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Research article

Assessing the cumulative exposure of wildlife to offshore wind energy development

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ABSTRACT

Governments and developers are pursuing offshore wind energy to address climate change, but multiple wind farms may cumulatively affect wildlife populations. Assessments of cumulative effects must first calculate the cumulative exposure of a wildlife population to a hazard and then estimate how the exposure will affect the population. Our research responds to the first need by developing a model designed to assess how different wind farm siting scenarios cumulatively expose wildlife. The model assesses cumulative exposure by identifying all locations where development could occur, placing wind farms within this suitability layer, and then overlaying wind engineering and biological data sets. The first model output is a graphical representation of how offshore wind farm siting decisions affect wildlife cumulative exposure. The second output is an index that ranks which offshore wind farm siting decisions will have the greatest influence on wildlife cumulative exposure. Together these outputs provide stakeholders with valuable information that could be used to guide siting and management decisions.

1. Introduction

Globally, offshore wind energy development (OWED) is increasing in response to climate change and coastal energy needs. In Europe, total installed capacity is 15.78 gigawatts (GW) and projected to increase to 25 GW by 2020 (Pineda, 2018). In the U.S., the potential capacity of offshore wind energy is estimated to be 4200 GW (Lopez et al., 2012). The U.S. Department of Energy (DOE) has set a goal of 54 GW installed by 2030 (DOE, 2011), and DOE is planning for 86 GW to be installed by 2050 (DOE, 2016). Although offshore wind is considered to have fewer environmental impacts than fossil fuels (Ram, 2011), there are concerns that deployment of thousands of turbines offshore may adversely affect wildlife (Goodale and Milman, 2016).

While a single offshore wind farm can adversely affect individual wildlife (Goodale and Milman, 2016), of greater concern is how multiple offshore wind farms will impact wildlife populations. These cumulative adverse effects (CAE) are considered an important ecological issue (Boehlert and Gill, 2010; Dolman and Simmonds, 2010; Drewitt and Langston, 2006; Fox et al., 2006; Gill et al., 2012; Langston, 2013; Larsen and Guillemette, 2007; Masden et al., 2010). However, there continues to be a lack of understanding of the CAE of offshore wind farms on wildlife, and managing cumulative effects is an ongoing challenge for regulators and ecologists.

Assessment of CAE is difficult because the adverse effects of an individual wind farm need to be combined with past, present, and future stressors to determine population level impacts (Goodale, 2018). Most existing assessments focus solely on individual adverse effects, and analyze vulnerability (Wade et al., 2016) and exposure (Cranmer et al., 2017; Spiegel et al., 2017), without attempting to relate those individual effects to CAE. Existing research on CAE is limited to conceptual models (Goodale and Milman, 2016; Masden et al., 2010; Willsteed et al., 2017) that frame assessments but lack applied methods, or assessments with a limited scope. To date, in Europe, researchers have conducted assessments that examine CAE at the level of an individual country (Poot et al., 2011) and a single species (Topping and Petersen, 2011). Assessments of multiple species and countries have been limited to ongoing and planned development scenarios (Busch et al., 2013). In the U.S., researchers have examined the vulnerability of West Coast birds to wind farm development, yet have not directly tied that vulnerability to offshore wind siting decisions (Kelsey et al., 2018). Uncertainty about how to conduct assessments and how to evaluate CAE is a cause for delays in OWED permitting (Masden et al., 2015; Willsteed et al., 2017). Therefore, there is a need to develop new processes for assessing CAE.

This research addresses this need by developing a method and a computer model that can be used in analyzing the cumulative effects of

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wind farm development on wildlife. We use cumulative exposure as a proxy for CAE due to the high degree of uncertainty associated with relating impacts from individual wind farms to populations. This uncertainty arises from limitations in detecting wildlife mortality at wind farms; a lack of data on wildlife vital rates; and a lack of knowledge on total population numbers. The customizable model ("CE model") analyzes the relationships between potential OWED siting scenarios and cumulative wildlife exposure. For each potential siting scenario, the CE model estimates the cumulative exposure of wildlife to OWED by identifying all locations where OWED could occur, placing wind farms within this suitability layer, and then overlaying wind engineering and biological data sets to develop two outputs. The first model output, the cumulative exposure (CE) curve, is a graphical representation of how OWED siting decisions affect wildlife cumulative exposure. The second model output, the CE index, identifies the OWED siting decisions that will cause highest initial rates of cumulative exposure. These outputs are able to answer the question, for multiple species simultaneously: Can siting reduce cumulative exposure, and thus potentially CAE?

