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A Review of Current, Emerging, and Potential Future Tools for Predicting North Atlantic Right Whale Presence

U.S. Department of the Interior
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Sterling, VA

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ABOUT THE COVER

Cover photo credit: Skim feeding North Atlantic right whales, Cape Cod Bay - NOAA

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List of Abbreviations and Acronyms

Long Form	Short Form
agent-based model	ABM
artificial intelligence	AI
artificial neural networks	ANN
boosted regression trees	BRT
climate monitoring	CM
decadal prediction	DP
deep learning	DL
dimethyl sulfide	DMS
ecological-niche factor analysis	ENFA
environmental niche model	ENM
generalized additive model	GAM
generalized linear model	GLM
genetic algorithm for ruleset prediction	GARP
Google Earth Engine	GEE
habitat suitability model	HSM
individual-based model	IBM
inverse reinforcement learning	IRL
kernel density estimation	KDE
long short-term memory	LSTM
machine learning	ML
North Atlantic right whale	NARW
passive acoustic monitoring	PAM
population consequences of acoustic disturbance	PCAD
random forests	RF
recurrent neural networks	RNN
reinforcement learning	RL
relative environmental suitability	RES
sea surface temperature	SST
species distribution model	SDM
Subseasonal Experiment	SubX
weather forecasting	WF

1 Introduction

Data on species distribution are essential to conservation and management practices. However, ecosystem shifts, such as those resulting from climate change or anthropogenic disturbance, can alter the distribution and movement patterns of these animals (Guisan and Thuiller 2005; Van der Putten et al. 2010). The relatively rapid nature of these shifts can be problematic if mitigation efforts are focused on static critical habitat areas that are based primarily on historical distribution patterns, particularly for highly mobile species (Oestreich et al. 2020). Although real-time species presence can inform management decisions (e.g., dynamic management areas), real-time monitoring is typically aimed at shorter temporal scales, particularly in ocean environments and in areas where the target species is already known to be present (Oestreich et al. 2020). Thus, efforts to predict the future distribution of a species over varying temporal scales (e.g., weeks, months, or years) are needed when developing long-term conservation plans.

The North Atlantic right whale (NARW) is a critically endangered species. There are an estimated 340 individuals remaining in the population (Pettis et al. 2022). They are currently facing a population decline primarily due to interactions with fishing gear and vessel collisions (Kraus et al. 2016). The historical habitat and migration routes of NARWs are well documented, and successful management efforts relied on this regularity (Record et al. 2019). However, in 2010, an ecosystem shift altered the distribution and movement patterns of NARWs (Davies et al. 2019; Record et al. 2019; Meyer-Gutbrod et al. 2021). North Atlantic right whales are now observed more frequently in areas that have not yet been designated as critical habitats (e.g., the Gaspé area in the Gulf of St. Lawrence, Canada; ([DFO] Fisheries and Oceans Canada 2021) that offer more protection from anthropogenic threats (Record et al. 2019). Alternative and dynamic conservation approaches are essential, including a focus on identifying potential new and alternative critical habitats and predicting the future temporal and spatial distribution of this species (Davies and Brillant 2019; Pettis et al. 2022).

The goals of this review are to 1) review the current predictive tools used to determine the presence and distribution of NARWs; 2) assess what alternative predictive techniques are currently in use for other species that could be adapted and applied to NARWs within the next two years; and 3) discuss the development of future tools that could be applied within the next five years.

2 Current Prediction Methods (Available Now)

The methods described in this section have been applied to NARWs, including both hindcasts of NARW presence and prediction of future NARW distribution. These techniques are available to be used in the immediate future with minimal modification (e.g., adding new or alternative predictor variables or including updated data).

Table 1. Summary of statistical methods that have been used to date to hindcast North Atlantic right whale presence and/or predict their future distribution.

Specific Model Type	Description	Relevant Publications
Species Distribution Models (SDMs)	Model the distribution of a species in geographic space	Moses and Finn (1997) Pendleton et al. (2012)
Habitat Suitability Models (HSMs)	Predict the occurrence of a species based on environmental variables	Department of Fisheries and Oceans Canada, (2021)
Prey Models	Correlate the distribution and abundance of Calanus spp. to NARW occurrence	Brennan et al. (2021) Fortune et al. (2013) Gavrilchuk et al. (2021) Pershing et al. (2009) Plourde et al. (2019) Ross et al. (2023)
Ensemble Models	Incorporate multiple models to more accurately predict occurrence	Ross et al. (2021)

