from situations most likely to displace animals, like extended arrays, because of the lack of operating arrays. However, there are modeling approaches for other stressors that could be applied to displacement with minor changes.

The spatial scale of reviewed models ranged from hundreds of meters to thousands of kilometers and the temporal scale from days to years. All the models reviewed for the displacement stressor were applied to single devices but are adaptable to arrays and can be used at different spatial and temporal scales. Although these models can be applied at different locations, they are dependent on site-specific data (hydrodynamic or species-specific). These models can also be used in marine spatial planning to predict species distribution and assess the effect of physical factors on species movement.

3.5.2 Model Types and Approaches

Two modeling approaches were available to study the displacement of marine species in the reviewed studies:

- Biophysical models: computational models consisting of the coupling of hydrodynamic and individual-based models (IBMs, also called agent-based or Lagrangian models). They simulate movements of individuals in their environment and can be used to predict distributions or exposure to stressors.
- Generalized linear models (GLMs): algorithms used to relate observations to multiple predictor variables. GLMs are used to relate data about species distribution to environmental factors and then predict how the distribution responds to stressors.

3.5.2.1 Biophysical Models

Biophysical models are couplings of hydrodynamic models and IBMs. Hydrodynamic models predict oceanic circulation (see the section about Changes in Oceanographic Systems below). Outputs from the hydrodynamic model are used as inputs to the IBM. Parameters describing behavior are applied to the individuals in the IBM to predict their movement and position as a function of life stage and their environmental conditions.

Several studies specific to MRE used biophysical models to represent harbor porpoise movement in tidal environments (Croft et al. 2013; Lake 2017; Lake et al. 2015, 2017; Nabe-Nielsen et al. 2018). Although these studies focused on how the distribution of food and noise affected porpoise behavior, the framework could also be used to simulate the effect of the presence of a potential device on animals behavior. Modeled factors affecting harbor porpoise behavior were water flow, water depth, food, and noise. Noise thresholds could be replaced by distances that individuals are unwilling to approach a device.

Grippo et al. (2017) used biophysical models to simulate the behavior of fish around a single tidal turbine in Cobscook Bay, Maine, United States. The model scale was 50 to 200 m, which is much smaller than the models in the previous paragraph but larger than that of collision risk models. It essentially focused on avoidance at greater distances. This approach could be used in the context of an array to simulate displacement behavior under different assumptions about responses to the turbines. Fish density was predicted to decrease with decreasing distances to the turbine when it was operating. The decrease in density was also observed in hydroacoustic surveys and indicated an avoidance behavior of the turbine. Although it was mentioned that avoidance could result in displacement of the fish from their preferred habitat, no distribution data were available for the area to confirm this. Authors suggested that installing the turbines in a strong current zone may reduce the potential for displacement of the fish (Grippo et al. 2017).

The hydrodynamic models used in the reviewed studies were the Finite Volume Coastal Ocean Model (FVCOM; used by Grippo et al. [2017]) and TELEMAC (used by Lake [2017]) and Lake et al. [2015, 2017]). They allow the representation of the local environment in three dimensions. The horizontal resolution of FVCOM and TELEMAC is large (order of meters) in those studies. The hydrodynamic model outputs (e.g., current velocities and water temperature) were inputs to the IBMs. Croft et al. (2013) and Nabe-Nielsen et al. (2018) did not use hydrodynamic modeling, just animal movement in space. Other necessary inputs were the biological parameters used to describe the behavior of the individuals; these can be functions of the hydrodynamic parameters or based on distance to features in the environment (like turbines). Essential habitat for feeding, migration, and breeding also needs to be characterized.

The outputs from the simulated movement of individuals from a biophysical model are the trajectories of the individuals and the predicted spatial distribution of the population. This information is useful for predicting distribution changes in the presence of planned or installed MRE devices and selecting among alternative array placements or designs. The models can also be used to estimate the impacts on life history, for instance the effects on growth, reproduction, or survival from reductions in accessible foraging area (e.g., Thompson et al. 2013) or increased exposure to predators. This application would require additional information about demographic rates, e.g., functions relating the food supply to the ability to reproduce.

3.5.2.2 Generalized Linear Models

Statistical models such as GLMs are designed to fit models to observational data in order to analyze those data and interpret the relationships between the variables of interest (Burch 2018). Two types of generalized linear models were reviewed for the displacement stressor: generalized linear mixed-effect models (GLMMs) and GAMs. Both models are an extension of generalized linear models. GLMMs are used when both fixed and random predictor variables are needed. Including random effects allows multiple sources of variability to be distinguished. GAMs are used to model nonlinear relationships between two variables. They use smoothing functions to capture the relationship between the predictor and the variable.

In ecology, GLMMs and GAMs can be applied to many questions, including those about habitat suitability (see the section above about Changes in Habitats). In the MRE context, they have been used in project planning to reduce expected impacts on species by characterizing habitat use by physical features so that devices can be sited in locations with lower expected impacts. Results can be used to inform mitigation measures for the installation or operation of devices depending on the location and season. They could be used to evaluate displacement after device installation by incorporating distance (and perhaps direction) from devices as a predictor variable. No studies using this approach for displacement were found for this review, but given sufficient data collected during turbine operation, the same analyses could be applied.