The aim of this paper is to provide an overview of the CE model, describe data inputs and the model analysis process, explain model outputs, and discuss how the model can be used to support offshore wind farm management decisions. To illustrate the use of the model, we also present and interpret hypothetical model results. We conclude with a discussion on further model development. The paper demonstrates the utility of the CE model, a novel method that has significant value in informing regional and project-specific planning.

2. Methods

2.1. Overview of the model

The CE model undertakes a series of sequential calculations to assess the cumulative exposure of wildlife to different OWED siting scenarios (Fig. 1). The model follows a five step approach: Step 1 establishes the spatial scope of analysis by developing an "OWED building suitability layer," which is a GIS map indicating where wind farm development is feasible based on an analysis of jurisdictional boundaries, wind engineering constraints, and exclusion areas. Step 2 fits a "wind farm grid" within the suitability layer. Step 3 spatially joins to the wind farm grid a) layers representing the elements stakeholders consider when siting OWED (hereafter "siting factors"), and b) wildlife relative abundance data. Step 4 develops OWED siting scenarios by ordering siting factors by favorability. Step 5 calculates the cumulative exposure of wildlife for each scenario, which is used to develop the CE curve and index outputs. The model is scripted in the R programming environment (R Core Team, 2015), an open source programming language, and can thus be used by anyone interested in running the model. Below we provide detailed methods for each step and example inputs.

2.2. Model steps

2.2.1. Create OWED building suitability layer (Step 1)

The OWED building suitability layer (i.e., where wind farm development is feasible) is created by combining siting factors using Boolean maplayering (Fig. 2) (O'Sullivan and Unwin, 2014) to determine the overall area where wildlife may be exposed to offshore wind farms. Three categories of siting factors are considered: exclusions, constraints, and decision factors. "Exclusions" are specific areas of the ocean that have physical hazards (e.g., unexploded ordinance), have specific regulatory exclusions (e.g., shipping lanes), or have been identified as having conflict with military activities. "Constraints" are OWED siting considerations that have thresholds beyond which OWED is no longer viable either technologically or economically (e.g., wind speed less than 7 m/s). "Decision factors" are factors that will influence,

