OCS Study
BOEM 2022-071

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U.S. Department of the Interior
Bureau of Ocean Energy Management
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November 2022

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Prepared under BOEM Intra-Agency Agreement No. M19PG00023

By

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U.S. Department of the Interior
Bureau of Ocean Energy Management
Office of Renewable Energy Programs

DISCLAIMER

This study was funded, in part, by the U.S. Department of the Interior, Bureau of Ocean Energy Management (BOEM), Office of Renewable Energy Program, Washington, DC, through Intra-Agency Agreement Number M19PG00023 with the Fish and Wildlife Service (USFWS). This report has been technically reviewed by BOEM, and it has been approved for publication. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the opinions or policies of BOEM or USFWS, nor does mention of trade names or commercial products constitute endorsement or recommendation for use.

REPORT AVAILABILITY

To download a PDF file of this report, go to the U.S. Department of the Interior, Bureau of Ocean Energy Management Data and Information Systems webpage (http://www.boem.gov/Environmental-Studies-EnvData/), click on the link for the Environmental Studies Program Information System (ESPIS), and search on 2022-071. The report is also available at the National Technical Reports Library at https://ntrl.ntis.gov/NTRL/.

CITATION

Adams EM, Gilbert A, Loring P, Williams, KA (Biodiversity Research Institute, Portland, ME and U.S. Fish and Wildlife Service, Charlestown, RI). 2022. Transparent Modeling of Collision Risk for Three Federally Listed Bird Species in Relation to Offshore Wind Energy Development: Final Report. Washington, DC: U.S. Department of the Interior, Bureau of Ocean Energy Management. 79 p. Report No.: OCS Study BOEM 2022-071. Contract No.: M19PG00023.

ABOUT THE COVER

SCRAM logo credit: Iain Stenhouse/BRI.

ACKNOWLEDGMENTS

We would like to thank David Bigger, Brian Gerber, Emily Argo, and Tom Wittig for their reviews of earlier versions of the models, user interface, and user manual; Susi von Oettingen, Wendy Walsh, and Anne Hecht for input on species data to incorporate into models; and David Bigger, Timothy White, and Michael Rasser for their reviews of an earlier version of this report. Sarah Dodgin and Wing Goodale supported aspects of this study. Chris Field and Brian Gerber of the University of Rhode Island conceived of and developed an initial version of the models. Additionally, Dr. Gerber continued to provide helpful project feedback after their portion of the project was complete. After the project transfer, BRI finalized and tested all the models, modified the user interface (UI) and automated reports, solicited feedback on the approach, UI and reports, and created documentation for the approach and the tool.

SCRAM builds upon significant intellectual and analytical contributions from earlier collision risk models, including models by Band (2012), Masden (2015), and McGregor et al. (2018).

FOR MORE INFORMATION

The SCRAM Tool for which this User Manual was written is available at: https://briloon.shinyapps.io/SCRAM/. For more information on the tool or to provide comments, contact Andrew Gilbert at the Biodiversity Research Institute (Andrew.Gilbert@briwildlife.org). The R code for

SCRAM is provided at the SCRAM GitHub repository: https://github.com/Biodiversity-Research-Institute/SCRAM. Update requests and bugs can be posted post at https://github.com/Biodiversity-Research-Institute/SCRAM/issues.

Contents

List of Figures

List of Tables

List of Abbreviations and Acronyms

ASL	Above sea level
BOEM	Bureau of Ocean Energy Management
BRI	Biodiversity Research Institute
CRM	Collision risk model
ESA	Endangered Species Act
GPS	Global Positioning System
GW	Gigawatt
HMM	Hidden Markov Model
HY	Hatch Year
MW	Megawatt
NES	United States Northeastern Continental Shelf Ecosystem
NWR	National Wildlife Refuge
RPM	Rotations per minute
RSZ	Rotor-swept zone
SCRAM	Stochastic Collision Risk Assessment for Movement
SD	Standard deviation
sCRM	stochastic collision risk model
URI	University of Rhode Island
USFWS	U.S. Fish and Wildlife Service

Glossary

Area-restricted behaviors	Movements that are slower and less directed than transient (i.e., migratory) movements, often focused in a specific location. Can include local movements during foraging or nesting. Estimated using a two-state Hidden Markov movement model.
Avoidance	Behavior in which birds choose to avoid coming into proximity with an offshore wind turbine. Can occur at a range of spatial scales; the avoidance metric commonly used in collision risk models typically incorporates meso- to micro-avoidance (e.g., avoidance of turbines within a wind farm or avoidance of turbine blades when in their immediate proximity), but does not include macro-avoidance, in which birds may choose to avoid entering a wind farm altogether.
Collision risk model	A model that predicts risk of avian collisions with offshore wind turbines. Most collision risk models combine an estimate of the number of birds available to collide with a turbine with the probability of a collision occurring; as reviewed in Masden and Cook (2016), this is “generally based on the probability of a turbine blade occupying the same space as the bird during the time that the bird takes to pass through the rotor.” Collision risk models thus typically include some type of bird density value, as well as a variety of parameters describing both bird behavior and turbine characteristics. The earliest collision risk model was developed in the 1980’s; more recent iterations for offshore use are often based on the Band (2012) model.
Cumulative impacts	Effects of multiple offshore wind farms on the same species or population, including effects throughout the lifespan of the wind farms. In the context of this report, cumulative risk of collisions is assumed to be additive across offshore wind farms.
Daily population size	Estimate for each grid cell of the number of birds present in that grid cell on that date. Derived by multiplying the estimated daily occupancy for the grid cell by the monthly regional population size.
Effects determination	Assessment by federal agencies as to whether an action affects species listed under the U.S. Endangered Species Act (ESA; 16 U.S.C. §§1531-1544). Typical findings are “no effect”, “not likely to adversely affect”, or “likely to adversely affect”.
Exposed population	Number of individuals estimated to be present in a grid cell and transit a wind turbine (and thus are available to collide with the turbine blades). Estimated from the daily population size estimate for a grid cell as well as factors such as the number and size of turbines and the proportion of birds in the grid cell that are estimated to be in a transient vs. area-restricted behavioral state. Added up to the monthly scale, the “exposed population” can be larger than the monthly regional population size if enough birds are estimated to be exposed to collision risk on multiple days within that month.
Flight height model	Model for estimating altitude of birds based on flight height data collected from Motus position estimates from previous work (Loring et al. 2019) for birds located over federal waters (e.g., >3 miles from shore) that were moving quickly enough to be flying (based on timing of sequential locations).
Hatch year	Bird born within the same calendar year as the time period of interest. Birds born in previous calendar years are “after hatch year” individuals.
Morphometrics	Body measurements of birds, such as wing length.
Motus Wildlife Tracking System	Also “Motus”. An international automated radio telemetry network on coordinated frequencies (Taylor et al. 2017, www.motus.org). Automated radio telemetry systems consist of radio tags (small transmitters attached to birds, bats, or insects) and stations (receivers with antennas that record signals from “tagged” organisms). When tagged animals are within detection range of a station, the receiver automatically records transmitter ID number, date, time stamp, antenna (defined by monitoring station and bearing), and signal strength value of each detection. All telemetry data currently used in SCRAM were obtained from previous Motus studies (Loring et al. 2018, Loring et al. 2019, Loring et al. 2021).
Movement model	Two-state Hidden Markov Model (HMM) in a Bayesian modeling framework that uses Motus tracking data to estimate two-dimensional (X,Y) position estimates for tagged animals. These models have two major components: a state-switching correlated random walk movement model and an observation model that describes

	measurement error in the process. In this case, we allowed there to be two independent movement models linked through the Markov state-switching process that described bird movements as either fast-moving, transient behaviors (e.g., migratory movements ranging from hourly to multi-day depending on the species) or slower, less directed area-restricted behaviors (e.g., foraging or nesting behaviors). Used to estimate daily occupancy rates.
Occupancy	Presence of a species in a grid cell. Estimated in this report by day or month. Daily occupancy rates within each grid cell are multiplied by the monthly regional population size to predict daily population size for each grid cell. Occupancy of all grid cells across the whole study area sum to one.
Regional population size	Also “monthly regional population size”. The number of individuals of a given species that are estimated to be present within the study area during a given month of the annual cycle (the study area on the Northeastern Continental Shelf is shown in Figure 2 in the text).
Sampled population	Also "tagged population". Subpopulation of birds that were tagged with Motus transmitters and that contributed data to the development of movement and flight height models.
Station	Also “tracking station”. Motus equipment is designed to detect animals tagged with automated radio transmitters such as nanotags. Most land-based stations included in this study had a 12.2-m radio antenna mast supporting six 9-element (3.3 m) Yagi antennas, which were mounted in a radial configuration at 60° intervals and connected via coaxial cables to a receiving unit (Lotek SRX). Detection range of stations vary with the height of the receiving antennas (meters above sea level: m asl), altitude of the tagged animal, and the signal gain properties of the transmitter and receiver.
Telemetry array	Network of Motus stations used to detect tagged animals.
Transient behaviors	Migratory movements ranging from hourly to multi-day depending on the species. Estimated using a two-state Hidden Markov movement model.
Transit	Movement of an animal through the rotor-swept zone of a turbine. In the current version of SCRAM, can occur no more than once per day per individual.
Transmitters	Also “tags” and “nanotags”. Motus transmitters used in this study, which included 0.67 g and 1.1-g models with a 16.5-cm antenna (brand name “nanotag”; Lotek Wireless, ON, Canada). All transmitters were programmed to emit signals at fixed burst intervals on a shared frequency of 166.380 MHz from activation through the end of battery life. Burst intervals were unique to each transmitter and ranged from 4 to 6 s.
Wintering population	Number of birds estimated to be present on the non-breeding grounds during the boreal winter. Can include specific subpopulations of birds that winter in different locations. For the three species discussed in this report, wintering grounds range from the southeastern United States to southern South America.

1 Overview

The University of Rhode Island and Biodiversity Research Institute (BRI), with support from the U.S. Fish and Wildlife Service (USFWS) and Bureau of Ocean Energy Management (BOEM), have developed a model to assess exposure and collision risk of federally protected birds from offshore wind energy development in the U.S. Atlantic. A stochastic collision risk model (sCRM) for seabirds is currently used to estimate collision impacts from offshore wind energy development in parts of Europe (McGregor et al. 2018). This model typically uses avian density data derived from observational survey datasets for a location along with a suite of behavioral and site-specific variables that predict collision risk. However, very limited survey data are available for the three federally protected bird species present in the U.S. Atlantic: the Roseate Tern (*Sterna dougallii*), Piping Plover (*Charadrius melodus*), and Red Knot (*Calidris canutus*). The majority of available data in the U.S. Atlantic on the offshore movements and distributions of these taxa come from studies funded by BOEM that used automated radio telemetry to track individuals in the proximity of receiving stations along the coast (e.g., Loring et al. 2018, Loring et al. 2019). This work was conducted in collaboration with the Motus Wildlife Tracking System ('Motus'; www.motus.org), an international automated radio telemetry network on coordinated frequencies (Taylor et al. 2017). Thus, in order to use the best available data to inform an understanding of collision risk for these species, we used movement modeling to determine monthly occupancy rates over a portion of the United States Northeastern Continental Shelf Ecosystem (NES) and then linked those values to monthly population estimates to estimate density across the NES. The collision risk model then used these density estimates at specific flight heights (data also derived from Motus tracking) along with other species and site characteristics (such as species-specific flight speeds and number of turbines in a specified turbine array) to estimate collision risk for locations across a portion of the NES where tracking data were available.