Waggitt et al. (2016) used GLMMs to assess how turbulence, current speeds, and water elevation relate to seabird distribution and to provide insights into the vulnerability of several species to displacement due to MRE devices. The model was applied to a tidal stream turbine test site at Fall of Warness (Orkney, UK) with capacity for eight turbines. Devices were operated occasionally during the study periods (at most, two devices were operated on the same day) but were not included in the analysis. In the model, the physical factors were continuous explanatory variables and seabird presence/absence was the predicted response. Waggitt et al. (2016) found that Atlantic puffins were likely to use the area during their breeding season and this should be considered in the post-installation monitoring and mitigation. Because the devices were not included in the model, and not representative of a functional array, this study did not directly evaluate displacement. A similar data collection protocol conducted in the presence of an operating array would allow for an analysis of differential use indicating whether birds were avoiding devices, though factors such as noise and prey availability would also have to be considered.

Gilles et al. (2016) used GAMs to predict harbor porpoise habitat in the North Sea (including Denmark, Germany, The Netherlands, and Belgium) where human activities such as offshore renewable energy are planned. Information about the location of MRE or other development was not included in the GAM itself. Their results provided seasonal distribution maps of harbor porpoise that could inform future development of anthropogenic activities such as MRE installations; for example, the maps could be used to identify sites for devices and seasonal timing of construction that would have the least impact. The results were also used as inputs to the IBMs used to further evaluate displacement and underwater noise (Nabe-Nielsen et al. 2018).

Variables for predicting the distribution of species are environmental data in the study domain that can be extracted from a hydrodynamic model such as FVCOM (e.g., Waggitt et al. 2016) or from empirical data (e.g., Gilles et al. 2016). Observed species distribution is required as an input to serve as the response variable. Additional or withheld distribution data can be used for verification, or cross-validation with the original data set may be performed to evaluate model accuracy (Gilles et al. 2016).

3.5.3 Relationship of Models to Monitoring

Biophysical models and GLMs require environmental data (e.g., current velocities, temperature, depth) that can originate from hydrodynamic models or monitoring data. Biophysical models also include biological parameters, typically related to behavior. When data are lacking for a species or location, information for a similar species or other location may be substituted, with appropriate caveats. The models may also use information about the availability of prey or other species. GLMs require data about the spatial distribution of the focal species along with the environmental parameters to be used as predictor variables. In the studies reviewed, distribution data were collected by vessel-based transect surveys for seabirds (Waggitt et al. 2016) and by aerial visual surveys for harbor porpoises (Gilles et al. 2016). Environmental parameters may be physical or biological aspects of habitat suitability.

Biophysical models would benefit from the collection of empirical data to refine the inputs required, particularly data about the swimming behavior of the individuals under typical conditions, and their response to the presence of devices. Species distribution data can be used for model validation. Monitoring for adult stages could be achieved through tagging techniques, acoustic surveys (e.g., Grippo et al. 2017), or sampling (for fish).

3.5.4 Gaps and Uncertainties

The models reviewed focused on predicting the behavior and distribution of individuals for a given species but did not assess their probability of displacement based solely on the physical presence of a device. This is partly due to a lack of behavioral data about the response of individual organisms to devices. Individual test devices may be less likely to cause displacement than arrays, which are currently scarce, and distinguishing behavioral responses among possible stressors is also difficult. Moreover, the potential consequences of displacement on the overall population were not considered. However, models such as those used to evaluate population responses to noise (e.g., Nabe-Nielsen 2018) could be adapted such that proximity to the device (and possibly related factors, such as visibility) rather than noise affected the behavior of individuals. In those instances, the PCoD model framework (King et al. 2015; New et al. 2014; Pirotta et al. 2018) could also be adapted to assess population and/or community effects of devices.

Models that use local environmental data as inputs require such information to be available from field monitoring or hydrodynamic modeling for the model domain. Currently, hydrodynamic model outputs are available for the entire ocean system but at very low resolution (i.e., HYCOM, horizontal resolution of 8 km). To study the displacement of marine species at MRE locations, hydrodynamic models require a high resolution (order of meters), which in most cases need to be developed by the program conducting the study. The other limitation observed in the reviewed models was the use of 2D rather than 3D hydrodynamic models. 3D models allow for representation of the current velocities along the water column that can affect the behavioral patterns of the individuals.

The biological components of the reviewed models were also poorly described. Few models have realistic biological parameters to describe the biology and ecology of the species of interest. For the biophysical models in which behavior was included, species-specific data were often limited and information from similar species was used. Behavioral data can vary by both species and location/habitat type. Similarly, biological inputs were limited in GLMs. Distributions of the modeled species were obtained from the literature or from a few tracked individuals. Key research needs to apply these types of models at the scale of MRE devices are high-resolution hydrodynamic models and knowledge of species characteristics such as swimming velocities and behavior to refine the biological parameters and distribution of individuals to validate the model outputs.