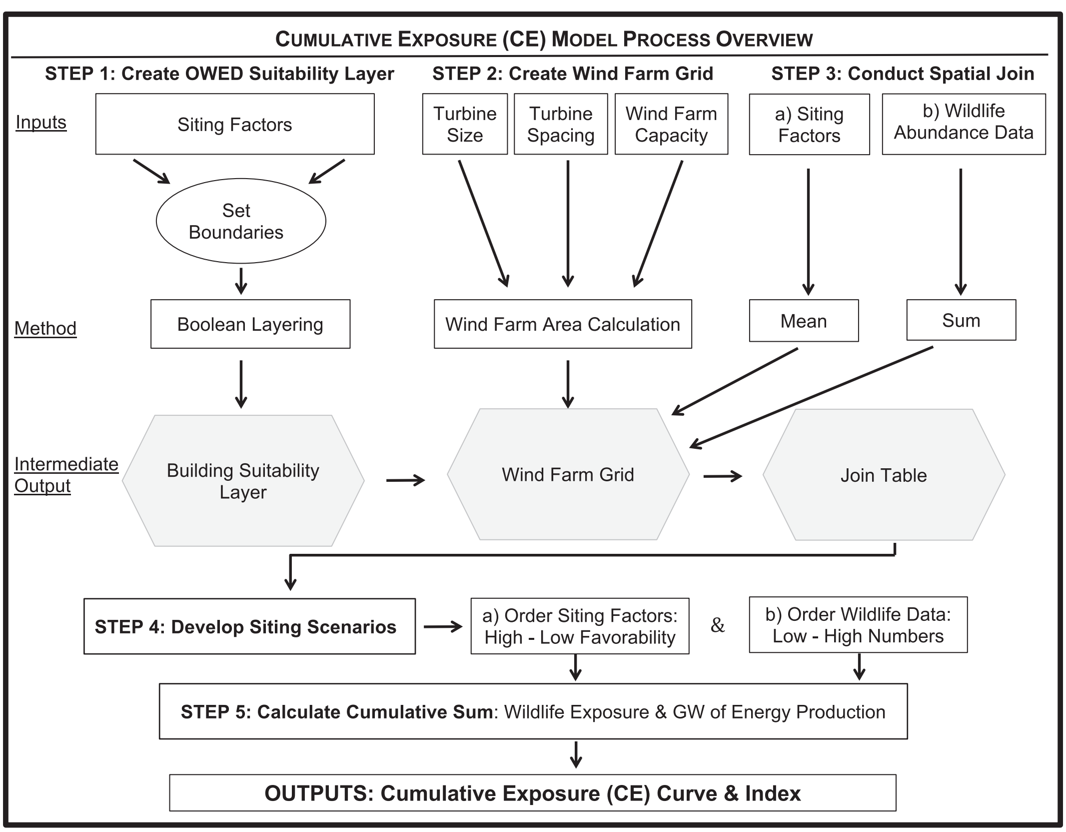


Fig. 1. The CE model creates an OWED building suitability layer (i.e., where development is possible); fits a wind farm grid within the suitability layer; spatially joins wildlife layers and siting factors to the wind farm grid; orders siting factors by favorability; and creates two outputs: cumulative exposure curve and cumulative exposure index.

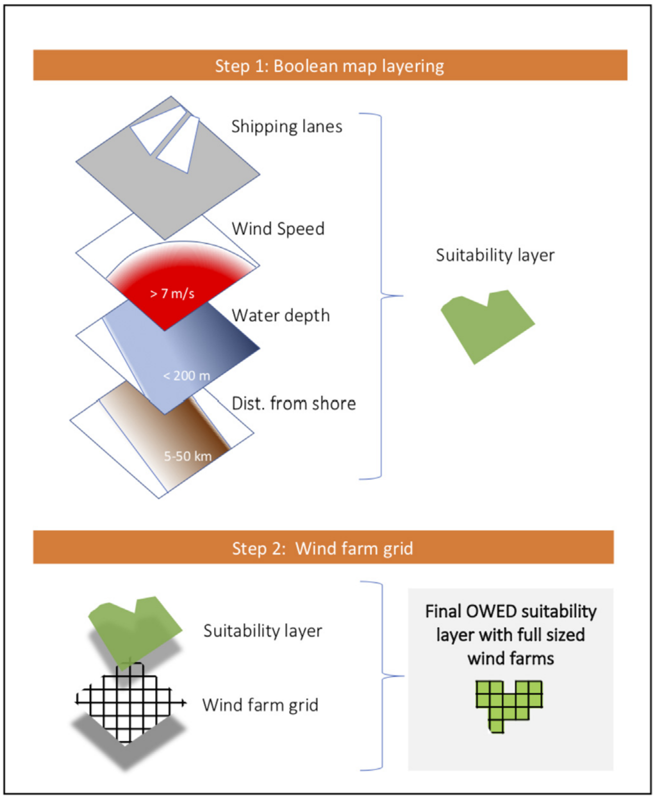
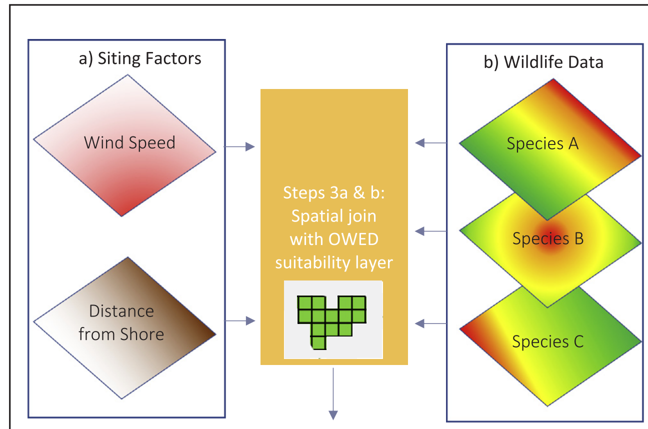


Fig. 2. Development of the OWED suitability layer and wind farm grid (Steps 1 and 2). As an example, shipping lanes are excluded from development, while areas with > 7 m/s wind speed, < 200 m water depth, and within 5–50 km of the coast are included. The wind farm grid is then fit within the suitability layer. The grid, for example, could be based upon 10 MW turbines that are spaced 8 rotor diameters apart, with an overall wind farm capacity of 500 MW.