2.1 Distribution models

Predictive geographical models aim to explain the relationship between environmental factors and the distribution of species and communities (Guisan and Zimmermann 2000). Predictive distribution models relate species occurrence to various predictors by using spatially explicit statistical models (Guisan and Zimmermann 2000; Roy et al. 2022). They can be used to answer various questions, including predicting new areas with high potential for species occurrence and considering the future distribution of a species in light of changing environmental conditions (Guisan and Thuiller 2005; Roy et al. 2022). Commonly used tools to predict the future movement of a species include species distribution models (SDMs), habitat suitability models (HSMs), and environmental niche models (ENMs) (Roy et al. 2022). Distribution models can incorporate a multitude of approaches, including regression analyses (e.g., generalized linear or additive models (GLM/GAM)). They also can include machine learning (ML) algorithms (e.g., classification and regression trees, random forests (RF), which are considered a subset of artificial intelligence (AI), and entropy models (Guisan and Zimmermann 2000).

2.1.1 Species distribution models

SDMs focus on the distribution of a species in geographic space (Peterson and Soberón 2012). Using an ML-based maximum entropy (Maxtent; Phillips et al. 2006) algorithm applied to a SDM framework, Pendleton et al. (2012) used presence-only data to correlate NARW occurrence based on environmental variables. The authors found that NARW presence could be predicted by sea surface temperature (SST), as well as bathymetry and chlorophyll concentrations, albeit to a variable extent dependent on the time of year. However, results were only applied to hindcasts of NARW distribution, and no predictions were made for current or future distributions.

Few studies have tried to predict alternative habitat areas and the future presence of NARW, although there are some exceptions. Moses and Finn (1997) used a regression model with environmental covariates

(SST and bathymetry data) to predict alternative summer foraging habitats for NARWs in the entire North Atlantic. The results suggested additional feeding areas in the Gulf of St. Lawrence, on the Grand Banks off Newfoundland, south of Iceland, and on the continental shelf around Ireland. As this study occurred in 1997, prior to the 2010 shift in NARW distribution, it provides an opportunity for some model validation. As predicted, the Gulf of St. Lawrence did prove to be an active feeding ground. In 2015, the number of right whale upcalls detected using passive acoustic monitoring (PAM) demonstrated a substantial increase in the number of NARWs using this area (Simard et al. 2019). It remains to be seen whether the remaining areas predicted to be viable NARW feeding habitats by Moses and Finn (1997) also prove to be important areas for this species.

2.1.2 Habitat suitability models

HSMs are a broad class of models that aim to predict the presence/absence or abundance of a species based on environmental variables (Hirzel and Le Lay 2008). Canadian researchers are currently developing and refining HSMs for NARWs with the intent of predicting the future distribution and presence of this species ([DFO] Fisheries and Oceans Canada 2021). However, the timeline to implementation, as well as the details of the models, need clarification.

Habitat-based density models are currently available that can be used to model the spatio-temporal distribution of NARWs. For example, the model by Roberts et al. (2016; 2023) incorporates environmental covariates with survey and abundance data to calculate the density of marine mammals in the U.S. Atlantic and Gulf of Mexico based on decades of data. The authors were able to estimate the monthly density of species that exhibit seasonal trends over the course of a year, including a NARW specific model (Roberts et al. 2022). It is likely that this and similar models could be readily adapted to predict the density and distribution of NARWs into the future. This would likely require updated environmental data and the incorporation of additional covariates, such as prey. Density models are often incorporated into other models (e.g., forecasting models; Stepanuk et al. 2023), and an updated NARW density model that incorporates more recent environmental data would be beneficial.

2.2 Prey prediction

The availability of prey (primarily *Calanus* spp.) has been shown to affect the distribution of NARWs (Pendleton et al. 2009; Pershing et al. 2009; Patrician and Kenney 2010; Davies et al. 2015; [DFO] Fisheries and Oceans Canada 2021; Meyer-Gutbrod et al. 2023). In fact, the distributional shift of NARWs from their historic (and protected) feeding grounds is thought to be linked to a change in prey distribution, possibly due to climate change (Meyer-Gutbrod et al. 2015; Meyer-Gutbrod and Greene 2018; Record et al. 2019). Analyses and models that can predict the distribution and abundance of *Calanus* potentially can be used to predict suitable NARW foraging areas and aid in conservation efforts (Sorochan et al. 2019; [DFO] Fisheries and Oceans Canada 2021; Gavrilchuk et al. 2021).