3.6 Changes in Oceanographic Systems

This section describes models that estimate how MRE devices change the physical environment in their vicinity, including changes to water elevation and currents, water properties, waves, and sediment.

3.6.1 Definition and Scope

The placement and operation of MRE devices can change currents, water surface elevation (WSE), water temperature, salinity, and other waterborne constituents or biota. Devices can also affect geomorphology and the formation and propagation of wind waves. Hydrodynamic and transport models, wave propagation models, and computational fluid dynamics (CFD) models have been used to estimate these physical effects. The models are based on the conservation of mass, momentum, and/or energy in the water column.

MRE devices are designed to harvest energy, reducing the energy in the currents or waves. They may also redirect momentum and change the strength and path of currents. In turn, changes in energy and flow direction alter the transport of sediment or other particles. The goal of oceanographic systems modeling for MRE devices is first to quantify how the balance of momentum or energy is altered by the MRE device placement and operation. Then, models can estimate the consequences to the environment due to the redistribution or harvesting the energy in the system. The models also provide information about velocity, temperature, salinity, and particle transport to numerous other models included in this review. In this way, physical models can improve the accuracy of models for other stressors while reducing the need for extensive field data collection.

3.6.2 Model Types and Approaches

Several types of numerical models have been applied to assess MRE-related oceanographic change. Generally, the distinction between the models is their underlying numerical solution scheme, level of spatial integration/resolution, and the nature of coupling with other types of models (e.g., wave propagation, sediment, and constituent transport submodels). Numerical models can be fully 3D or configured for vertically integrated, 2D simulations (i.e., depth along an x-y transect). Wave models may solve the wave action equation in the frequency domain (a form of the conservation of energy flux equation), which models a single point in time. There are also time-domain wave models that are more computationally intensive and applied at smaller scales around devices. Currently, most numerical approaches are based on variable spatial resolution in their simulations. They implement irregular meshes that conform to the topography, allowing for finer resolution in areas of higher complexity and coarser resolution in more homogeneous areas for efficiency.

For assessments of MRE device effects on waves, sediment transport, or geomorphology, the specific models can be applied as stand-alone models, coupled directly with a coastal hydrodynamic model, or they can incorporate coastal hydrodynamic model results as an input. The models may be run using the same numerical discretization of the environment or the discretizations may differ among models in a study.

3.6.2.1 Coastal Hydrodynamic Models

Coastal hydrodynamic models use bathymetry, tides, river discharges, wind forcing, bottom friction, and the impact of the Earth's rotation to model water properties and movement. In cases where the distribution of temperature and salinity are thought to significantly affect water circulation (e.g., stratification), coastal hydrodynamic models also need to account for surface heat loss and gain. They then estimate the effects of temperature and salinity on water density and density-driven flow. The studies summarized below are examples of hydrodynamic models and their applications and not an exhaustive list.

Five different coastal hydrodynamic models were implemented in the evaluated studies: FVCOM (Chen et al. 2003), Delft3D (Deltares), MIKE 3 (DHI Water and Environment), TELEMAC 2D (National Laboratory of Hydraulics and Environment, France), and Fluidity (Piggott et al. 2008). These models solve the Reynolds-averaged Navier-Stokes equations[1] with depth dependence, except for TELEMAC 2D, which solves the depth-averaged version of the equations. The 3D models mainly differ in their spatial and temporal solution schemes, boundary conditions, energy dissipation schemes, inclusion of sediment transport models, and biogeochemical models. Models have strengths in different areas or submodules; for example, FVCOM is strong for evaluations of changes in flow and circulation, while Delft3D is strong in modeling sediment transport.

There are several approaches to evaluating the effect of tidal devices using these models. A momentum sink can be used such that the velocity is reduced based on the flow-facing area of the turbines and an associated momentum extraction coefficient (Ashall et al. 2016; Yang et al. 2013). Another way to simulate turbines is by implementing porous plates that will reduce flow velocity (e.g., Waldman et al. 2017). The advantage of these approaches is that the turbines are

[1] The Reynolds-averaged Navier-Stokes equations are the time-averaged version of the equations of motion. To solve the equations, the high-frequency turbulent flow is parameterized using turbulent closure models.

abstractions. The parameters for their effects on flow can come from laboratory studies, small-scale numerical simulations of the turbine structure, or field data. With these abstractions, the mesh does not need to be fine enough to resolve the structures, which may be small relative to the model domain.

Coastal hydrodynamic models require finely detailed bathymetry to represent the study system at relevant scales. The model mesh is constructed to represent the features of the bathymetry and to optimize the numerical simulation (e.g., by using coarser resolution in open areas). For depth-resolving 3D models, the pressure gradient error that results from the vertical discretization of a stratified ocean can generate spurious density-driven currents; therefore, having knowledge of the stratification and bathymetry gradients can inform mesh generation.

Tidal elevation or velocity time series at the open ocean nodes are necessary inputs. These are usually taken from a global database such as the Oregon State University TPXO model (Egbert et al. 1994; Egbert and Erofeeva 2002). Information about salinity, temperature, and heat fluxes can be added to the 3D models to simulate density-driven currents. To evaluate the impacts of tidal devices on sediment transport, the models will require spatial maps of sediment composition/grain sizes.