An online web application of the model, called Stochastic Collision Risk Assessment for Movement (SCRAM), the accompanying user manual, and fully annotated computer code have been made publicly available to help transparently estimate collision risk for the three focal species from offshore wind farms in the U.S. Atlantic. This report serves as documentation to accompany the published model and presents associated case study data to guide evaluation of collision risk of Roseate Tern, Piping Plover, and Red Knot at offshore wind energy areas in the U.S. Atlantic. This report also includes a framework for using site-specific data to estimate cumulative collision risk across spatiotemporal scales.

The main deliverables from this study included:

- Functioning and well-supported collision risk models, movement models, and flight height distributions for the three initial case study species
- Fully-annotated code for the above models and web application
- Open-source graphical web application (SCRAM) that implements a sCRM with Motus data, with data for the three initial case study species hard-coded into the application
- User manual for SCRAM
- Final report to BOEM (this document), including a basic framework for estimating cumulative collision risk as well as identification of further development steps for SCRAM.

This report refers to SCRAM Version 1.0.3, which is live at https://briloon.shinyapps.io/SCRAM/. Code and annotation for all project components is publicly available on GitHub at https://github.com/Biodiversity-Research-Institute/SCRAM.

2 Introduction

Due in part to difficulties with direct detection of avian collisions with offshore wind turbines, collision risk models have been developed to estimate the risk posed to birds from offshore wind energy development (Allison et al. 2019). Most collision risk models combine an estimate of the number of birds available to collide with a turbine with the probability of a collision occurring; as reviewed in Masden and Cook (2016), this is "generally based on the probability of a turbine blade occupying the same space as the bird during the time that the bird takes to pass through the rotor." Collision risk models thus typically include some type of density value, as well as a variety of parameters describing both bird behavior and turbine characteristics.

In the United States, the use of collision risk models (CRM) is one aspect of analysis of avian risk of collision with proposed offshore wind energy development. Up until very recently, BOEM has used the original offshore version of the Band Collision Risk Model (Band 2012) to make an effects determination (e.g., no effect, not likely to adversely affect, or likely to adversely affect) when evaluating avian collision risk for species listed under the U.S. Endangered Species Act (ESA; 16 U.S.C. §§1531-1544). Due to limitations of the Band (2012) model, summarized by Masden (2015), this analysis is lacking in transparency and does not account for fundamental uncertainties. In particular, Masden (2015) noted that the 2012 Band model does not allow for easy reproducibility (e.g., review of underlying code and data), thus preventing the transparent verification of results. The data used in risk analyses include estimated quantities (e.g., bird flight speed and height) that have measures of uncertainty (e.g., standard errors, confidence or credible limits), which must be accounted for in risk analyses to properly estimate uncertainty in likely outcomes. Such estimation of uncertainty is essential for decision-making (Conroy and Peterson, 2013; Nicholson and Possingham, 2007). It is also important to consider natural stochasticity in ecological processes, which leads to a range of possible outcomes (i.e., the probability of collision risk and the projected number of bird collisions per unit time). Further, analysis using the original Band (2012) model is not flexible in its ability to utilize data for the full range of species for which these models are needed. Specifically, many species of conservation concern are not well documented by boat or aerial survey data, and habitat use throughout the annual cycle must be carefully documented to accurately assess collision risk. Without these considerations, the cumulative impact across all wind farms may be underestimated.

BOEM determined that improving the CRM process was critical for assessing the potential "take" of bird species protected under the ESA and would help to inform effects analyses of wind energy project development using best available science. The improved CRM and accompanying web application presented in this report provide BOEM and offshore wind energy developers with an improved ability to design wind energy projects that consider risk to migrating and locally transiting avian species (Masden and Cook 2016). Our goal with this effort was to improve the modeling process to support effects analyses for three listed species (Roseate Tern, Piping Plover, and Red Knot) in the NES. We do so by i) improving the transparency of the collision risk modeling, ii) beginning to consider the cumulative effects of exposure to multiple offshore wind leases, and iii) properly accounting for multiple sources of uncertainty (i.e., stochasticity, parametric variability, and model uncertainty). Project components (Fig. 1) include:

- Use of telemetry data from the Motus Wildlife Tracking System for the three focal species (Roseate Tern, Piping Plover, and Red Knot), as well as flight height distribution data, as model inputs.
- Development of movement models and flight height distribution models for the three focal species, including modifications to models/code as determined necessary based on scientific/technical judgement and model fit assessments.
- Adaptation of the McGregor (2018) version of the stochastic CRM for use in the NES including implementation using Motus telemetry data for the three focal species.

- Sourcing and evaluation of species input data for use in the CRM model, including monthly regional population size estimates, body morphometric data, avoidance rate estimates, and other parameters (see Section 3.2 for details); and population of the CRM with these species-specific data for the three case study species.
- Development of an open-source graphical web application of the stochastic CRM with a user interface designed to facilitate ease of use, transparency, and communication of results, available at https://briloon.shinyapps.io/SCRAM/. The application supports transparent effects determinations through report generation of downloaded pdfs and model outputs as data files that contain all relevant model inputs and outputs.
- Preparation of a user manual for the web application, which communicates the basic mechanisms of the model, guides users in the execution of the model, and briefly addresses the limits of inference that can be made based on the model and data inputs. The latest version of the user manual is available for download from the web application or from the GitHub site (below).
- Publicly available code and annotation for all project components on GitHub at https://github.com/Biodiversity-Research-Institute/SCRAM.
- Results from this application reported as case studies (this document).

This project was initiated by a cooperative agreement between the USFWS and University of Rhode Island (URI) in spring 2020 and completed by the Biodiversity Research Institute (BRI) in 2022 via a new USFWS cooperative agreement. This report refers to SCRAM Version 1.0.3. The codebase and application will be updated periodically as needs arise, which will be reflected in the GitHub and ShinyApps.io sites.

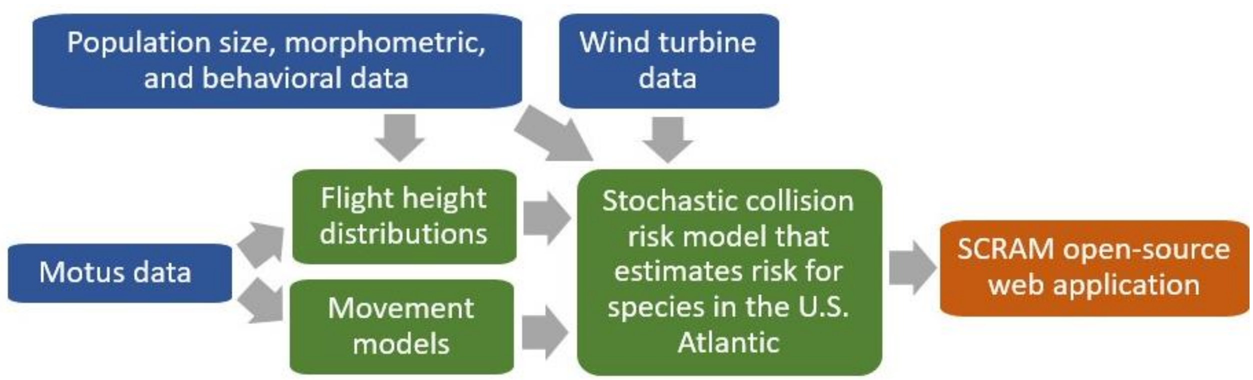

Figure 1. Project components.
Species input data are shown in blue; models in green; and the web application for implementing the CRM in orange.

3 Stochastic Collision Risk Assessment for Movement (SCRAM)

The goal of this project was to create a collision risk decision support tool based on current knowledge of United States ESA-listed bird species on the NES (Fig. 2). To this end, we built on previous collision risk models (Band 2012, Masden 2015, McGregor et al. 2018) and adapted them for use with individual tracking data, particularly data from the Motus Wildlife Tracking System (Appendix A). There were four main components of the collision risk process: (1) movement modeling to determine monthly occupancy rates over the NES, (2) linking of monthly population size estimates to occupancy rates to estimate density across the NES, (3) flight height estimation from Motus data to further refine the proportion of the population at risk for collision, and (4) a collision risk model that uses density estimates at specific flight heights (along with a suite of other species- and location-specific parameters on species morphometrics/behavior and turbine specifications) to estimate collision for a specified turbine array. These models were packaged into a web application accessible via the SCRAM public user interface.

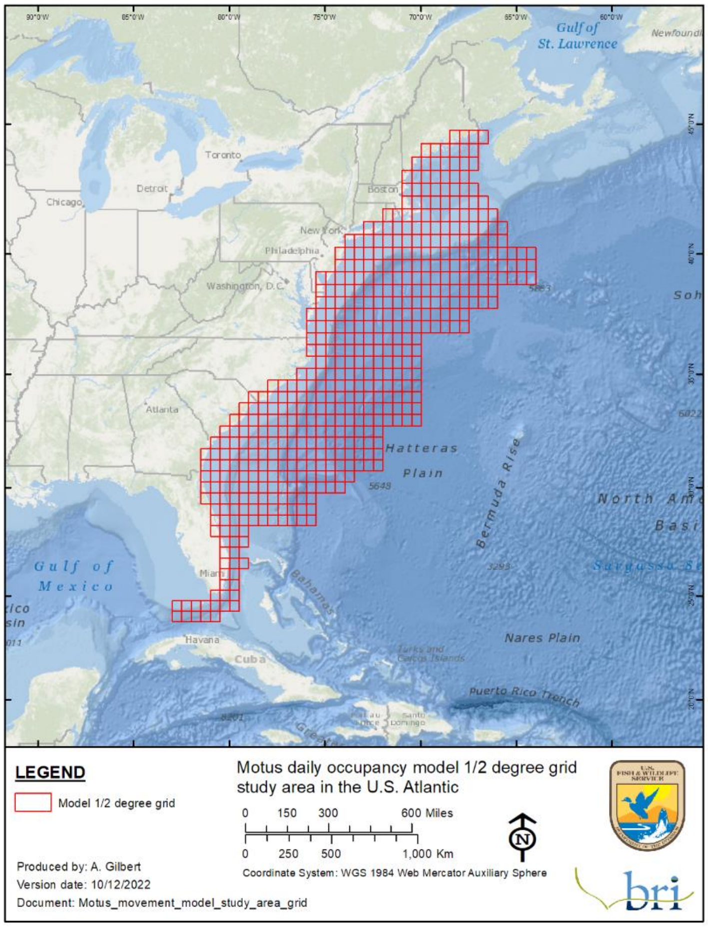

Figure 2. Map of the study area with a ½ degree grid throughout the Northeastern Continental Shelf Ecosystem (NES).
Grid cells are based on ½ degree BOEM lease blocks, which are approximately 55 km E-W x 60-75 km N-S depending on their specific latitude and longitude.