Some prey models focus on the behavior and/or environmental covariates associated with the presence of *Calanus* and associate their findings with NARW sightings data. For example, Pershing et al. (2009) incorporated a model of *C. finmarchicus* densities with satellite observations to infer NARW distribution and found strong spatial and temporal correlations between the presence of NARWs and their prey. Brennan et al. (2021) examined the link between variation in environmental conditions and the abundance of *Calanus*, overlaying data on NARW observations to assess foraging habitat suitability. The authors demonstrated that *Calanus* abundance patterns have contrasting drivers that depend on habitat and noted the need for further research that can account for the interactions between *Calanus* populations and environmental forcing (Brennan et al. 2021).

Other prey models incorporate the bioenergetic needs of NARWs. Bioenergetics models have been used to assess the prey requirements for successful population growth (Hansen et al. 1993), a technique that could help determine suitable foraging areas for right whales. For example, Plourde et al. (2019) validated an approach that used 3D preyscapes (i.e., the latitudinal, longitudinal, and vertical distribution of *Calanus* spp.) in combination with NARW bioenergetic data to determine new suitable foraging areas. Ross et al. (Ross et al. 2023) used machine learning RF algorithms to determine the density threshold of *C. finmarchicus* needed to attract feeding right whales (i.e., the density is energetically advantageous). Similarly, Gavrilchuk et al. (2021) coupled a NARW foraging bioenergetics model with *Calanus* abundance and distributional data on a feeding ground. Using a 12-year dataset, they were able to determine that the availability of suitable foraging habitat varied between years and may be insufficient to support population growth. Similarly, Fortune et al. (2013) considered the energetic requirements of different age and sex classes of NARWs based on prey sampling. They determined that some demographics are not currently consuming enough prey to meet their energetic needs. These results may be useful in estimating the suitability of habitats based on the density of *Calanus* in other areas.

2.3 Ensemble models

There are a variety of statistical methods available to determine species distribution. However, the results of SDMs can be highly variable depending on the method used (Grenouillet et al. 2011). Combining multiple modeling approaches (ensemble modeling) has been suggested as an appropriate method to reduce uncertainty in the results (Araújo and New 2007). For NARWs in the Gulf of Maine, an ensemble species distribution model was created which integrated GAMs, boosted regression trees (BRTs), and artificial neural networks (ANNs) and projected onto the year 2050 under a range of climate scenarios (Ross et al. 2021). The results of the projections indicated decreased habitat suitability in 2050 between July and October, with some exceptions. Model performance decreased at other times of the year, indicating the model did not adequately capture all of the important predictors, and more work is needed to accurately predict NARW distribution in the future (Ross et al. 2021).

3 Emerging Prediction Methods (< Two Years)

The aim of this section is to determine what predictive techniques have been used in other species or systems that have not yet been applied to NARWs and have the potential to be implemented immediately or with moderate refinement (less than 2 years).

3.1 Distribution models

3.1.1 Ecological niche models

Ecological niche models are a type of predictive model that attempt to identify the environmental conditions that best predict the geographical distribution of a species (Rocchini et al. 2015). Although both SDMs and ENMs rely on ecological niche theory, ENMs use a correlative approach to define the relationship between environmental variability and occurrence using multiple algorithms (Rocchini et al. 2015), whereas SDMs model the geographical space (Melo-Merino et al. 2020). ENMs are useful when the goal is to predict potential distribution (Melo-Merino et al. 2020). They require an explicit estimation of a species' fundamental niche, thus modeling the processes that shape their distribution (Melo-Merino et al. 2020). Once established, it can be possible to project the correlations in time and space (Peterson and Soberón 2012). Note that in the literature, the terms ENMs and SDMs are often used interchangeably, which is theoretically incorrect (Peterson and Soberón 2012).

One of the main benefits of ENMs is the ability to predict occurrences for locations with little or no survey data (Franklin 2010). For example, some models only require presence data rather than data on both presence and absence (Elith et al. 2006; Rocchini et al. 2015). Using the Genetic Algorithm for Ruleset Prediction (GARP), a relatively common approach to ENM, Siqueira and Peterson (2003) used presence-only data on 966 species of trees to predict current and future distribution in the context of climate change. Similarly, Hirzel et al. (Hirzel et al. 2002) used an ecological-niche factor analysis (ENFA) to compute habitat suitability functions for Alpine ibex (*Capra ibex*) with presence-only data.