At a minimum, models provide outputs of WSE and current velocity. Additional outputs may include estimates of turbulent kinetic energy and bed-shear stresses. The latter can be used to estimate sediment mobility if a physics-based sediment transport model is not included. Other common outputs are time series of temperature and salinity or other constituents.

Many researchers have used FVCOM (Adams et al. 2014; De Dominicis et al. 2017; Smith et al. 2013; Wang et al.; Yang and Wang 2015; Yang et al. 2013) for hydrodynamic modeling and assessment of effects based on the change in flow patterns. For instance, Yang et al. (2013) investigated the effects of tidal turbine farm on the flushing time of a bay. They used an idealized setting of a tidal channel and bay to validate a tidal turbine module in FVCOM relative to an analytical solution using the momentum sink approach. They also compared 1D, 2D, and 3D model formulations to find that less-than-3D models overestimate the effects of turbines on tidal flux. De Dominicis et al. (2017) used a similar modeling approach for tidal turbine arrays in the real-world setting of Pentland Firth, Scotland. They include estimates of farfield effects and a brief review of other modeling studies of farfield effects of tidal energy extraction. MIKE 3 and Delft3D have also been implemented for analysis of tidal turbines in Pentland Firth (Gallego et al. 2017; Waldman et al. 2017).

Delft3D is well-known for its capability to simulate sediment transport. Multiple studies used Delft3D to evaluate the impacts of tidal or wave energy devices on erosion or sediment transport (e.g., Ashall et al. 2016; Jones et al. 2018; Rodriguez-Delgado et al. 2018; Smith et al. 2013). Ashall et al. (2016) used Delft3D coupled with Simulating WAves Nearshore (SWAN) wave model (see the Wave Propagation Models section below) to evaluate the impacts that high- and low-density tidal turbine arrays, represented as semi-porous plates, would have on suspended sediment transport in the Minas Basin (Bay of Fundy, Canada). They showed the impacts of the high-density array were considerable but the impacts of the low-density array were minimal. The model was validated for WSE, currents, and suspended sediment concentration without turbines but not for nearfield effects around turbines. Jones et al. (2018) used a coupled hydrodynamic-wave model framework, Delft3D-FLOW-SNL-SWAN, to evaluate the effects of a wave energy buoy array on near-bed sheer stress and seabed elevation, both considered indicators of benthic habitat quality.

TELEMAC 2D was used in applications to those of Delft 3D, where researchers investigated the effect of a proposed array of tidal turbines, explicitly modeled, on bed-shear stresses and the potential for scouring or accumulation of sediment and sediment transport volumes (Haverson et al. 2018). They noted that 2D depth-averaged models may underestimate the flow velocity below turbines and underestimate nearfield bed-shear stress. Robins et al. (2014) used TELEMAC 2D coupled with the SWAN wave model to investigate changes in bed-shear stress and sediment context caused by tidal turbines in the context of changes due to natural variability in wave dynamics. Martin-Short et al. (2015) used Fluidity, another 2D model, similar to how Haverson et al. (2018) used TELEMAC 2D, with similar caveats about modeling nearfield effects using a depth-averaged model.

3.6.2.2 Wave Propagation Models

Most wave modeling for MRE evaluation has used models suitable for larger scales. The most common software is SWAN (Delft) and models derived from SWAN. The software has been used together with hydrodynamic models (Abanades et al. 2014; Bergillos et al. 2018; Iglesias and Carballo 2014; Jones et al. 2018; Robins et al. 2014; Rodriguez-Delgado et al. 2018) or for stand-alone wave modeling (O'dea et al. 2018). SWAN is a spectral model developed to simulate wave activity from deep to shallow water. It includes wave breaking induced by the seabed and allows for complex interactions between waves. This model is suitable for evaluating farfield effects of MRE devices on waves such as changes in a coastline (O’Dea et al. 2018).

An example application of SWAN evaluated how the distance from wave energy converter (WEC) arrays to the shoreline would affect nearshore wave energy and where on the coastline the impacts would occur (Iglesias and Carballo 2014). The model uses a nested grid, with a resolution smaller than the WECs to accurately represent diffraction and the wakes of individual devices. It has also been used to assess whether wave farms could provide coastal protection in areas with erosion problems by coupling SWAN, or its derivative Delft-WAVE, to a morphodynamic model (XBeach) that models sediment dynamics of the nearshore and beaches (Abanades et al. 2014; Bergillos et al. 2018). O’Dea et al. (2018) provide a generic study of the nearshore effects of WECs and a review of previous applications of SWAN.

SWAN can be directly coupled with hydrodynamic models so that waves and currents interact, allowing waves to affect the sediment transport in the hydrodynamic model. Ashall et al. (2016) used a coupled Delft3D-SWAN model to assess turbine impacts on suspended sediment as described above; the model coupling allowed waves to increase bed-shear stress, turbulent dissipation, and other factors important to sediment dynamics in intertidal mudflats. A modification of SWAN, also coupled with Delft3D-FLOW (Delft3D-FLOW-SNL-SWAN; Sandia National Laboratories), was used to show the effects of wave shadowing from WECs on sediment deposition (Jones et al. 2018).