3.1 Automated Radio Telemetry Data

The current version of SCRAM uses automated radio telemetry (Motus) data to model bird movements within a portion of the NES. Automated radio telemetry systems consist of radio tags (small transmitters attached to birds, bats, or insects) and stations (receivers with antennas that record signals from "tagged" organisms within detection range). Motus is an international collaborative research network that uses cooperative automated radio telemetry to track tagged organisms on coordinated frequencies. All telemetry data currently used in SCRAM were obtained from previous Motus studies (Loring et al. 2018, Loring et al. 2019, Loring et al. 2021). Key information from these studies is summarized below.

3.1.1 U.S. Atlantic Coast Motus Array

A targeted array of land-based automated radio telemetry stations tracked tagged birds along a portion of the U.S. Atlantic Coast, in coordination with the broader Motus Wildlife Tracking Network (Taylor et al. 2017). Loring et al. (2019) provided a detailed description of the locations, specifications, and operational dates of each tracking station in the U.S. Atlantic coast array. In 2015, the array included sixteen coastal stations at sites ranging from Cape Cod, MA to Long Island, NY. During 2016, 14 additional stations were installed at sites ranging from Cape Cod, MA to Back Bay, VA. The expanded array of 30 stations remained in operation through the fall of 2017.

Most of the stations in the Atlantic coast array had a 12.2-m radio antenna mast that supported six 9-element (3.3 m) Yagi antennas mounted in a radial configuration at 60° intervals. At some sites, stations consisted of up to 4 Yagi antennas, or a single omni-directional antenna, attached to existing structures. At each of the tracking stations, the antennas were connected to a receiving unit (Lotek SRX) via coaxial cables. Each receiving station was operated 24 hours per day using one 140-watt solar panel and two 12-volt deep-cycle batteries.

When tagged birds were within detection range of a station, a receiver automatically recorded transmitter ID number, date, time stamp, antenna (defined by monitoring station and bearing), and signal strength value of each detection. The detection range of each station varied with the height of the receiving antennas (meters above sea level: m asl), altitude of the tagged bird, and the signal gain properties of the transmitter and receiver. The maximum estimated detection range of the stations was up to 20 km for birds flying at altitudes of 25 m asl and up to 40 km for birds flying at altitudes of 250 m asl (Loring et al. 2019).

3.1.2 Transmitters

The studies used two types of transmitters ('Avian Nanotags', Lotek Wireless, ON, Canada): 0.67 g nanotag (LNTQB-3-2; 12 × 6 × 5 mm) and 1.1-g nanotag (NTQB-4-2; transmitter body: 12 × 8 × 8 mm). Both tag models had a 16.5-cm antenna. All transmitters were programmed to emit signals at fixed burst intervals on a shared frequency of 166.380 MHz from activation through the end of battery life. Burst intervals were unique to each transmitter and ranged from 4 to 6 s. The expected life of the 1.1-g nanotags ranged from 146 days (4-s burst interval) to 187 days (6-s burst interval). The expected life of the 0.67-g nanotags ranged from 72 days (4-s burst interval) to 92 days (6-s burst interval).

3.1.3 Piping Plover data

Piping Plover movement data used in SCRAM were collected during 2015 to 2017 (Loring et al. 2019). A total of 150 adult Piping Plovers were tagged during the incubation period (3–14 days prior to estimated hatching dates) at nesting areas in Massachusetts (n=75) and Rhode Island (n=75), USA. Tagging sites in Massachusetts included Monomoy National Wildlife Refuge (NWR; 41.6004°N, -69.9911°W) and adjacent South Beach (41.6309°N, -69.9594°W) in the town of Chatham, on Cape Cod. In Rhode Island, tagging sites included several locations along the state's southern coast, ranging from Napatree Point in Westerly (41.3103°N, -71.8742°W) to Sachuest NWR in Middletown (41.4862°N, -71.2524°W).

Each plover was fitted with a 1.1 g nanotag in 2015 and 2016, and a 0.67-g nanotag in 2017. All tags were attached to clipped feathers in the dorsal inter-scapular region with cyanoacrylate gel. Of the 150 individuals tagged, 82% (n=123) were detected by the telemetry array, including tracking stations installed within or near nesting sites where birds were tagged. Piping Plovers that were detected by the telemetry array (n=123) were tracked for an average of 46 days (SD 27 days, range 0-102 days).

3.1.4 Roseate Tern data

Roseate Tern movement data used in SCRAM were collected during 2015 to 2017 (Loring et al. 2019). Adult Roseate Terns were tagged during the incubation period at nesting colonies in the USA on Great Gull Island, NY (41.2028°N, -72.1186°W) and in Buzzards Bay, MA (Bird Island 41.6695°N, -70.7170°W and Ram Island 41.6181°N, -70.804381°W). A total of 90 Roseate Terns were tagged from 2015-2017 on Great Gull Island (n=30 per year). A total of 60 Roseate Terns were tagged from 2016-2017 in Buzzards Bay. During 2016, Roseate Terns were tagged on Bird Island (n=30) and during 2017 Roseate Terns were tagged on Bird Island (n=19) and Ram Island (n=11).

Each Roseate Tern was fitted with a 1.5 g nanotag (NTQB-4-2 model) coated with a waterproofing material and custom-fit with 1-mm tubes at the front and back of the transmitter body for attachment. All tags were attached to the dorsal inter-scapular region using cyanoacrylate adhesive and two polypropylene sutures that were inserted subcutaneously and secured to the end-tubes of the transmitter. Of the 150 individuals tagged, 97% (n=145) were detected by the telemetry array. Most detections were from tracking stations installed at nesting colonies where birds were tagged, but many terns were also tracked at non-colony sites during the breeding period and during post-breeding dispersal. Roseate Terns that were detected by the telemetry array (n=145) were tracked for an average of 32 days following tagging (SD 21 days; range 0 to 95 days).

3.1.5 Red Knot data

Red Knot movement data used in SCRAM were collected during 2016 (Loring et al. 2018). Red Knots were tagged during the fall migratory staging period (late July through late October) at several sites: James Bay, ON, Canada (n=9; 51.6578°N, -80.5675°W); Mingan Archipelago, QC, Canada (n=244; 50.1911°N, -63.9094°W); Chatham, MA, USA (n=99; 41.6768°N, -69.9371°W); North Brigantine Natural Area, NJ, USA (n=28; 39.4264°N, -74.3418°W), Stone Harbor Point, NJ, USA (n=1; 39.0299°N, -74.7756°W) and Avalon, NJ, USA (n= 6; 39.0740°N -74.7388°W). Tagged birds included multiple age classes (hatch year, after hatch year, second year, and after second year) identified by plumage characteristics and molt.

All tags were attached to clipped feathers in the synsacral region using cyanoacrylate gel adhesive. Of the 388 Red Knots tagged, 32% (n=125) were detected by the telemetry array. Red Knots that were detected by the telemetry array (n=125) were tracked for an average of 23 days following tagging (SD 29 days; range 0 to 131 days).

3.1.6 Limitations of Motus movement data

A primary limitation of using automated radio telemetry methods to collect data on offshore movements is that tagged birds can only be detected when they fly within detection range of a tracking station, which is a maximum of 20-40 km from the station but can be highly variable depending on topography, electromagnetic interference, and other physical and environmental factors (Loring et al. 2019). Data used in SCRAM were collected by up to 30 land-based tracking stations distributed between Cape Cod, MA to Back Bay, VA. Therefore, information on offshore movements of birds was limited to model-estimated flight paths between these land-based stations with limited detection coverage relative to the NES and locations of offshore wind energy lease areas.

In addition, birds were tagged at a limited number of sites throughout their migratory range, so the movement data may not be representative of the broader populations using the NES. Movement data were also limited to specific time periods per species, given limitations on tag retention using temporary attachment methods, tag battery life, and geographic coverage of tracking stations. Piping Plovers were tagged during the mid-incubation period and tracked during a portion of their fall migration. Roseate Terns were tagged during the mid-incubation period and tracked during the post-breeding dispersal period. Red Knots were tagged during the fall staging period and tracked during a portion of their fall migration.

Not all tagged birds were detected by telemetry arrays, and there was a wide range in tracking duration among individuals for each species tagged. Lack of detections by the telemetry array may be attributed to tag loss, tag malfunction or failure, bird mortality, or birds moving away from the study area and/or outside of the detection range of stations. Therefore, due to incomplete detection data from tag loss and incomplete spatial coverage of the receiving station array, modeled movements may not be representative of the entire tracking period for many individuals. However, given the challenges and technological limitations of tracking small-bodied species offshore, the Motus dataset used in SCRAM represented the best available information for the three case study species at the time that this collision risk modeling approach was developed.

3.2 Species Input Data

3.2.1 Regional population size

For each species, population size (*n*) was estimated on a monthly basis using expert consultation and species-specific monitoring methods. Here, n is the maximum number of animals within the NES grid system (Fig. 2) for a given month. Monthly variation is due to migration to or through the study area and annual breeding productivity. Piping Plover and Roseate Tern population sizes were estimated using survey data from the breeding grounds. For Piping Plovers, information on nesting pairs across their Atlantic coast breeding range are regularly compiled across a large number of monitoring organizations and projects, and this compilation is thought to represent a census of the breeding population. For Roseate Terns, colony counts are implemented at the three biggest colonies in the United States. While this number represents a census of the population, it is an underestimate of the entire population. However, the vast majority of Roseate Terns are in these colonies and should represent >90% of the population. For Red Knots, we used estimates of the *C. c. rufa* subspecies population at their wintering grounds, and assumed that the entire population migrates through the project study area. The source of regional population size data used in the model included: U.S. Fish and Wildlife Service 2022 (Piping Plover); U.S. Fish and Wildlife Service 2020 and Lyons et al. 2017 (Red Knot); and Mostello 2021 and Gochfeld and Burger 2020 (Roseate Tern). Additional detail on the derivation of these monthly population size estimates for the study region is included in Appendix B.

3.2.1.1 Assumptions and limitations of the monthly regional population size estimates

The most recent population size estimates are thought to be reasonably accurate, but do not incorporate changes in population size over time (e.g., for populations that may be increasing or decreasing in size). Thus, for populations that are changing in size over time, collision risk estimates for longer time periods (for example, over the 30-year life of an offshore wind energy project) may become increasingly unreliable.

At the monthly scale, estimates of the percentage of the population in the study area are approximations. For the two species that breed along the U.S. Atlantic coast, we assumed the entire population was present during the breeding season and during migration, though in all likelihood some proportion of the population had either not entered or already left the study region during the early spring and late fall migration periods, respectively (Appendix B). For Red Knots, we assumed the entire wintering population of the *C. c. rufa* subspecies was present during peak months of migration and a lesser proportion (e.g., only specific wintering populations) was present during the latter portion of migration. It is also possible that some Red Knots do not pass directly through the NES and may be flying farther offshore, as suggested by several interpolated tracks in Loring et al. (2020a, Fig. 13), though the proportion of the population following this migration route is currently unknown. Various assumptions were also made regarding the number of hatch-year birds produced per year (Appendix B). A more comprehensive model of where birds are throughout the year, drawn from a range of data sources, could help refine these monthly estimates in future.