Join Table

WF ID	Species A	Species B	Species C	Wind Speed	Distance from Shore
1	8	108	56	8.2	5.8
2	6	129	78	8.1	6.9
3	1	90	34	7.8	10.3
4	5	76	89	8.1	5.6
5	2	156	23	7.5	7.8
6	9	168	32	7.4	9.6
7	3	143	16	9.1	11.7

Fig. 3. Spatial join (Steps 3a & b). As an example, layers for two siting factors and three species are spatially joined to the OWED suitability layer, resulting in an average siting factor value and a total number of individual animals for each wind farm. Species A is a coastal species with a northerly bias distribution (e.g., seaduck), Species B is a common, broadly distributed species (e.g., gull), and Species C is a pelagic species (e.g., shearwater).

but not dictate, where developers consider siting OWED projects (i.e., hurricane risk and proximity to high energy use areas).

Boolean logic assigns true (1) and false (0) values to each cell for each siting factor layer included in the analysis. The siting factors are then multiplied together using raster math, and all areas coded to false are excluded from development. Given the uncertainty about which siting factors will be most important for OWED siting (Musial and Ram, 2010; Schwartz et al., 2010), Boolean logic provides simplicity and transparency and reduces the number of input assumptions. The assumptions in Boolean layering are that relationships between layers are Boolean, that inputs do not have measurement error, that categorical attributes are exactly known, and that boundaries within an input layer are certain (O'Sullivan and Unwin, 2014). Since Boolean layering requires establishing an absolute suitable/unsuitable boundary (values of 1 and 0 respectively; e.g., development cannot occur in water depths greater than 200 m), error in the values of input layers can lead to the erroneous inclusion or exclusion of development areas. An overly constrained OWED suitability layer would exclude areas from development that could potentially be developed, and thus exclude areas where wildlife may actually be exposed to development, leading to an underestimate of the exposure. Therefore, for each siting factor constraint, Boolean values are selected that allow for the inclusion of a greater area for OWED development to ensure that all possible locations of development are included in the assessment.

2.2.2. Create wind farm grid (Step 2)

The second model step predicts the number of wind farms that would fit within the suitability layer. Within the building suitability layer, the model creates a square-shaped wind farm grid using three input parameters: wind turbine size, wind turbine spacing, and overall wind farm capacity (Fig. 2). The input parameters are selected by the user to reflect the current wind turbine technology and most common wind farm size. The model only accepts full-sized wind farms, and any non-square wind farms are excluded from the final OWED suitability layer.

2.2.3. Conduct spatial overlay (Steps 3a & 3b)

Next, the model summarizes the siting factor and wildlife data for each wind farm in the grid through two sub-steps. First, Step 3a merges the siting factors data with the wind farm grid, using a spatial join function, to calculate the average siting factor value (e.g., 7.8 m/s wind speed or 24 m water depth) for each wind farm (Fig. 3). The resulting table is used to develop siting scenarios in Step 4 that order development from high to low favorability for each siting factor. Second, Step 3b merges the wildlife data (multiple species concurrently) with the wind farm grid, also using a spatial join function, to calculate the total number of animals (e.g., 132 gannets) for each wind farm (Fig. 3). The resulting table is used to develop siting scenarios in Step 4 that order development from low to high numbers animals for each species included in the assessment.

The wildlife data inputs can be modeled from satellite tracking, survey data, or other measures of wildlife abundance. The abundance data must have full coverage of the area being considered for development. If the data does not include the entire study area, then the CE model would consider areas with no data to have no wildlife. The abundance data is then used to calculate the proportion of a wildlife population that is expected to use each wind farm area over a year.. The user defines the population level that is relevant to the analysis, which can be limited to only the animals exposed to the suitability layer or expanded to regional or global populations. Thus, the measure of cumulative exposure is relative to the boundaries of analysis.