The SWAN model requires time series of incoming wave spectra, sea level, and wind, as well as bathymetry and bottom drag coefficient(s). Because wave events are far more unpredictable than tides, characterizing the directionality and variance in wave height and period is important for realistic modeling and may require extended observational data and probabilistic analyses (e.g., Jones et al. 2018). If coupled with a hydrodynamic model, SWAN can also use horizontal and vertical eddy viscosity parameters. WECs have been incorporated in SWAN by using a transmission coefficient that is either independent or dependent of the wave frequency and determines how the WEC alters the waves as they pass the device. Realistic values of the transmission coefficient can come from CFD models (below), field measurements, or laboratory measurements. Some studies have used very fine grids to model wave dynamics near the WECs in more detail (e.g., Iglesias and Carballo 2014).

Nearfield effects where diffraction of the waves is important—i.e., the effects of the device on the structure of a wave that passes by or through it—cannot be accurately modeled with spectral models like SWAN. The performance of SWAN is also limited when the obstacles, including WECs, are smaller than the resolution of the model grid, and for oscillating WECs that create radiated waves. The model WAMIT (MIT) is a “wave-structure interaction solver” that has the capability to simulate diffraction and include source terms that account for the wave reflection, absorption, and radiation associated with the presence of WECs (Sjökvist et al. 2017). WAMIT is a Boundary Element Method model that, like the CFD models described below, are only computationally practical for small domains and also must be used with constant water depths.

Models that simulate the sea surface as a function of time can overcome some limitations of spectral models (Beels et al. 2010). These models are based on conservation of mass and momentum and can be used to model the effect of specific device geometries and operations on waves. One model, MILDwave, is described as a mild-slope wave propagation model. It has been used at fine scales to model the impact of overtopping WECs, alone and in arrays, over a distance of approximately 2 km (Beels et al. 2010). The model is specialized for modeling diffraction accurately as linear waves move from deep to shallow water. MILDwave also been used together with simulations of Oscillating Surging WEC device arrays over a 6 km model domain (Balitsky et al. 2019).

Wave models can be combined to simulate both nearfield interactions between WECs and farfield effects (Stratigaki et al. 2019). In this approach, a wave propagation model is used to estimate the incident waves arriving at a WEC. A wave-structure interaction solver models the wave as it is perturbed around the WEC. Then the perturbed waves (including the diffracted waves and radiated waves, if applicable) are returned to the original propagation model to travel over longer distances and varying bathymetry; the process is repeated for additional WECs. This approach can be used with different model combinations. Stratigaki et al. (2019) demonstrated it with a coupling of MILDwave as the propagation model and WAMIT as the wave-structure interaction model. MILDwave is able to calculate the diffracted waves from the WECs, so the additional information provided by WAMIT is the radiated waves from a heaving WEC.

Another wave model, MIKE21 SW, has been implemented together with the hydrodynamic model MIKE3 in the simulations of WECs (Gallego et al. 2017; Venugopal et al. 2017). The model accommodates nonlinear waves in shallow water with high accuracy (Beels et al. 2010). MIKE21 SW does not have a built-in WEC module, so in these instances WAMIT was used to characterize the WEC arrays to provide parameters for MIKE21 SW. This was not a coupled model as in Stratigaki et al. (2019) because there was no feedback between models; WAMIT was used separately to provide parameters about the effects of the WECs for MIKE21 SW run separately.

3.6.2.3 Computational Fluid Dynamics Models

CFD models are designed for smaller, higher-resolution spatial domains than the numerical models discussed above. CFD models can characterize flows in the immediate area of a device or array, and thus can resolve flow characteristics that the other models do not. Conversely, they are not typically used to model large-scale flow phenomena because of the computational complexity and time involved. These models can be used in complementary ways: CFD models can inform larger-scale models about the effect of specific MRE devices or arrays on local flows (allowing the abstractions of devices described above); the large-scale models can inform CFD models by specifying boundary conditions.

There are numerous examples of small-scale evaluations of the design and performance of MRE devices and site-specific energy potential estimates using CFD. Laín et al. (2019) reviews applications of CFD models to tidal turbines. Software included ANSYS FLUENT (Li et al. 2019), which was used to model the nearfield effects of a tidal turbine on surface waves. The local changes in wave height and length were used to parameterize an FVCOM model for larger-scale simulation. COMSOL Multiphysics was used to characterize hydrodynamics around a wave buoy in comparison with the WAMIT model (Sjökvist et al. 2017).

3.6.3 Relationship of Models to Monitoring

Hydrodynamic and wave models require some fundamental physical characteristics of the system being modeled, such as bathymetry (preferably at a relatively fine scale) and the bottom friction or drag. CHD models with sediment modules require additional details about sediment type and distribution. They also require time-series inputs. CHD models require, at minimum, tides, river discharge, wind, and current velocity at the open-ocean boundary conditions. Initial conditions of temperature, salinity, etc. are also necessary. Wave models require, at minimum, the WSE from observations or CHD model output, wind, and incoming wave spectra. Ocean currents and tidal forcing should also be included in wave models if they are strong enough to affect the waves. Descriptions of the MRE devices being studied are also needed, and the level of detail required varies depending on the model approach and resolution.