3.2.2 Morphometrics and Behavioral Data

The stochastic collision risk model incorporates several species-specific morphometric and behavioral parameters intended to inform estimates of collision risk at offshore wind turbines. These include wingspan and body length, as described in Liddy (1990), as well as flight speed, movement type (flapping or gliding), flight height, and avoidance rates (Tables 1-3).

Estimated means and standard deviations for wingspan and body length metrics were based on available ranges from the species accounts in the Birds of the World (https://birdsoftheworld.org/), which compiles peer-reviewed and unpublished sources. Flight speed data was drawn from individual tracking projects for each species. Piping Plover flight speeds were estimated from Motus-tracked individuals (Loring et al. 2020b) and Roseate Tern flight speeds were estimated from Common Terns tracked with ARGOS satellite transmitters (Loring et al. 2019). The flight speed of Red Knots was estimated based on a radar-tracking study of European populations (Alerstam et al. 2007). When possible, movement speeds were estimated during calm winds. Each species was classified with a 'flapping' movement type based upon Hedenström's definitions (1993).

Direct information on behavioral changes around turbines is lacking. We know that some species are displaced from the turbine area (up to ~15-16km away in the most extreme cases; Mendel et al. 2019, Heinänen et al. 2020), and avoid turbine areas on migration (Fox and Petersen 2019). This avoidance can occur at a range of spatial scales, from outside the wind farm (macro-avoidance) to within-wind farm avoidance of turbines or even individual rotor blades (meso- and micro-avoidance, respectively; Cook 2018). However, we lack data on meso- and micro-avoidance rates for species within the turbine area for most species (Cook 2018). Cook (2021) generated meso- and micro-avoidance estimates using an intensive field study as part of the ORJIP Bird Collision and Avoidance Study (Skov et al. 2018). While these data were generated for gulls and terns, they currently represent the most precise available estimates of these values and their uncertainty, are recommended for use with the European stochCRM model (McGregor et al. 2018; https://github.com/dmpstats/stochCRM), and are used for all species in SCRAM. We use the recommended extended avoidance values (Table A2 in Cook 2021) as they represent more conservative values than those for the basic model and align with our recommendations to use the extended model for all analysis. However, this means that when running the basic model (which runs faster, so is more convenient for initial testing and exploration), the model likely overestimates collision risk.

Flight height data are estimated from Motus-tracked animals and uncertainty is incorporated into the risk assessment from those 3D movement models. See *Flight Height* for more details.

Table 1. Piping Plover morphometric and behavioral traits used to parameterize the model.

For each parameter, the mean and standard deviation of the parameter value is indicated alongside the derivation of those values and the source of the data. Sources are listed in the literature cited section of this report.

Parameter	Parameter definition	Value	Source	Derivation
Avoidance	Mean Proportion of birds that avoid turbines	0.9295	Cook 2021	"All gulls and terns" avoidance rate from Table A2 - recommended value for terns using extended sCRM model (also almost the exact same value used for Red Knots in Gordon and Nations 2016 collision risk model)
Avoidance SD	Standard deviation of the avoidance rate	0.0047	Cook 2021	"All gulls and terns" avoidance rate from Table A2 - recommended value for terns using extended sCRM model
Body length	Mean body length of the target species (m)	0.175	Elliot-Smith and Haig 2020	Midpoint of listed range of body length values
Body length SD	Standard deviation of body length (m)	0.0025	Elliot-Smith and Haig 2020	Calculated from listed range of body length values
Wingspan	Mean species wingspan length (m)	0.381	Palmer 1967	
Wingspan SD	Standard deviation of the species wingspan length (m)	0	N/A	No values found in the literature. Per McGregor et al. 2018, using zero SD until appropriate value can be estimated
Flight speed	Mean species flight speed (m/s)	11.7	Loring et al. 2020b	From modeled migratory routes of Motus-tagged Piping Plovers across the mid-Atlantic Bight (n=17)
Flight speed SD	Standard deviation of the species flight speed (m/s)	4.7	Loring et al. 2020b	From modeled migratory routes of Motus-tagged Piping Plovers across the mid-Atlantic Bight (n=17)
Flight type	Flight type, either flapping or gliding	Flapping	Hedenström 1993	Per definition provided for flapping vs. gliding

Table 2. Roseate Tern morphometric and behavioral traits used to parameterize the model.

For each parameter, the mean and standard deviation of the parameter value is indicated alongside the derivation of those values and the source of the data. Sources are listed in the literature cited section of this report.

Parameter	Parameter definition	Value	Source	Derivation
Avoidance	Mean Proportion of birds that avoid turbines	0.9295	Cook 2021	“All gulls and terns” avoidance rate from Table A2 - recommended value for terns using extended sCRM model
Avoidance SD	Standard deviation of the avoidance rate	0.0047	Cook 2021	“All gulls and terns” avoidance rate from Table A2 - recommended value for terns using extended sCRM model
Body Length	Mean body length of the target species (m)	0.37	Gochfeld and Burger 2020	Midpoint of listed range of body length values
Body Length SD	Standard deviation of body length (m)	0.02	Gochfeld and Burger 2020	Calculated from listed range of body length values
Wingspan	Mean species wingspan length (m)	0.76	Gochfeld and Burger 2020	Midpoint of listed range of wingspan values
Wingspan SD	Standard deviation of the species wingspan length (m)	0.02	Gochfeld and Burger 2020	Calculated from listed range of wingspan values
Flight Speed	Mean species flight speed (m/s)	12.77	Loring et al. 2019 (appendix)	Average speed across Mid-Atlantic U.S. Wind Energy Areas for PTT-tagged Common Terns (n=7 exposures from n=3 individuals)
Flight Speed SD	Standard deviation of the species flight speed (m/s)	4.8	Loring et al. 2019 (appendix)	Average speed across Mid-Atlantic U.S. Wind Energy Areas for PTT-tagged Common Terns (n=7 exposures from n=3 individuals)
Flight	Flight type, either flapping or gliding	Flapping	Hedenström 1993	Per definition provided for flapping vs. gliding

Table 3. Red Knot morphometric and behavioral traits used to parameterize the model.

For each parameter, the mean and standard deviation of the parameter value is indicated alongside the derivation of those values and the source of the data. Sources are listed in the literature cited section of this report.

Parameter	Parameter definition	Value	Source	Derivation
Avoidance	Mean Proportion of birds that avoid turbines	0.9295	Cook 2021	"All gulls and terns" avoidance rate from Table A2 - recommended value for terns using extended sCRM model (also almost the exact same value used for Red Knots in Gordon and Nations 2016 collision risk model)
Avoidance SD	Standard deviation of the avoidance rate	0.0047	Cook 2021	"All gulls and terns" avoidance rate from Table A2 - recommended value for terns using extended sCRM model
Body Length	Mean body length of the target species (m)	0.24	Baker et al. 2020	Midpoint of listed range of body length values
Body Length SD	SD for body length of target species	0.005	Baker et al. 2020	Calculated from listed range of body length values
Wingspan	Mean species wingspan length (m)	0.495	Baker et al. 2020	Midpoint of listed range of wingspan values
Wingspan SD	Standard deviation of the species wingspan length (m)	0.0225	Baker et al. 2020	Calculated from listed range of wingspan values
Flight Speed	Mean species flight speed (m/s)	20.1	Alerstam et al. 2007 (as calculated in Gordon and Nations 2016)	Estimate of cruising ground speed under calm conditions based on predicted relationship between body mass and wing loading
Flight Speed SD	Standard deviation of the species flight speed (m/s)	1.9	Alerstam et al. 2007 (as calculated in Gordon and Nations 2016)	Estimate of cruising ground speed under calm conditions based on predicted relationship between body mass and wing loading
Flight	Flight type, either flapping or gliding	Flapping	Hedenström 1993	Per definition provided for flapping vs. gliding

3.2.2.1 Assumptions and limitations of behavioral and morphometric data

Collision risk models are extremely sensitive to changes in estimated avoidance rate (Masden et al. 2021). We make the assumption that our three focal species have avoidance rates similar to the Cook (2021) combined gull/tern estimate. This rate is similar to other estimates that have been used for our case study species in the literature (e.g., Hatch and Brault 2007, Stantial 2014, Gordon and Nations 2016), and we feel it to be the best-supported avoidance rate estimate currently available, but we have limited or no evidence to validate this assumption for our three case study species. Additionally, it is even rarer to be able to pair estimates of meso- to micro-avoidance with macro-avoidance values to produce a complete picture of a given species' avoidance rates (but see Skov et al. 2018 for an example with Northern Gannets), and moreover it is likely that avoidance rates vary with weather conditions, life history phase (Henderson et al. 1996), and other factors.

Flight speed is also an influential variable in collision risk models (Masden et al. 2021). For purposes of collision risk estimation, we assume that wind direction at each site does not significantly alter mean flight speed. However, flight speed has been found to be correlated with altitude and wind speed/direction (Alerstam 1985), and also changes based on life history stage and whether birds are changing altitude. For example, Alerstam (1985) found that Common and Arctic Terns flew fastest when decreasing in altitude. While our model accounts for variation in wind-unassisted flight speed, it does not account for directional bias in flight speed.

Wingspan and body length are not common measurements for field studies; as such, these data are often approximations from collections or older studies, and may be derived using small sample sizes. When only a range of values were reported for these morphometric parameters, we estimated the mean as the midpoint value and the standard deviation (SD) as the range divided by 4. If no information was found to inform estimates of standard deviation (e.g., if only a single value was identified from the literature), then SD was assumed to be zero. For the purposes of this study, we also assumed the following:

Assumption 1: These morphometric data are representative of the populations at risk of collisions with offshore wind farms in the NES.

Assumption 2: The Gaussian mean/SD approximation technique is reasonable for these data. Morphometric data are usually well described by a Gaussian distribution (see a large data set in Jirinec et al. 2021), and the data that we could observe in this study met that expectation.

3.3 Movement Modeling

Motus detection data were used to parameterize a movement model that was used to estimate space use for the three species in the NES and the adjacent coastal areas. First, Motus data was formatted to fit into a daily movement model framework. Motus data can be noisy with a high number of false positives, so detection events with fewer than three runs (i.e., consecutive detections at a Motus station) in a row were removed. Next, if there were multiple detections within a 24h period only the first detection in each 24h period was retained for modeling.

From these data, we implemented a two-state Hidden Markov Model (HMM) in a Bayesian modeling framework (Jonsen et al. 2005, Jonsen et al. 2006), using Motus detection data (Baldwin et al. 2018). These models have two major components: a state-switching correlated random walk movement model and an observation model that describes measurement error in the process. In this case, we allowed there to be two independent movement models linked through the Markov state-switching process that described bird movements as either fast-moving, transient behaviors (e.g., migratory movements ranging from hourly to multi-day depending on the species) or slower, less directed area-restricted behaviors (e.g., foraging or nesting behaviors).

The observation model was simplified from the more typical Jonson et al. (2006) approach. Unlike satellite telemetry devices for which these models were designed, we lack data on position estimation uncertainty for Motus models when using a single daily estimate to track regional movements. This approach was similar to Baldwin et al. (2018) and Loring et al. (2019) but discards multiple detection per day to focus on coarser daily-scale movements and does not attempt to estimate altitude. As such, these movement models are similar to previous efforts, but they assume a highly accurate observation process (as we have high certainty in the Motus station locations) and do not attempt sub-daily movement estimation.