2.2.4. Develop siting scenarios (Step 4)

To assess how wildlife will be cumulatively exposed to different development scenarios, the model develops each siting scenario for

Scenario 1, Wind Speed: Order development from high to low wind speed

	Step 4					Step 5	
WF ID	Species A	Species B	Species C	Wind Speed	Distance from Shore	Species A cumulative exposure	GW of cumulative energy production
7	3	143	16	9.1	11.7	3	0.5
1	8	108	56	8.2	5.8	11	1.0
4	5	76	89	8.1	5.6	16	1.5
2	6	129	78	8.1	6.9	22	2.0
3	1	90	34	7.8	10.3	23	2.5
5	2	156	23	7.5	7.8	25	3.0
6	9	168	32	7.4	9.6	34	3.5

Scenario 2, Distance from Shore: Order development from close to far from shore

WF ID	Species A	Species B	Species C	Wind Speed	Distance from Shore	Species A cumulative exposure	GW of cumulative energy production
4	5	76	89	8.1	5.6	5	0.5
1	8	108	56	8.2	5.8	13	1.0
2	6	129	78	8.1	6.9	19	1.5
5	2	156	23	7.5	7.8	21	2.0
6	9	168	32	7.4	9.6	30	2.5
3	1	90	34	7.8	10.3	31	3.0
7	3	143	16	9.1	11.7	34	3.5

Scenario 3, Species A: Order development from low to high number of animals

WF ID	Species A	Species B	Species C	Wind Speed	Distance from Shore	Species A cumulative exposure	GW of cumulative energy production
3	1	90	34	7.8	10.3	1	0.5
5	2	156	23	7.5	7.8	3	1.0
7	3	143	16	9.1	11.7	6	1.5
4	5	76	89	8.1	5.6	11	2.0
2	6	129	78	8.1	6.9	17	2.5
1	8	108	56	8.2	5.8	25	3.0
6	9	168	32	7.4	9.6	34	3.5

Fig. 4. Scenario development (Step 4) and cumulative sum calculation (Step 5). Step 4 develops scenarios by ordering development for each siting factor and species. In this example, Scenario 1 orders the wind farm grid from high to low wind speed and calculates the cumulative sum of Species A exposure and GW of energy production; Scenario 2 orders development from close to far from shore; and Scenario 3 orders development from low to high numbers of Species A. The process is repeated for all siting factors and species included in the analysis.

wind farm development and then in Step 5 calculates the number of animals exposed under each scenario (Fig. 4). One siting scenario is created for each siting factor, reflecting the order in which wind farms would be developed if siting were to occur in the order of least to highest levelized cost of electricity (LCOE) for that factor (e.g., build in the windiest places first, or shallow places first). That order is determined using the siting factor values calculated in Step 3a. The final siting scenario reflects the development pathway that would result in the least exposure of animals to wind farm development. This scenario orders the wind farm grid from low to high number of animals based on the values calculated in Step 3b.

2.2.5. Calculatie cumulative exposure (Step 5)

Finally, to calculate exposure of wildlife as development occurs, for each scenario the model follows the order of development identified in Step 4 and sums, one wind farm at a time, the number of wildlife exposed (values identified in Step 3b).

2.3. Model outputs

The first model output is a cumulative exposure (CE) curve for each siting factor/species combination, including avoiding wildlife exposure (Fig. 5). The output displays the relationship between wildlife cumulative exposure (y-axis) and GW of OWED production (x-axis) from zero OWED to full build-out of the OWED suitability layer. The GW of OWED