(Friedlaender et al. 2011) developed ENMs using a Maxent approach, combining presence-only data from multiple Antarctic predators with environmental factors that predict suitability. Campos et al. (2023) also created ENMs using MaxEnt (specific maximum entropy software) but integrated their model into the Google Earth Engine (GEE). A benefit of this approach is the wide array of remotely sensed variables available in GEE (e.g., Visible Infrared Imaging Radiometer Suite Surface Reflectance and Landsat Net Primary Production CONUS), as well as climate and topographic data. However, the model was limited in some analyses and outputs (e.g., automatic selection of background data). In addition, the authors note that they were unable to use this method with marine species because of the paucity of data surrounding future environmental predictors.

3.1.2 Species distribution models

Typical SDMs, such as those used to predict the distribution of NARWs, have also successfully been applied to closely related species. Torres et al. (2013) used BRTs, a type of ML algorithm applied to SDM frameworks, to predict the distribution patterns of southern right whales (*Eubalaena australis*) in the year 2100.

3.1.3 Habitat suitability models

HSMs frequently have been applied to other species, including those with life history characteristics similar to NARWs. For example, Finucci et al. (2021) used ensembled HSMs to determine the driving factors in basking shark (*Cetorhinus maximus*) distribution and predict habitat suitability. Hazen et al. (2017) developed a tool called WhaleWatch that combined telemetry data from satellite-tagged blue whales with environmental data and telemetry-based habitat models. They were able to predict blue whale habitat in near-real time (days to months) as well as whale density. Hazen et al. (2018) created daily predictions of habitat suitability for marine species using a predictive modeling framework combined with remotely sensed environmental data and satellite-linked tracking data.

A relative environmental suitability (RES) model was developed to predict the distributions of 115 cetacean species, including NARWs (Kaschner et al. 2006). The RES model differed from typical HSMs in that the model output more closely corresponded to the niche of a species rather than the probability of occurrence (Hirzel et al. 2002; Kaschner et al. 2006). However, this model was not dedicated to NARWs. In addition, it only included predictor variables that were available for all or most species (bathymetry, SST, and distance to ice edge), and thus only broadly applicable to the distribution of NARWs as indicated from other HSM and SDMs. Further, all data sources were from studies before 2003, and the results are likely not applicable to current or future distributions, particularly considering the distribution shift in 2010. A RES model could prove to be a useful predictive tool with the inclusion of more species-specific predictor variables and data collected after the 2010 shift in NARW distribution.

Entropy models have also been applied to determine habitat suitability. There are several drawbacks of Maxent models however, including the inability to account for sampling bias and the need for a large number of environmental covariates (Phillips et al. 2006). As such, the habitat prediction can only be described as relative occurrence rather than true probability. One alternative is the use of minimum cross entropy (Minxent) models, which are a generalized type of Maxent model that include data on sampling rate (Merow et al. 2016). De Rock et al. (2019) used a Minxent model to determine habitat suitability for nine cetacean species in Namibia. When compared to a Maxent approach on the same data, the Minxent model was able to more closely match the observed distribution of the species in Namibian waters (De Rock et al. 2019). Minxent models may represent a valuable method of predicting distribution for challenging species, such as NARWs, where data is often presence-only and there are known sampling biases (Merow et al. 2016).

3.2 Deep learning

More complex models exist that are able to use hierarchical layers of latent variables to make predictions (Polson and Sokolov 2017). Examples include recurrent neural networks (RNNs) and long short-term memory (LSTM). RNNs model sequential information (time series data) and can include information on previous states when computing subsequent states. LSTM, a variant of RNNs, can additionally retain information for longer time intervals (minutes compared to seconds), which improves the power of the model to learn and predict (Schmidhuber 2015; Wijeyakulasuriya et al. 2020).

For long-range simulations of animal movement, Wijeyakulasuriya et al. (2020) showed that LSTM models performed the best out of the ML and deep learning (DL) techniques they tested. Rew et al. (2019) used kernel density estimation (KDE) to construct an image sequence based on the movements of GPS-tracked long-billed curlews (*Numenius americanus*). They then used LSTM to predict their movement. They were also able to compensate for gaps in spatio-temporal data, a common problem in marine animal research, by interpolating data points with RFs.

3.3 Environmental forecasting

Weather forecasting (WF) incorporates a multitude of factors to predict atmospheric conditions (Jaseena and Kovoor 2022). Methods for WF include statistical models (Stepanuk et al. 2023), ML techniques (Grover et al. 2015; Lim and Zohren 2021), and ensemble models (Gneiting and Raftery 2005; Araújo and New 2007). Model frameworks using near real-time data (i.e., recent satellite-derived measurements) to predict distribution may be useful over relatively short time scales (weeks to months) (Stepanuk et al. 2023).