Information such as tides and open ocean conditions can be obtained from global databases, and many river discharges are measured. Incoming wave spectra may be the most difficult to obtain for a site, because wave patterns are driven by numerous variables and typically require extended observations to accurately capture weather patterns and storm events. All of these data must be site-specific but some may be readily available, albeit not necessarily at a sufficient resolution. CFD models require data similar that for CHD models, depending on location, but may require much finer-scale data for a smaller area.

Model calibration and validation require observations of the modeled metrics, such as water temperature, salinity, WSE, velocities, and wave spectra. Ideally validation data would be collected across seasons and the spatial extent of the model. When modeling MRE devices, observations need to be made both upstream and downstream of the array to provide complete model validation. Bathymetric surveys before and after the deployments are necessary to validate the model predictions and quantify the effects of devices on sediment transport. It has been suggested, through numerical modeling, that suspended sediment concentrations increase along the array sides and decrease upstream and downstream (Ahmadian et al. 2012). Active monitoring of the sediment concentrations can complement bathymetric surveys.

Most of the information needed for oceanographic modeling is straightforward to collect via surveys or observation stations (e.g., buoys) but may require investment to collect data at the resolutions required and for the duration necessary to adequately characterize natural variability. Nearshore data are especially important. Shallow and/or bathymetrically complex areas tend to be more challenging for hydrodynamic models than open/deep water, but routine data collection, with sufficient resolution, does not usually occur in the nearshore as often as it does in open water.

3.6.4 Gaps and Uncertainties

Our review of the literature did not locate a comprehensive discussion of uncertainty for hydrodynamic modeling, and it is not addressed in the publications as frequently as for other types of models. Some studies validate the models for the existing conditions extensively (e.g., Haverson et al. 2018), while others consider idealized conditions. Li et al. 2019 provided extensive validation of the CFD model based on experimental studies. Besides Contardo et al. (2018), who validated their numerical model during a short period (less than a month) for a two device array, no study compared effects of operational full-scale devices with their model results, presumably because of lack of publicly available data.

Most studies evaluated the effects that large arrays would have on the physical environment, which included changes in waves and currents due to the presence of the devices. Multi-device arrays have not been deployed and thus no data for validation currently exist. Phase-averaged wave models like SWAN have been the most widely used to evaluate the effects of WECs in the wave field, however their ability to resolve highly variable wave fields at short time scales (less than an hour) has been questioned (Contardo et al. 2018).

4.0 Synthesis

This section contains a brief summary of the results of the model review discussed across stressor groups to identify commonalities and themes important to advancing model development and integrating modeling with monitoring.

4.1 Availability and Maturity of Models and Applications

Models that have been used to evaluate environmental impacts of MRE devices vary in the level of model development for different stressors (Table 2). Collision risk models have been developed specifically for MRE devices, but the lack of data about species avoidance and evasion behavior and sublethal effects have limited the conclusions that can be drawn from those models. Many underwater noise models are available, but only a few MRE-specific applications are available. Similarly, the physical modeling of EMF is relatively straightforward, but related information, modeling of species interactions with EMF, and MRE-related models are scarce. The ecological modeling literature for habitat change is extensive, but model studies involving MRE remain largely theoretical and have not been validated with operating devices.

Displacement of marine animals, according strictly to the definition used in this review, has not yet been modeled for MRE. Other modeling approaches used for underwater noise and habitat change could be adapted to model displacement. However, application of all models that include behavioral aspects (collision risk, noise, and displacement) has been hindered by lack of species-specific data, especially regarding behavior at various distances from MRE devices.

Physical models are well-established and have been applied to assess the environmental impacts of tidal and wave MRE devices, but models that thoroughly model the effects of devices on currents and waves at fine resolutions are new and relatively unusual. The accuracy of physical models in predicting effects near MRE devices or arrays and the propagation of these effects is very important because hydrodynamic or wave model outputs may be used as inputs for many models in the other stressor categories.

Each stressor has at least one example that could be used as a starting point for modeling the environmental effects of MRE devices. Tidal energy devices were addressed for all stressors except EMF, and wave devices for all but EMF and displacement. Arrays and single devices have all been modeled. Models would require varying degrees of adaptation for specific MRE devices, along with any adjustments needed for the particular site. EMF models have been applied to DC cables, which are not as complex to model as the AC cables likely to be used for MRE, and software may not accommodate the structure at an MRE site. Additional work may be needed to assure the MRE system (generators on devices and transmission lines) is properly represented. Displacement models have had very limited MRE application; future modeling may be best accomplished by adapting from approaches used for population disturbance by underwater noise or statistical models of habitat change.

Table 2. Model applications identified in this review, by stressor.