A model was estimated from the beginning to the end of the detection history for each individual, then the posterior two-dimensional (XY) position estimates were used to determine daily occupancy rates. For each daily posterior draw, we determined how many individual positions were found within a grid cell (i.e., a ½ degree BOEM lease block[1]) and summed the number of positions within the block for an entire month. Next, we divided by the number of tracked individuals for that month to determine the cumulative daily occupancy probability of the grid cell for the entire month. Only months with greater than five tracked individuals were used in the collision risk estimation. Previous versions of the model allowed position estimation to occur after the day of final detection, and we found these estimates to be of poor quality and precision, so they were not included in this version of the model. Mean monthly occupancy rates show variable space use between species, but all had higher rates near the Mid-Atlantic and southern New England coasts where Motus towers were located (Fig. 3).

Collision risk models (discussed below) require more than occupancy to work properly; we must know the number of individuals passing through a turbine over a period of time. The Band (2012) model requires unbiased density estimates to properly assess collision risk for seabirds, and, as we are using this same general collision risk framework, we must convert occupancy to density. To do this, we made the assumption that if we knew the total population size of animals in this region during this time period, then we could use the daily occupancy rates to determine spatial distribution of that population as a function of occupancy. For example, if a given grid cell had a 0.5 occupancy probability for a given day and the total population size was 10,000 individuals, then we would determine there were 5,000 individuals in that cell that were exposed to collision risk on that day. This estimated density for the grid cell is then converted into a rate of individuals/km of "migratory corridor width" (Band 2012), where the migratory corridor width is defined as the width of the grid cell. While this is smaller than ecologically relevant migratory corridors, this assumption incorporates the most locally relevant data into the estimate of transits through a potential wind farm. Grid cells close to the coast contained estimates of birds that were in both transient (e.g., migration) and area-restricted states (such as birds that may be on migratory stopover, for example), but collision risk is only related to migratory/directed movements for these species. Therefore, we determined the proportion of animals estimated to be in the transient state versus all behavioral states for each grid cell and multiplied this proportion by the number of birds estimated in a grid cell (daily occupancy * regional monthly population est.). This distributes the monthly population size around the study depending on daily occupancy estimates. For example, if the proportion of transients in the same example grid cell is 0.2, then the total number of transients in the grid cell is 1,000, which would be used as the base number of individuals in a grid cell that could be exposed to a wind farm. This number of individuals was used similarly to the flux parameter in the Band (2012) model, and combines with time in the model structure to identify the number of animals that could collide with a turbine (see below for details).

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[1] Each BOEM lease block is ½ degree square, or approximately 55 km E-W x 60-75 km N-S depending on its specific latitude and longitude (https://www.boem.gov/oil-gas-energy/mapping-and-data).

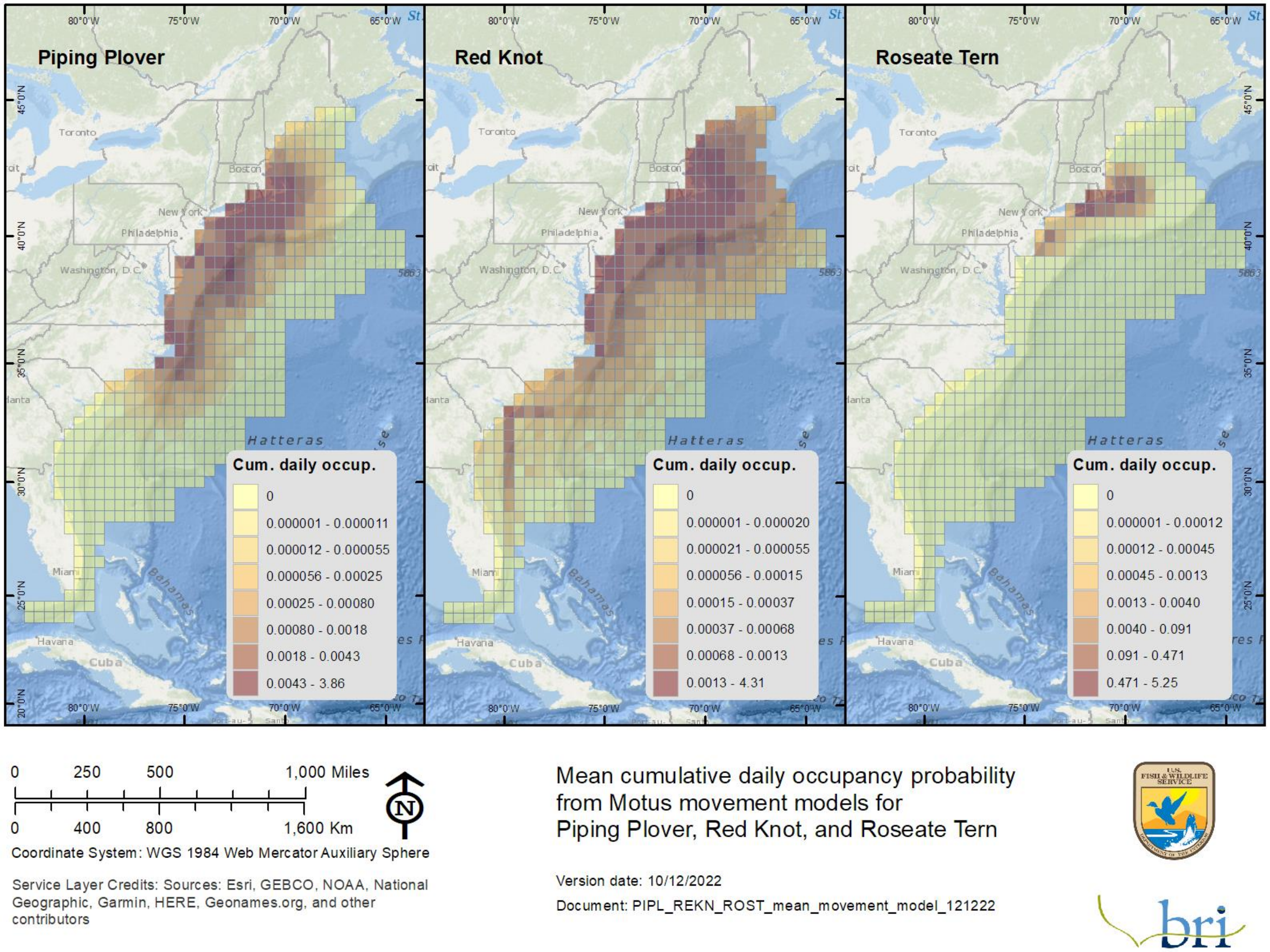

Figure 3. Average cumulative daily occupancy estimates for the three study species.
Estimates are based on multi-state movement models using Motus data and the number of tagged individuals in the study area. “Cumulative daily occupancy” sums daily occupancy probabilities estimated via SCRAM for each month (the temporal unit of summary in the model) then averages these values across all months with data for a given species. Values were divided into octiles for display purposes, so each color represents 12.5% of the range in values.

3.3.1 Assumptions and limitations of the movement models and associated density estimates

Assumption 1: These sampled populations are an unbiased representation of the species' habitat use/movements for the time periods of interest for the population as a whole.

Assumption 2: The true population sizes are known for the species of interest (or at minimum we have appropriately propagated population size uncertainty into the models). For endangered species we often have a reasonable estimate of population size, but it is certainly not perfect. At the beginning and end of migration there is uncertainty as to the monthly population size. In this study we were conservative with this estimate as to not underestimate collision risk.

Assumption 3: The movement models represent bird space use in an unbiased manner. Model evaluation using a simulated data set suggested that these models were reasonably accurate nearshore (where the vast majority of the Motus stations are) but less accurate further offshore. Most windfarms appeared to be close to enough to shore where occupancy precision estimates were high, but the models could have coastal biases due to the limited detection ranges of Motus stations. Moreover, even in nearshore areas, movement estimates are biased by the detection range of Motus stations (which varies with altitude of the tagged bird, but is around 20 km on average for birds in flight). As Motus stations are unequally distributed on the landscape, and different numbers of Motus stations were operated per year, the locations of each year's Motus stations inevitably biased resulting estimates of bird space use.

Assumption 4: Estimates of movement behavior are unbiased estimates of population-level risk over space and only animals in the transient movement category are vulnerable to collision.

Assumption 5: Average rates of post-construction migratory transit will be similar to the current dataset. Both macro-avoidance and attraction are assumed to be minimal.

3.4 Flight Height Distribution Modeling

Flight height information is lacking for many marine species. While data on flight height were available from Motus tracking efforts for the species included in SCRAM, the precision and accuracy of these data were variable. Motus tracking provides novel opportunities to collect flight height information, but current modeling efforts do not always estimate flight height precisely. Position accuracy is dependent on the number of simultaneous detections at different Motus stations, so there is high variation in the quality of these estimates (Paton et al. 2021). To account for this, the precision of individual position and flight height estimates were incorporated into the analysis.

Flight height data were collected from Motus position estimates from previous work (Loring et al. 2019) for birds located over federal waters (e.g., >3 miles from shore) that were moving quickly enough to be flying (based on timing of sequential locations). A Monte Carlo process was used to bootstrap flight heights to account for variance in the process across individuals. Individuals were each sampled 10 times with replacement with a non-parametric Monte Carlo bootstrap process. Then each replicate of that individual-balanced simulation was resampled 1000 times. After the bootstrap process, the probability density of flight for each 1m interval was calculated. While these flight height estimates do have model uncertainty, the estimates of this uncertainty were biased via the position estimation process. As such, model uncertainty was ignored in this process. Future developments in Motus position estimation processes should include clear methods for uncertainty estimation.

3.4.1 Assumptions and limitations of the flight height distribution models

Assumption 1: As flight height estimates are model-derived, we are making the assumption that these estimates are accurate. These modeling techniques are new and we often lack data to properly validate these models (something we are planning to change with upcoming projects) and more work is needed to validate these approaches.

Assumption 2: Flight height estimates are unbiased; weather patterns, individual characteristics, life history stage, and other factors can all influence flight altitude of individuals, and we have assumed that the sampled population (and the times at which they were sampled) represent an unbiased sample of flight heights of animals transiting through an offshore wind farm.

3.5 Collision Risk Modeling

The conceptual approach of SCRAM's collision risk model is the same as previous approaches based on the Band model (2012), like Masden (2015) and Trinder et al. (2017). This modeling approach estimates the collision probability for a single passage of a single turbine and scales up to multi-passage, multi-turbine applications. The overall model is translated from Band (2012):

$$E(c) = N_{transits} \times \overline{CR} \times Q_{op}$$

Where $E(c)$ is the expected number of collisions, $N_{transits}$ is the number of animals transiting through a single turbine rotor swept zone (RSZ), $\overline{CR}$ is the average collision risk estimate in the RSZ, and Q_{op} is the probability of the turbine operating when the transit occurs. The number of transits is estimated by utilizing the daily population size estimate for each grid cell. We assume that each migrating animal within the grid cell has the opportunity to transit through a turbine RSZ once per day. This assumption best matches migratory flights of animals in the offshore environment, where they are likely to pass through a location a single time *en route* to their destination. This assumption differs from the Band (2012) migratory flux model in that we only account for transits from animals actively migrating, not animals that may be staging in the vicinity. For seabirds that spend a large proportion of their time in marine environments this assumption could be inappropriate. Currently, it is unclear how this difference between Band (2012) and SCRAM in estimating the number of individuals available to collide with a turbine on a daily or monthly basis influences the accuracy of final collision risk estimates from each approach.