Some forecasting technology has recently been applied to marine mammals. Stepanuk et al. (2023) created a humpback whale (*Megaptera novaeangliae*) density model and integrated it into the Subseasonal Experiment (SubX), a NOAA project that provides subseasonal global forecasts at weekly to monthly timescales. They used GAMs to predict the arrival of migrating humpback whales to the northeast United States. Their model was successful in capturing the spatial and temporal variability in the whales' distribution and predicting the arrival of the animals; however, predictions were limited to one to two weeks in advance.

Longer-term "ecological forecasting" involves incorporating SDMs into environmental forecasts that can predict future environmental conditions (Stepanuk et al. 2023). For example, Hazen et al. (2012) incorporated climate change projections with animal distribution data into habitat models to predict rates and patterns of habitat shifts in Pacific top predators. They modeled changes in distribution for 15 species from 2001 to 2100, as evidenced by changes in species richness indices. Hazen et al. (2017) developed a tool called "WhaleWatch" that used state-space models applied to blue whale (*Balaenoptera musculus*) tracks to predict weekly, monthly, and yearly density estimates. This tool is also useful for examining seasonal and interannual changes in habitat use.

Similar to the challenges facing researchers that model the distribution of marine animals, weather and climate forecasting can be uncertain due to incomplete spatial data (Alley et al., 2019). Weather and climate forecasting are limited by the models' sensitivity to the initial parameterized conditions (Alley et al., 2019), and rely on substantial amounts of data (i.e., "big data") (Dewitte et al. 2021). However, there is a massive investment to improve WF, which could be advantageous to advancing predictive modeling based on this technology (Alley et al. 2019). This includes the incorporation of DL, which uses a pure data-driven AI model that requires no a priori physical knowledge (Dewitte et al. 2021).

3.4 Prey prediction: dimethyl sulfide

Dimethyl sulfide (DMS) is a volatile compound found in the ocean, primarily resulting from the breakdown of phytoplankton (Hulswar et al. 2022). Because a small amount of DMS is released into the atmosphere, increased concentrations of DMS in the ocean result in enriched atmospheric concentrations (Lana et al. 2011). DMS is a scented compound that acts as a biogenic cue and adds to the olfactory landscape of the ocean (Nevitt et al. 1995). DMS has been associated with the presence and foraging of animals that predate on plankton. Therefore, it is hypothesized that increased DMS concentrations may provide a way for species that rely on chemosensory methods for prey detection to locate dense patches of prey (Procter et al. 2019). This includes copepods, the primary prey of NARWs, which perceive phytoplankton using chemosensory cues (Poulet and Marsot 1978).

It is unknown how NARWs locate prey (Kenney et al. 2001). It has been proposed that some mechanisms may include chemical cues originating from copepods, detected via gustatory or olfactory senses. However, there is no empirical evidence to support this at present. Additionally, there is currently no established scientific method for detecting copepods directly. However, seawater concentrations of DMS can be measured (e.g., Bates et al. 1994; Owen et al. 2021) and predicted from climatology models (e.g., Owen et al. 2021; Hulswar et al. 2022). Additionally, recent research has indicated that there is a correlation between zooplankton biomass and DMS concentrations in both air and seawater (Owen et al. 2021). The authors conclude that DMS concentrations could act as a foraging cue that attracts zooplankton predators, such as copepods. Because NARWs prey on copepods, it may be possible to predict where NARWs will occur based on the presence of high DMS concentrations.

3.5 Agent-based models

Agent-based models (ABMs), also known as individual-based models (IBMs), are simulation models that can be used to describe how autonomous individuals ("agents") interact with each other and respond to their environment (Grimm et al. 2005; Grimm and Railsback 2005). These models take a "bottom-up" approach, considering the behavior and interactions of the smaller components of a system (i.e., individuals or agents) to describe the higher level ("top") system properties (Grimm et al. 2005). The agents can be programmed to high levels of detail, with the ability to incorporate internal state (e.g., behavioral and motivational) as well as external state (e.g., environmental) variables (DeAngelis and Diaz 2019). Models can then be designed to simulate the consequences of individual decisions on a population or community (DeAngelis and Diaz 2019). The models provide forecasts of behavior but also can provide predictions of behavior under certain conditions (Houser 2006). This is particularly valuable for conservation and management decisions, as ABMs generate more realistic forecasts and predictions than traditional statistical models (Grimm et al. 2006).