Applications	Collision Risk	Under-water Noise	EMF	Habitat Changes	Displace-ment of Animals	Oceano-graphic Systems
Theoretical systems	X	X	X	X		X
Actual devices (planned)	X	X		X		X
Actual devices (implemented)	X	X	X[(a)]		X	X[(b)]
Use of field data to parameterize/initiate	X	X				X
Model validation with field data		X	X			X
Model of stressor range or propagation		X	X			X
Model of biological effects	X	X		X		
Used in environmental assessment for MRE devices	X	X				X
Used with post-installation monitoring of MRE devices	X				X	
Tidal turbine	X	X		X	X	X
Tidal kite	X					
Wave energy		X		X		X
Offshore wind		X	X	X	X	X
Pile driving		X				
Single device	X	X		X	X	X
Array of devices	X	X		X	X	X

(a) Submarine electrical cables that are not part of MRE projects.
(b) Includes laboratory-scale devices.

For a number of models, software is available that requires only input data for the site of interest and minimal adjustments or calibration. It would be unlikely, however, to find ready-to-use models for all stressors that would work for a specific project without modification or further development. Nor would the same suite of models be appropriate for all projects. The choice of some models, especially for oceanographic systems and underwater noise, depends not just on the type of device and the receptor species but also on the physical setting of the site and its complexity. Finally, clear statements of the questions to be answered using models are important for determining the best model(s) to use.

We reviewed models that could apply to multiple stressors. Two examples are Nabe-Nielsen et al. (2018) and Middel and Verones (2017), who modeled the effects of underwater noise on species distribution. A similar approach could be used for predicting displacement of species by changing the behavioral responses to noise to responses to distance from the device itself. Approaches to modeling habitat change could also be adapted to model displacement. Generally, however, studies addressing two or more stressors were rare (Adams et al. 2014). A number of studies used the output of hydrodynamic models as inputs to models for other stressors (e.g., Adams et al. 2014; Goodwin et al. 2006; Rossington et al. 2013; Waggitt et al. 2016), but these studies evaluated the effects of the focal stressor (habitat change, noise) and not the full range of physical changes.

4.2 Model Information Needs

The information required for implementing various models can be grouped into parameters that must be site-specific and others where site-specific data are ideal but not obligatory (Table 3). Site-specific inputs can be further categorized as static or dynamic, the latter requiring for more data to characterize. Inputs that are static or nearly so include bathymetry, sediment type and roughness, and sediment material properties (e.g., bed-shear stress). These inputs can change over time but do so relatively slowly. For many planning assessments, a single survey may be sufficient. Additional surveys would be needed after devices have been operational if physical changes were expected, e.g., in sediment distribution.

Dynamic inputs are temporally variable and include water properties like temperature and salinity and weather factors like wind. Tides are mostly predictable, but river discharge and incoming wave spectra are partly determined by weather and thus highly variable. To be realistic, many models would require time-series data long enough to include key sources of variability.

Site-specific data of either type may be found in existing data sets or collected as baseline monitoring data. It was common among the models we reviewed for at least some data about bathymetry, sediment type, and/or water properties to be publicly available, but the spatial resolution was too coarse (e.g., on the order of kilometers rather than the necessary resolution on the order of meters). The appropriate spatial resolution of a model is not easily known *a priori*. It depends on the resolution of the inputs and the variability of the system. Thus, it is recommended that convergence analyses be performed during the model development stage.

Hydrodynamic models may be used to simulate water properties for habitat or noise at the necessary temporal and spatial resolutions, and may have been developed for other purposes at the site. However, the quality of physical model output depends on the accuracy of the inputs and sufficient model calibration and validation. Data used as inputs for hydrodynamic models and observations for comparison may be prioritized because their accuracy carries forward to other models.

Environmental input data can also be used directly for underwater noise, habitat change, and displacement models. The common need for many physical data sets to parameterize models for multiple stressors suggests that it is worth the resources required to collect them. The possibility of using similar data sets should be coordinated in advance to make sure surveys collect data suitable for all models and avoid redundancies.

The distributions of the receptor animal(s), and possibly their prey/food resources, are also site-specific. For well-studied species or locations, some information may already be available. Larger animals, as well as birds and mammals that spend time on the surface, are more easily surveyed visually or through tagging studies. Fish and other smaller animals may require more extensive sampling. The role of seasonality and other conditions must be kept in mind; site-specific data may also be specific to the time of year. Resource distribution has been inferred in some studies to match the distribution of the receptor animal when undisturbed, because of the greater difficulty in mapping the distribution of typically smaller prey organisms. This simplifying assumption may work if the resource is not also affected by the MRE devices; important prey that are also expected to respond to devices may also need to be surveyed and/or modeled.

Table 3. Input data and parameters used in reviewed (existing) models by stressor, indicated by 'X'. Not all reviewed models, within a stressor category, used all of the inputs or parameters. Shaded cells indicate information used by most or all of the models.