The collision risk model is a physical model that is specified based on the size and speed of the animals and the turbine blades. As above, it is the same model described in Band (2012):

$$\Pr(r, \varphi) = (b\Omega/2\pi r v)[\ \pm\ c sin\gamma\ + \alpha\ c\ cos\gamma\ |\ max(L, W\alpha F)]$$

Here, the $\Pr(r, \varphi)$ is the probability of a bird flying through a rotor at the rotational coordinates of r and φ. It is a function of the number of blades (b), Ω (the rotational velocity of the turbine), and the velocity of the bird (v). The second component of this equation estimates collision risk with the pitch angle of the blade (γ), the chord width of the blade (c), the ratio of bird velocity to angular velocity and radius of the turbine (α), and the longest aspect of the bird (either the length or the wingspan, L or W) that has been adjusted for relative velocity and flight type (F). In brief, this combines the probability of colliding with the front of the blade and the probability that the side of the blade hits the animal as it is passing through. Some of these parameters are measured and others are derived; for example, turbine angular velocity is estimated using turbine specifications and average wind speed (see Table 4 for measured input parameters).

Using this collision model, SCRAM provides two different options for estimating collision risk using the above equation, referred to as the Basic (Option 1) and Extended (Option 3) based on the 2012 Band formulation (Band 2012, Masden 2015). For the Basic Model, flight height distributions are used to determine the probability that an individual would be flying in the altitude range where a collision could occur (e.g., within the altitude of the RSZ).

Collision probability is estimated by integrating the risk of collision throughout the RSZ and reducing the number of transits by the proportion of birds estimated to fly at the altitude of the RSZ. However, collision risk is not likely to be equal throughout the rotor swept zone, as bird density is unevenly distributed through the same area. Thus, the Extended Model calculates collision risk and density for each $1/40^{th}$ of RSZ increment in altitude. While this version takes longer to calculate, it is thought to provide more precise results and is the preferred option for decision-making (Cook 2021). For both options, both upwind and downwind collision rates are estimated independently and added together.

After this basic probability of collisions is estimated, birds are allowed to avoid the turbine at two different scales: the meso-scale, in which birds inside the wind farm avoid the vicinity of turbines, and then the micro-scale, in which birds that do not evince meso-scale avoidance then avoid the actual turbine blades in the RSZ (Masden and Cook 2016). These probabilities are notoriously difficult to estimate due to lack of data on collisions (Masden and Cook 2016, Skov et al. 2018, Cook 2021). Using estimates from the literature as the best available science, the expected number of collisions are reduced by the micro-/meso-avoidance probability (Tables 1-3). As with previous CRMs, macro-avoidance, in which birds avoid entering a wind farm altogether, is not considered in this collision risk framework.

3.5.1 Assumptions and limitations of the CRM

Assumption 1: After the exposure model estimates the number of individuals that could collide with a turbine, the collision risk model assumes that each individual in a grid cell can only collide with a given turbine once a day. For some migratory species this might be reasonable, though one collision per migratory season could be more appropriate in some circumstances, but for other species—particularly seabirds that are making foraging flights offshore and thus may pass by a wind farm multiple times per day—this assumption could lead to an underestimation of collision risk.

Assumption 2: The proportion of headwinds and tailwinds are equal at the wind farm.

Assumption 3: SCRAM picks a single windspeed for each model iteration, which is a simplification of real-world conditions.

Assumption 4: All turbines have equal probability of collision; micro-siting differences in collision probability are ignored. Wind wakes from the turbines are not considered in their effects on collision risk.

Assumption 5: Daily variation in weather like the presence of fog and rain are not accounted for in the collision risk model and are assumed to not materially influence collision risk. However, as birds were tracked in a variety of environmental conditions, these, weather factors are incorporated to some degree into occupancy estimates.

Assumption 6: While meso-/micro-avoidance is accounted for, the potential for increased collision risk due to attraction is not considered. For example, some species may use turbine foundations or other structures as perches, and could experience higher collision risk as a result. This possibility is not accounted for in this model.

Assumption 7: The current model structure assumes that there is no macro-avoidance behavior (in which birds avoid the entire wind farm and thus are unavailable to collide, and thus could experience lower collision risk as a result). Macro-avoidance could be incorporated into estimates in the future if reliable estimates of macro-avoidance rates were developed for the focal species.

3.6 SCRAM Interface, User Manual, and Code

SCRAM was developed as an online web application in RShiny (https://shiny.rstudio.com/). SCRAM was adapted directly from the first sCRM in RShiny by McGregor et al. (2018; "stochCRM"), which in turn was adapted from the first stochastic version of the CRM developed by Masden (2015) and coded in R, which was derived from the original offshore CRM coded by Band (2012) as an Excel spreadsheet calculator (Fig. 4).

The use of RShiny as an interface greatly simplifies interaction with the underlying model and provides visual checks and outputs that allows non-technical users to conduct sCRM analyses without needing to learn the statistical language R. SCRAM is built as a self-contained app that operates in the cloud using Shinyapps.io dedicated servers to process models and deliver outputs. Thus, users do not need a sophisticated modeling computer; the only requirement is a computer (mobile or otherwise) with a modern web browser.

3.6.1 Updates and bug tracking

Updates to the SCRAM web application and the user manual will be published at https://briloon.shinyapps.io/SCRAM/ and at the SCRAM project webpage at https://briwildlife.org/SCRAM. The user does not need to do anything to update the tool; the latest version will be available to users when they open the app on a web browser. SCRAM code and changes are tracked with version control at the project's GitHub repository (https://github.com/Biodiversity-Research-Institute/SCRAM). Users experiencing problems with the operation of the tool or wanting to request a feature can post a request at the GitHub site (https://github.com/Biodiversity-Research-Institute/SCRAM/issues) or contact Andrew Gilbert (Andrew.Gilbert@briwildlife.org). Users that have species data to contribute for the three included species can contact Andrew Gilbert (Andrew.Gilbert@briwildlife.org). Links to the GitHub repository and to submit bug requests are also located in the header for the web app.

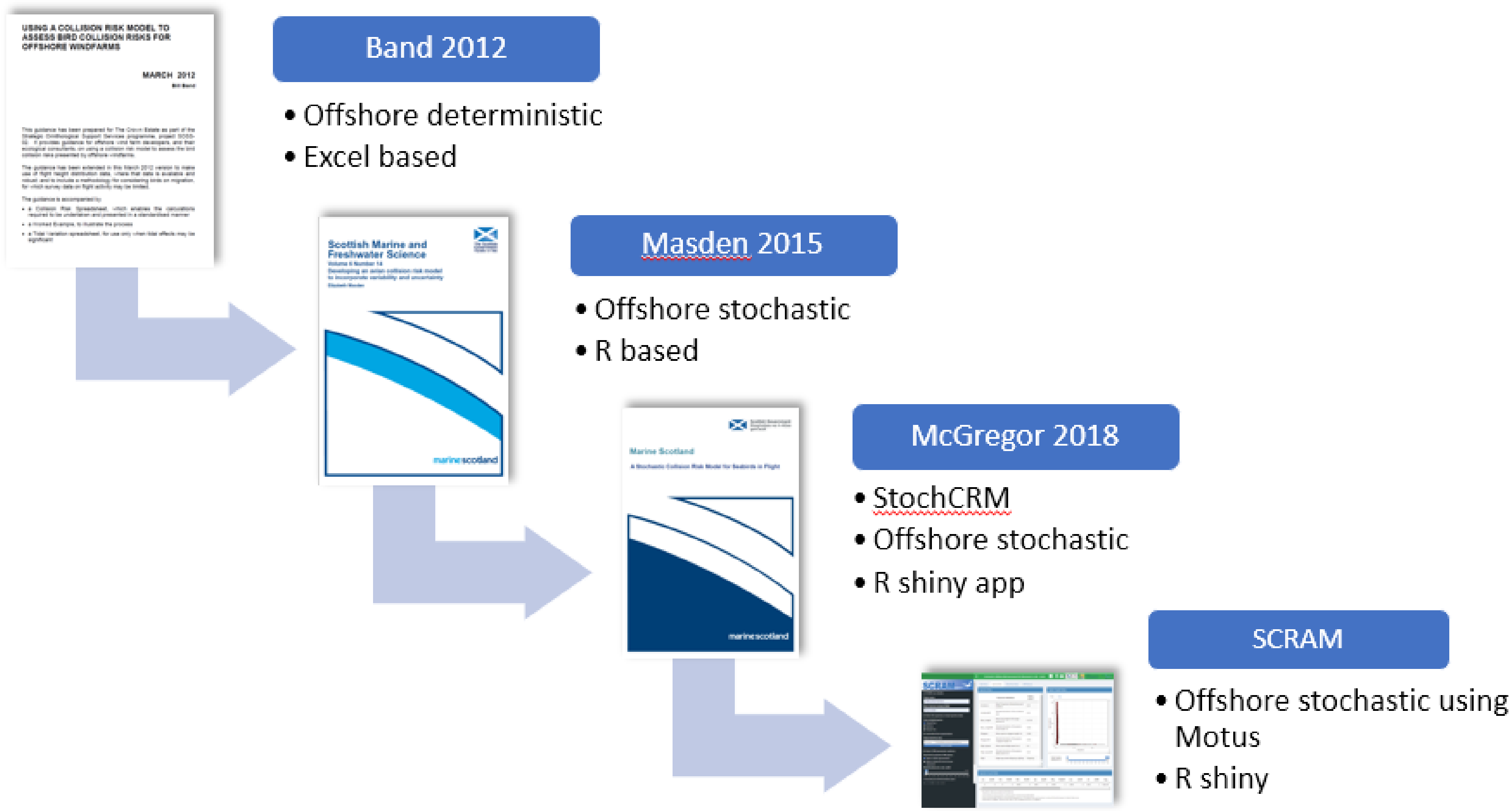

Figure 4. Derivation of SCRAM from prior offshore CRM models.
References for previous model iterations include:

Band B. 2012. Using a collision risk model to assess bird collision risks for offshore windfarms. The Crown Estate as part of the Strategic Ornithological Support Services Programme, Project SOSS- 02.
Masden E. 2015. Developing an avian collision risk model to incorporate variability and uncertainty. Scottish Marine and Freshwater Science 6(14).
McGregor R, King S, Donovan C, Caneco B, Webb A. 2018. A stochastic collision risk model for seabirds in flight. Marine Scotland, Issue 1, Document number: HC0010-400-001.

3.6.2 Running the SCRAM web application

A brief introduction to using SCRAM online is outlined below. Examples of SCRAM use are also provided in this report in the form of case studies (Section 4). Step-by-step instructions for using SCRAM can be found in the user manual, the most recent version of which is accessible by clicking the book button in the header of the web app (https://briloon.shinyapps.io/SCRAM/).