There are many ecological applications of ABMs, including drivers of migration and habitat selection. For example, Duriez et al. (2009) studied the decision-rules of pink-footed geese (*Anser brachyrhynchus*) for migratory departure. By incorporating real-world observations on the departure dates of geese, the authors were able to determine that decision-rules relating to plant phenology best explained their departure timing. In a similar way, ABMs that incorporate habitat selection can use decision-rules based on habitat suitability. Kramer-Schadt et al. (Kramer-Schadt et al. 2004) used movement rules that based the dispersal direction of Eurasian lynx (*Lynx lynx*) on habitat quality, as evidenced by real-world lynx behavior data. The model was particularly useful because of the paucity of data on this species. ABMs are also flexible, and realistic ABMs can be built from relatively small amounts of data (Pirotta et al. 2018), a problem often encountered with wild, free-roaming animals.

An emerging use of ABMs is the study of potential impacts of anthropogenic disturbance and environmental changes at the individual and population level (Pirotta et al. 2018). An ABM simulating the movement of orangutans (*Pongo pygmaeus*) incorporated field observations on habitat preference and locomotory behavior (Widyastuti et al. 2022). The results of this study demonstrated a change in the movement behavior of the simulated animals with changes in habitat (forest structure). ABMs also have the potential to be used within other frameworks to further explore the effects of disturbance (e.g., the population consequences of acoustic disturbance (PCAD) framework, [NRC] National Research Council (US) (2005)). Population-level frameworks often lack an explicit spatial component, which limits their use in linking changes in the behavior of individuals with population-level effects (Mortensen et al. 2021). By including ABMs, several studies have expanded these disturbance models to predict impacts on individual and population distribution and displacement (see review by Mortensen et al. (2021)).

4 Future Prediction Methods (< Five Years)

4.1 AI, ML, DL from other disciplines

AI, ML, and DL techniques are useful for analyzing large datasets of both unstructured and heterogenous data (Dewitte et al. 2021). They are particularly relevant for WF, climate monitoring (CM), and decadal prediction (DP). The earth sciences field has benefited from DL techniques specifically due to the large amounts of data that can be collected from remotely sensed platforms (Dewitte et al. 2021). It is even possible to move to a pure data-driven AI-based forecasting model that includes no prior physical knowledge (Dueben and Bauer 2018). Aside from WF, AI has also been used to predict the energy use of buildings using both single and ensemble models (Wang and Srinivasan 2017).

4.1.1 Trajectory models with reinforcement learning

Reinforcement learning (RL) and inverse reinforcement learning (IRL) are ML techniques that can be used to predict the trajectories of animals based on their tracks obtained using GPS positions (Hirakawa et al. 2018). The aim of RL is to generate an action sequence for an agent that will maximize the reward (Hirakawa et al. 2018). Similar to ABM, the action of the next step relies on the current time step. The IRL algorithm builds on RL by using a reward system that is “learned” based on movement trajectories and the agent's environment (Hirakawa et al. 2018). The main drawback to RL and IRL is that they rely on both a start and end position at the very least. For example, RL has been applied to the field of robotics, where robots were able to navigate a maze given an endpoint.

5 Data Gaps

Currently, there are a limited number of methods to predict the future distribution of NARWs. Although many of the above models provide an indication of habitat suitability and the possible presence of species in a specific area, there is often little information on the likelihood of their occurrence. In other words, a habitat may be deemed suitable for right whale foraging based on model predictors, but it may not be used by the animals. Developing some measure of model confidence could help resolve this issue (Pendleton 2010). This could be in the form of confidence intervals or predicted probabilities (as in Moses and Finn (1997).

As mentioned above, the accuracy of distribution models relies on selecting appropriate predictor variables. Currently, remote sensing technology is mostly used to provide data on environmental variables for use in HSMs and SDMs. The recent use of high-resolution satellites to detect NARWs can also provide data for predictive models, particularly if they provide both presence and absence data (He et al. 2015). These data can potentially provide more predictive power if combined with other emerging or existing technologies. Additional predictors for current NARW distribution are needed to potentially improve the performance of distribution models, as well as more interdisciplinary approaches. In addition, more advanced knowledge of sub-annual ecosystem and oceanographic dynamics is needed, as well as how these systems respond to rapid change (Record et al. 2019). Aside from determining the important predictor variables for model inputs, it is also essential to establish the spatial and temporal scales at which they are relevant (Kenney et al. 2001).

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