Site specificity	Time/ species specificity	Inputs/ Parameters	Collision Risk	Under-water Noise	EMF	Habitat Changes	Displace-ment of Animals	Oceano-graphic Systems
Site-specific	Static	Bathymetry	X	X		X	X	X
		Sediment type/roughness		X	X	X		X
		Sediment material properties		X	X	X		X
		Model of device	X	X	X[a]			X
	Dynamic (empirical/ modeled)	Water temperature		X		X	X	X
		Salinity		X		X	X	X
		Water velocity	X			X	X	X
		Tides/Depth	X	X		X		X
		Wind		X			X	X
	Species-specific	Distribution of organisms or food	X	X		X	X	
Not site-specific		Organism shape/size	X					
		Animal swimming/diving behavior	X	X			X	
		Animal vital rates	X	X		X	X	
		Audiograms		X				

(a) Study modeled the transmission cable, not the device.

Most non-site-specific input is biological. Some parameters for physiology, behavior, and reproduction and survival can be obtained from literature. Use of data from similar and/or nearby locations is helpful, to account for genetic differences between populations and behavioral changes such as those that may occur near coastlines vs. the open ocean (Nabe-Nielsen et al. 2018). However, it is usually challenging enough to acquire data for the species of interest from any location. In reviewed studies that could not obtain data for their focal species from the literature, most, but not all, used data from similar species rather than collecting new data for the project. A few studies have used tagging (Thompson et al. 2016), recordings of porpoise clicks (Nabe-Nielsen et al. 2018; Williamson et al. 2016), video or acoustic cameras (Bevelhimer et al. 2016; Grippo et al. 2017; Hammar et al. 2015), or other means of observation to estimate behavior.

Collision risk, displacement, and some noise models were most reliant on behavioral parameters. Models simulating the effects of EMFs on populations will also need a unique set of behavioral parameters, but such models have not yet been developed. Reproduction and survival rates are required for studies examining population-level effects of stressors. Baseline values may be available from the literature, but the effects of the stressors may require expert opinion and/or simplifying assumptions unless adequate studies have been conducted. For many species, long-term information would likely be too time-consuming and expensive to collect for individual MRE projects. However, to achieve the goal of understanding how MRE affects populations in the long term, this information is an important research topic that could benefit many future assessments.

Physical (hydrodynamic and wave), collision risk, and underwater noise models were used in environmental assessments for specific MRE projects identified for our review. Models of changes in habitat relative to MRE were only conducted for research purposes and were not part of the planning or monitoring of specific projects. We did not find examples of EMF models applied to MRE.

Model validation is rare, especially in studies specific to MRE devices (Table 3), and is most often done for baseline conditions rather than in the presence of operating devices. Validation is more common for the physics-based models (i.e., oceanographic systems and underwater noise propagation) than for the more biology-oriented models. This is reasonable considering the nature of the data and the relative difficulty in collecting physiological and demographic data compared to measuring physical characteristics. Underwater noise studies had several model validation examples but most were for pile driving, which differs in nature and duration from device operation, so their applicability is limited. A limited amount of validation has been conducted for EMF models for submarine cables.

Collision risk, displacement, and habitat change studies did not include validation with field data for MRE-specific models, but habitat change modeling approaches have examples of validation in other contexts. Overall, validation has been limited by the small number of devices deployed for operation and testing. Continuing efforts to validate models will be important for improving their usefulness in project planning and evaluation. Monitoring that is designed in coordination with model development and application will facilitate model validation in the future.

5.0 Next Steps

This review has provided an overview of models relevant to the environmental effects of MRE devices, their strengths and weaknesses, and their data requirements. Each stressor has multiple modeling approaches. One or more may be suitable for a project depending on the device technology, site characteristics, existing information about the projects and any previous deployments, and if there are specific receptors of interest (e.g., protected or commercially important species).

To apply this review to inform field testing and monitoring, a first step would be to describe the project site, the device and the receptors, and align those characteristics with the modeling options and examples. This comparison and other considerations (e.g., time, software requirements) help to determine the most suitable approach and the degree of adaptation that may be necessary. In some cases, software may be commercially or freely available for applying models once provided with input information. In others, particularly for less-studied stressors or devices, some additional development may be necessary. After selecting an approach, existing information can be compared to data needs for the model to determine what needs to be collected, at what resolution, and to what spatial and temporal extents. Describing the types and levels of uncertainty to be expected is also helpful for future decision-making.

Choosing appropriate models prior to baseline data collection can provide scenarios based on different data inputs for developers and regulators to constructively consult on. After baseline data are collected, appropriate models can be used to predict the effects of stressors on receptors in the project area. These predictions are useful for consultation, and provide a foundation for discussion of possible project impacts and how to prevent or mitigate them.

Furthermore, the modeling can inform development of a salient and efficient monitoring program related to the impact concerns from consultation once a device is installed and operating. Models can also be employed during operation to evaluate environmental status, estimate the effects of changes in the project, and periodically evaluate the value of monitoring information and identifying improvements.

A significant effort for the TFiT project is testing field data collection methods at various sites to inform guidelines for future efforts. Doing so will streamline the process of choosing appropriate sensors, data collection methods, and data processing and analysis steps. The choice of sensor and data collection method will consider this modeling review and choose the most appropriate model based on the site characteristics, stressors, receptors, and known concerns of regulators.

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