SCRAM requires two types of input data: 1) "Wind farm data," which users provide via a single spreadsheet of turbine and array characteristics, and 2) "Species data," which are incorporated into the tool for the three target species. Custom species data cannot be uploaded in the current version of SCRAM (Version 1.0.3), so the "baked-in" species data for the three case study species cannot be changed by users.

The application is built using a dashboard-type layout in which input is added on the left-hand side of the screen (the sideboard) and outputs are available on the tabs to the right of the sideboard in the main body of the dashboard (Fig. 5). Additional links and information are available in the header bar of the app. There are currently four tabs in the main body of SCRAM: "Start Here", "Species Data", "Wind Farm Data", and "CRM Results":

1) Start Here – this tab includes some basic instructions for use of SCRAM, as well as a button to download example wind farm data for use as a template for wind farm inputs.
2) Species Data – this tab includes tables of species data, monthly count data, and a plot of the flight height data that are included with SCRAM for Red Knot, Roseate Tern, and Piping Plover.
3) Wind Farm Data – A table showing the wind farm specifications and operational data for the uploaded wind farm, as well as a map of the wind farm location with the ability to look at the predicted occupancy probabilities for the target species. Multiple sets of wind farm characteristics (such as different turbine models) can be included in the same table, though the location (latitude and longitude) of the wind farm must be the same for all iterations included in the same model run.
4) CRM Results – This tab is where basic output is provided following a model run. Outputs are provided as a histogram of the number of collisions per year for each iteration. This tab is also where the user can perform a sensitivity analysis, download data, and download a PDF report of the SCRAM results.

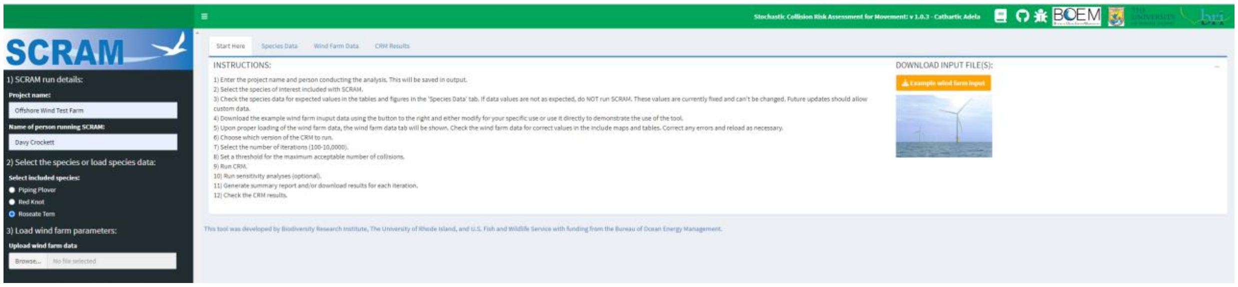

Figure 5. SCRAM overview screen.

Before running SCRAM, the user must gather the data for turbine and array characteristics to input into the model. An example input file is available through the "Example wind farm input" button on the start screen, which can be populated with wind-farm specific parameters. Details on wind farm input are discussed below (Section 4). The interface was created to lead users through the processes for data input and model run, with some inputs not available to the user until the prior input has been entered in SCRAM. This provides an efficient and intuitive workflow designed to maximize efficiency and minimize errors.

SCRAM is currently only designed to work with the three focal species Red Knot, Roseate Tern, and Piping Plover. Once the wind farm data are loaded and the species is selected, the wind farm and species data are presented on two separate tabs as maps and tables to review (Figs. 6-7). The user is encouraged to review these data to make sure that the included parameters for species are appropriate for your application and that the wind farm data are accurate prior to running SCRAM. However, currently, species data can't be changed and so the only options are to proceed with the provided data or terminate the model run. Also, only one wind farm location may be inputted at a time, and if the wind farm data includes more than one set of geographic coordinates (latitude/longitude), only the coordinates from the first row will be used for model output. To run multiple locations for SCRAM, you must run SCRAM multiple times and change the geographic coordinates for each run. So long as the geographic coordinates are the same, multiple sets of wind farm characteristics (such as different turbine models) can be included in the same wind farm data table.

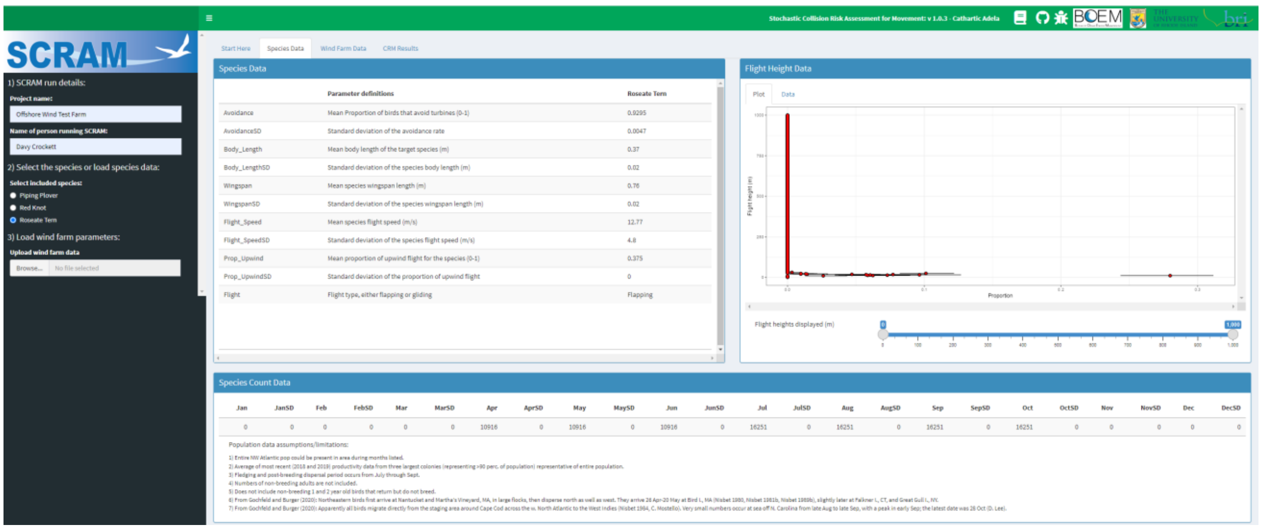

Figure 6. Species data tab showing the species data used in SCRAM for modeling.

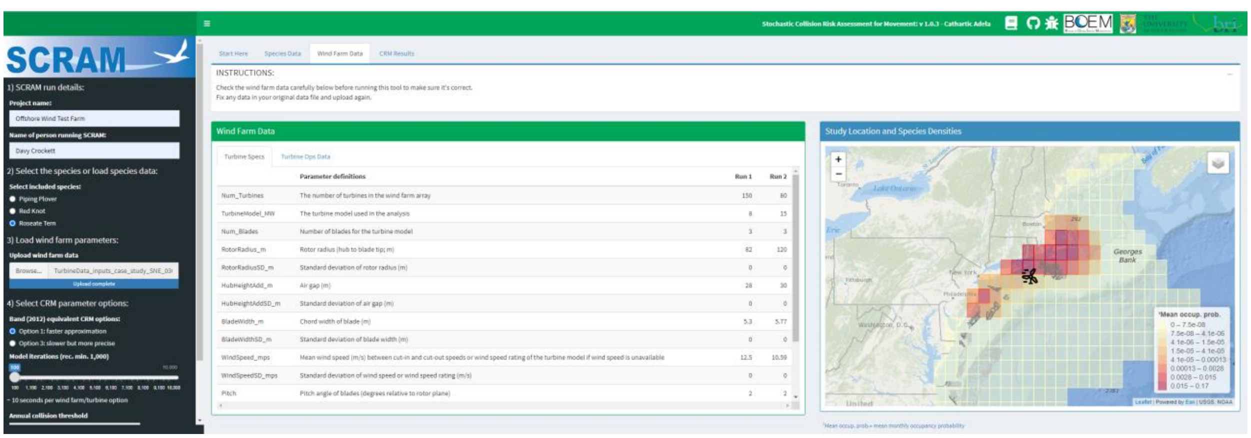

Figure 7. Wind farm data and species occurrence modeling probability of occurrence map on the Wind Farm Data tab.

The principles that CRMs use to simulate collision risk are relatively simple, but there are two options for how these principles are executed that differ in how input data are used in the underlying calculations (see "Collision risk modeling," above). Band (2012), Masden (2015), and Trinder (2017) provided several options, which we synthesized to provide two options – one that we have shown performs best and one that gives approximate estimates in much less time (Fig. 8). When the user selects "Option 1: faster approximation", SCRAM does not model risk along the rotor; it is presumed to be constant throughout the RSZ, and as a result the model is faster to run. When using "Option 3: slower but more precise", SCRAM allows collision risk to vary at different altitudes along the rotor blades and thus provides a more precise accounting of collision risk (Trinder 2017) but is slower to run. We recommend selecting "Option 3: slower but more precise" whenever the user is not severely limited by computation time, and ONLY Option 3 should be used to develop final estimates of collision risk.

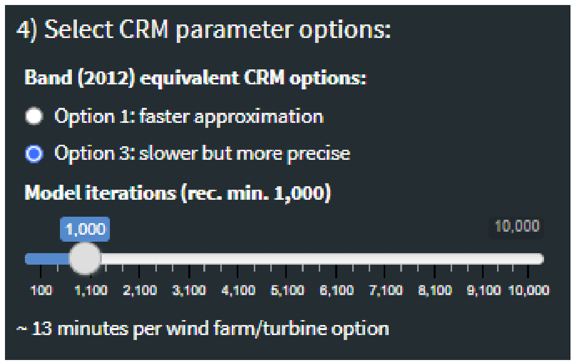

Figure 8. SCRAM CRM model options.

SCRAM asks the user to specify the number of model iterations (Fig. 8) in order to propagate the influence of parameter uncertainty on the simulation results. In this sCRM framework, uncertainty – i.e., variation in the results among iterations – is a result of the variance estimates provided for the input parameters. Increasing the number of iterations will give more precise estimates for the model outputs, until the error associated with estimating outputs via stochastic simulation is arbitrarily small, which is around 10,000 iterations for this model, beyond which additional iterations do not provide better information. Thus, we have capped the number of iterations at 10,000 in SCRAM.

Finally, the user can provide a threshold of annual maximum acceptable number of collisions (this number can be zero). This value does not affect the model, but will ensure that the report includes a probability that the selected value will be exceeded in a year. This is done by calculating the proportion of all model runs that have annual collision estimates in excess of that value. For example, if 200 iterations were run of the model and 28 runs exceeded an annual collision threshold value of 2, then the result would be a 14% chance (28/200*100) of collisions exceeding that threshold in a year.

The user can select "Run CRM" when they have all parameters set. The tool will provide a dialog box showing the percentage completed so that the user can follow progress of SCRAM. A separate button allows SCRAM to be canceled once started.