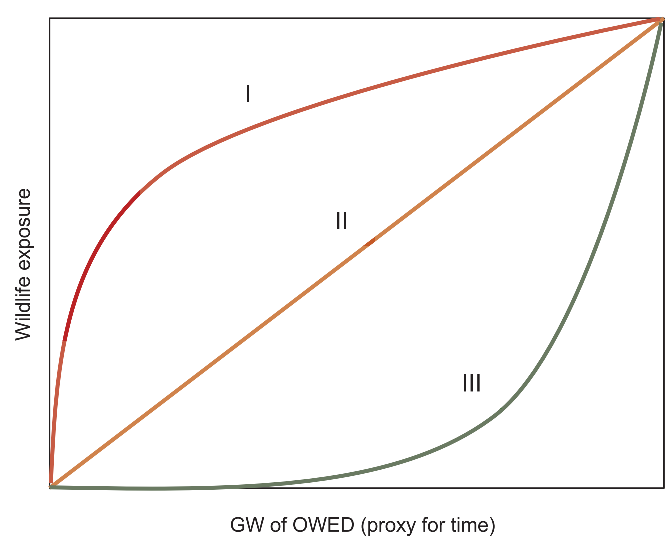


Fig. 5. Conceptual representation of cumulative exposure: A Type I curve is high initial exposure rate, a Type II is a constant exposure rate, and a Type III is a low initial exposure rate. The Y-axis will be the number of individuals, or proportion of a population, cumulatively exposed.

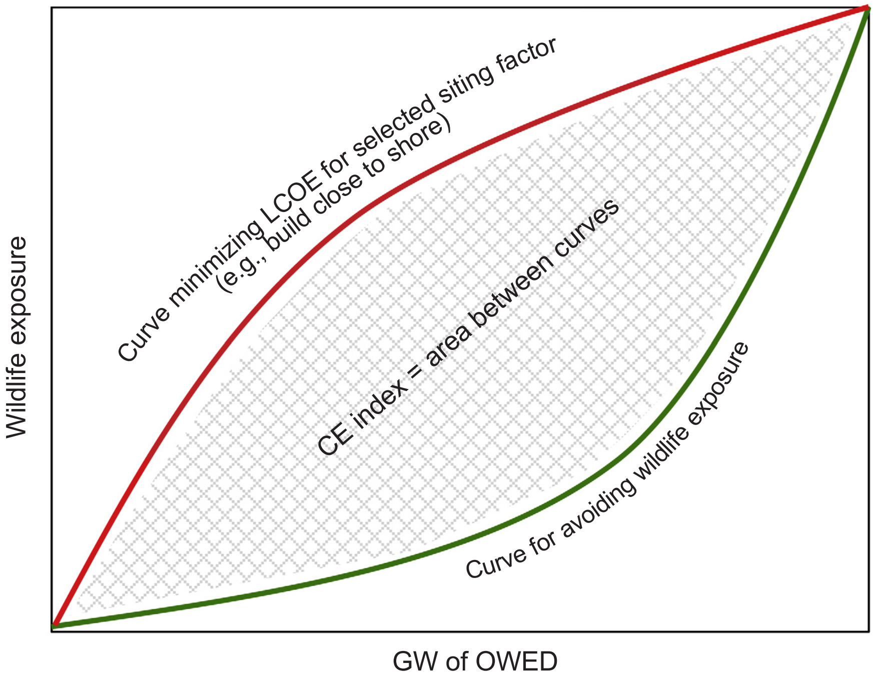


Fig. 6. The CE index is the area (grey hatched area) between a curve for a particular development decision (red line; e.g., building in shallow areas) and the curve for siting OWED in areas with the least wildlife abundance (green line). The index indicates the percentage an OWED siting decision diverges from avoiding exposing wildlife.

development (x-axis, Fig. 5) is a proxy for time; thus, the curve represents a rate that wildlife will be cumulatively exposed based upon how OWEDs are sited. The y-axis can represent the number of individual animals or the percentage of a species' population exposed to development. The closer the curve is to the x-axis, the lower the initial rate of exposure (i.e., Type III); the closer the curve is to the y-axis, the higher the initial rate of exposure (i.e., Type I). Example CE curves are presented in the Results section.

The second model output is the CE index that identifies the siting decisions that will cumulatively expose wildlife at a higher rate. An index value for each species/siting factor combination is developed by subtracting the area below the siting factor curve from the area below the wildlife avoidance curve (Fig. 6). Dividing the area calculation by the total area of the plot normalizes the area to a metric between 0 and 1. The closer the value is to 1, the higher the initial rate of cumulative exposure. Example CE index outputs are presented in the Results section.

3. Results

To illustrate model outputs and how they can be interpreted, below we display the results from an example analysis (Fig. 7). In this example, full development of the OWED suitability layer results in 10% of the population of Species A, 20% of the population of Species B, and 5% of the population of Species C being exposed to wind farm development. The CE curves for Species A indicate that it will be cumulatively exposed at a higher initial rate when OWED is sited close to shore and at a slightly lower rate when projects are built in high wind areas; however, neither OWED siting scenario effectively avoids exposing Species A. The CE index value indicates that building close to shore is the siting scenario that will lead to the highest exposure of Species A. The CE curves for Species B indicate that its rate of cumulative exposure is only marginally less if building close to shore relative is prioritized over building to maximize wind speed. The difference between these scenarios is small due to the fact that Species B is broadly distributed throughout the OWED suitability layer. The CE curves for Species C indicate that it will be cumulatively exposed at a higher rate when development occurs based on wind speed and at a lower rate when development occurs based on distance to shore.

The hypothetical results demonstrate how the CE model outputs can identify the species most at risk of CAE. First, the model outputs show the species that will have the highest potential exposure to development regardless of siting decision. In the example, Species B has the most exposure, Species C the least. Second, for each species, the outputs indicate which wind farm siting decisions will lead to higher (or lower) exposure rates. Third, when cumulative exposure is combined with prior knowledge of species' behavioral and population vulnerability to OWED (Desholm, 2009; Furness et al., 2013; Garthe and Huppop, 2004; Goodale and Stenhouse, 2016), the individual species, or groups, most at risk can be identified, and the most effective management action determined. For example, if Species A was considered vulnerable to displacement from OWED development and had a declining population, then decision makers could prioritize mitigation (e.g., creating movement corridors) for projects built close to shore. If Species B was considered vulnerable to collision with offshore wind turbines, the CE model outputs show avoidance is not an effective mitigation strategy and that all projects, regardless of site, should consider minimization measures such as reducing lighting. Finally, if Species C was not documented to be vulnerable to OWED and near-term wind farm development was generally focused in shallow areas, then mitigation would not be a focus for this species. The hypothetical results represent a simplistic example of the CE model outputs, but the model is scripted to be used in any geographic location, to be tailored to any OWED build-out scenario, and to accept unlimited wildlife and OWED siting decision inputs.

4. Discussion

We developed a model to analyze the cumulative effects of offshore wind farm development on wildlife, an important ecological and regulatory issue. The CE model is a simple applied tool that can be used at any location; can be used to evaluate the incremental impact of wind farm development; can forecast alternate future development scenarios; and can assess the cumulative exposure of many species simultaneously. The model outputs identify, by species, if project siting is an effective management action to reduce cumulative adverse effects.

The strength of the CE model is that the input parameters can be tailored to the needs of the user. Users can explore how different

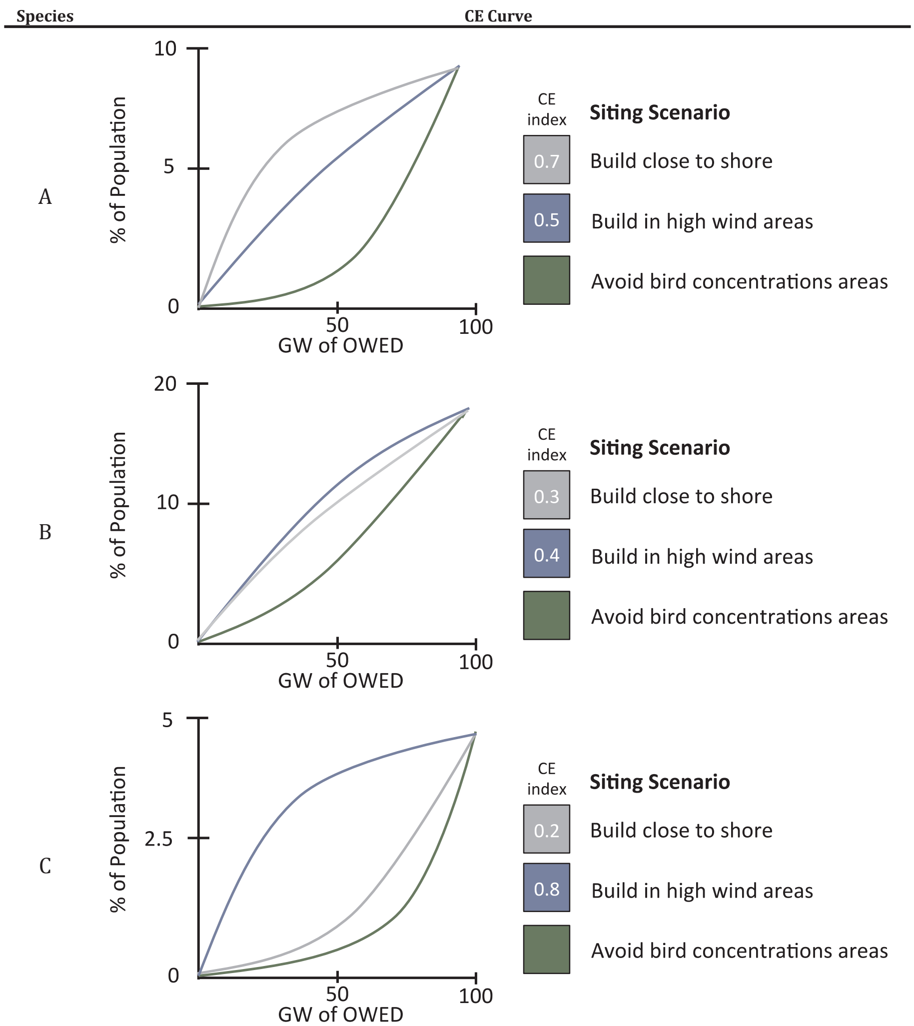


Fig. 7. An example of the CE curves and index (displayed in legend box) produced for three hypothetical species (A, B, & C) exposed to two different siting scenarios. For all species the green curve represents selecting areas for development that always have the lowest wildlife abundance.

assumptions about future development influence assessment of CAE today, including assumptions about wind farm parameters, siting factor inputs, and wildlife data. The user can also examine any geographic area and can apply the model to any wildlife type. As with any model, results and the uncertainties will depend upon the quality and the nature of the input data. Yet, the model's flexibility allows the user to examine the sensitivity of the results to input parameters. Users can compare how different sources of data and differing assumptions about siting feasibility influence CAE assessments.

Currently the CE model is deterministic, both with respect to wind farm siting and wildlife locations. In the future, the model can be modified to adopt a stochastic approach, which would better simulate variation that naturally occurs. In terms of wind farm siting, rather than developing scenarios that reflect an ordering based on ranking of the development factors, the model could select the order of wind farm development using a probabilistic approach. In terms of wildlife exposure, the CE model could be revised to consider intra- and inter-annual variation in species abundance. The CE model could also be modified to accept inputs for each season and/or year of available data to develop a mean and standard deviation of exposure for each species at each wind farm within the grid. The resulting table could then be used to develop CE curves with confidence bands for each scenario.

In addition, the CE model code could be integrated into a simple-to-use, interactive web-based decision-support model, not requiring R scripting knowledge, to allow stakeholders to conduct their own cumulative exposure assessments. As OWED progresses in the U.S., the online tool could begin to estimate the cumulative exposure based upon existing and proposed projects, and then forecast how future OWED siting decisions would contribute to cumulative exposure.

5. Conclusions

CAE is an important issue that regulators and developers are required to address. However, the complexity of addressing many species simultaneously and the uncertainty of predicting the order of future offshore wind development leads to delays and inconsistent approaches to assessments. Therefore, there is a need for tools that provide standardized means by which decision makers can identify the species most at risk of CAE and the best management actions to reduce CAE. The CE model addresses this need by creating a systematic approach for predicting and aggregating expected exposure of wildlife to OWED. Results from the model help to identify the efficacy of avoiding cumulative impacts through siting decisions. The CE model now allows decision-makers to evaluate, on a regional scale, which wildlife populations may be impacted by future development and to prioritize mitigation measures. When the CE model is applied across a broad spectrum of wildlife classes, negative impacts of OWED on wildlife can be reduced and wind farm development maximized to reduce carbon emissions.

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