Once the model has completed, the CRM results tab (Fig. 9) displays basic results including details of the model run times, the model that was run, probability of exceeding the selected annual collision threshold, and histograms (one for each wind farm option) of the number of collisions per year for each iteration.

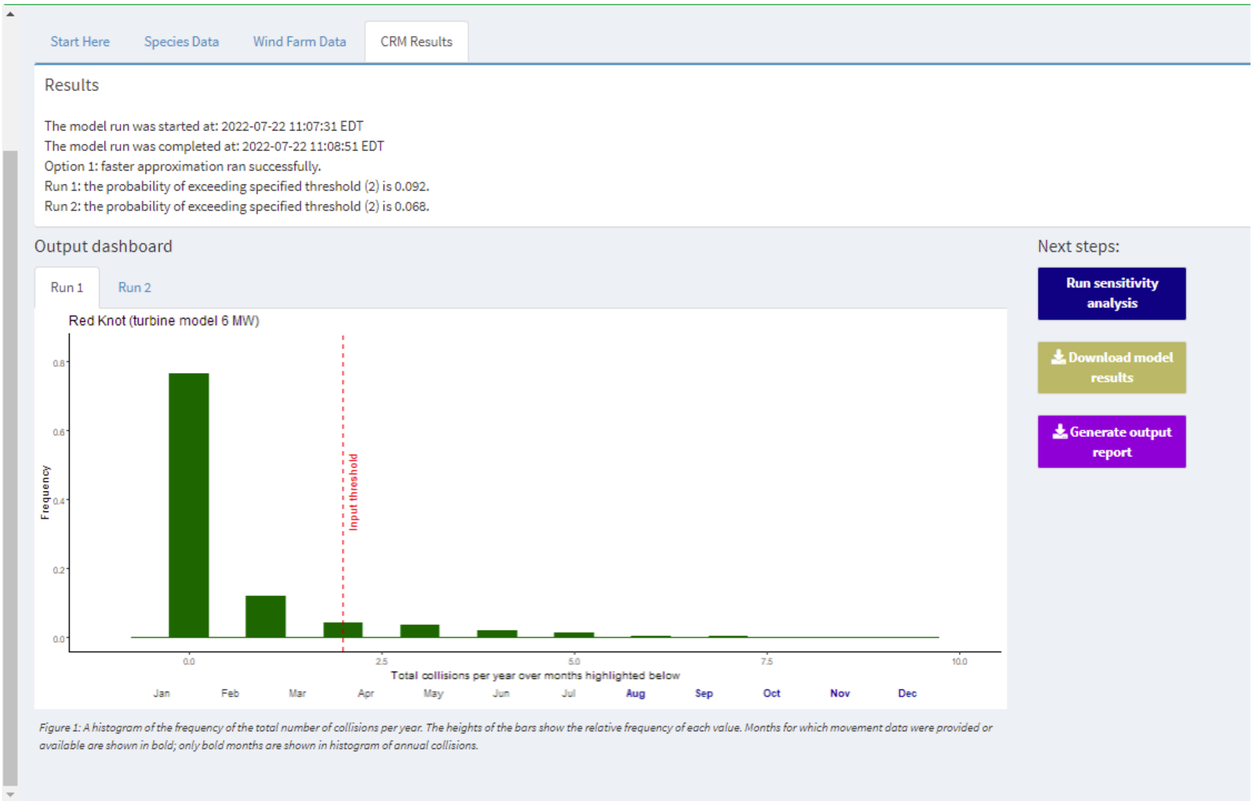

Figure 9. SCRAM results tab.

The CRM results tab provides three buttons to complete the SCRAM analysis.

1. Run sensitivity analysis (optional)
2. Download model results (optional)
3. Generate output report (optional)

SCRAM provides the option to run a simple sensitivity analysis that determines the relative contribution of the input parameters to the uncertainty bounds of the results. We have provided this option as a general guide for determining where (e.g., for which parameters) more precise data are likely to lead to the biggest gains in our understanding of collision risk for the species and arrays of interest. We do not recommend running sensitivity analyses when the number of iterations is less than 1000. For the 10 most influential parameters, the analyses provide estimates of the proportion of the variation in the results that is contributed by each parameter. For example, if the value for turbine avoidance rate is 0.12, approximately 12% of the width of the final uncertainty bounds is a result of uncertainty in our understanding of avoidance behavior. The analyses provided in SCRAM are approximate (see Borcard 2002 for details on the methods) due to computational constraints, so we recommend using this option as a rough guide for understanding parameter sensitivity or potentially planning additional sensitivity analyses. The results are saved to a .csv file that can be exported from the application using the "Download model runs" button.

Once the model has run successfully, the option to download the full results will appear. When the user clicks the button, a file save dialog box will appear with the ability to browse to a location for saving as well as change the compressed file name. A compressed file will be downloaded containing the following files:

1. The original wind farm data file that was uploaded

2. Species movement model data files (zipped)
3. Species flight height modeled data as a .csv file
4. Species population data
5. Model output Rdata file that can be directly loaded in R
6. Estimated number of birds in the model cell and wind farm per day as .csv files
7. Collision estimates for each month as daily and monthly estimates in each iteration as .csv files
8. The stochastic draws of all input parameters for each iteration as a .csv file
9. Sensitivity analysis results as a .csv file (if run)

The user can also download a custom PDF report for the model runs by clicking the "Generate output report" button. The report provides details about the model run (SCRAM version, number of model iterations, type of model run, model options, proportion in transient mode, project, user, run times, and probability of exceeding the user-specific collision risk threshold), model input parameters including both species and wind farm parameters, wind farm and species occurrence map, a table of the monthly mean and 95% prediction intervals for estimated collisions and the annual cumulative number of collisions and range, a histogram of the number of collisions per year for all iterations, and a figure showing the mean and 95% prediction interval number of collisions per month for each species and turbine model combination along with the estimated monthly collision threshold.

4 Case Studies: Estimating Single Project Impacts to Three Federally Protected Species

We used SCRAM to assess collision risk for a hypothetical 1.2 GW offshore wind project located in the NES region. We evaluated risk for two turbine models (8 MW and 15 MW) selected to represent a range of capacities currently under consideration for development in the NES (Table 4). The specifications for each turbine came from published documentation on reference turbines for 8 MW (Desmond et al. 2016) and 15 MW (Gaertner 2020) models. The 8 MW reference turbine document did not have blade width information, so we used methods in Ju et al. (2020) to estimate blade width using a scaling factor.

The wind project area used for the case study is located in the southern New England portion of the NES region offshore of Rhode Island Sound. We selected this location because there are no active BOEM lease or planning areas within the project footprint and it is centrally located among tag deployment locations for the three focal species. The project footprint covers an area of 24 km^2 with a centroid at 40.709, -71.2739. This project footprint can accommodate 150 8-MW turbines spaced at approximately 1 nautical mile (1.852 km) or 80 15-MW turbines spaced at 1.44 nautical miles (2.67 km) for a total wind farm capacity of 1.2 GW.

Information on estimated operational data for wind farms in the U.S. is currently lacking. Therefore, wind farm operational data used in the case studies were from Masden (2015) and originated from an Environmental Statement from a wind farm in Europe (Table 5). The same operational data are used in the example wind farm input file for SCRAM.

For the case studies, we ran collision risk models with default species input data for each species: Piping Plover, Red Knot, and Roseate Tern. To estimate collision risk, we used the recommended Model Option 3 (slower but more precise), the minimum recommendation of 1,000 model iterations, and set the annual collision threshold = 1 (default).

Species-specific results are presented in the following sections. Risk estimates were calculated automatically by SCRAM and appear in the automated report generated by SCRAM. Results generated by SCRAM include monthly estimates and 95% prediction intervals for estimated collisions during each month with available movement data, and the annual estimates of collision risk calculated by summing the monthly posteriors from the model across all months with movement data and then calculating the mean and 95% prediction intervals from the summed posteriors. It is important to emphasize that annual collision estimates do not include months that lack movement data. Therefore, annual estimates should be considered minimum estimates that only pertain to the months for which at least 5 birds were tracked for a given species (noted in the below case studies and in Tables B1, B3, and B5 of this report, as well as in output reports generated during SCRAM model runs). **Assessments of take should use the 95% prediction interval, rather than the mean estimate of monthly collisions across all model iterations. The 95% prediction interval better accounts for uncertainty in the input data and in resulting model estimates. Thus, to assess collision risk over the operational lifespan of the facility (assumed 30 years), we multiplied annual collision risk prediction intervals by 30.** These case studies are intended to serve as a general template for species-specific collision risk assessments conducted using SCRAM.

Table 4. Input parameters and source information for turbine specifications used in the case studies.

Parameter	Parameter definitions	Run 1	Run 2
Num_Turbines	The number of installed turbines	150	80
TurbineModel_MW	The turbine model option or MW rating of the turbine. In SCRAM, this is purely for labeling purposes only and does not affect the results.	8	15
Num_Blades	The number of installed blades on each turbine	3[1]	3[2]
RotorRadius_m	The radius (meters) of the rotor from blade tip to middle of the rotor nacelle (axis of rotation)	82[1]	120[2]
RotorRadiusSD_m	The standard deviation of the rotor radius (meters). We recommend setting this value to 0.	0	0
HubHeightAdd_m	The distance between sea level at highest astronomical tide and the lower blade tip (meters), also referred to as the air gap. From this value the hub height is calculated and presented in the output.	28[1]	30[2]
HubHeightAddSD_m	The standard deviation of the air gap (meters). We recommend setting this value to 0.	0	0
BladeWidth_m	The turbine blade width (meters).	5.3[3]	5.77[2]
BladeWidthSD_m	The standard deviation of the turbine blade width (meters). We recommend setting this value to 0.	0	0
WindSpeed_mps	Mean wind speed at the wind farm (meters per second) for the periods during which wind speeds are between cut-in and cut-out speeds of the turbine (i.e., turbines could be spinning); or if not available, the rated wind speed of the turbines. The turbine wind speed rating is the wind speed at which maximum power production occurs.	12.5[1]	10.59[2]
WindSpeedSD_mps	The standard deviation in wind speeds or wind speed rating (meters per second). We recommend setting this value to 0 unless data can be obtained on the variation in wind speeds or wind speed rating relative to the model turbine.	0	0
Pitch	The average angle of the blade (degrees) relative to the rotational plane of the blades while the turbine is spinning.	2[4]	2[4]
PitchSD	The standard deviation in pitch (degrees).	0.1[4]	0.1[4]
WFWidth_km	Wind farm width (km). If the wind farm is not square, use (length + width)/2 of the wind farm or total perimeter length/4 if an irregular shape.	24	24
Latitude	Latitude (decimal degrees) of wind farm centroid	40.709	40.709
Longitude	Longitude (decimal degrees) of wind farm centroid	-71.2739	-71.2739

Sources: [1] Desmond et al. 2016, [2] Gaertner 2020, [3] Ju et al. 2020, [4] Donovon 2017, [5] Band 2012

Table 5: Monthly wind farm operational parameters used in the case studies.

Values represent percentages of operational time per month. Source: Masden 2015.

Month	Op[1]	OpMean[2]	OpSD[3]
Jan	96.28	6.3	2
Feb	96.53	6.3	2
Mar	95.83	6.3	2
Apr	92.78	6.3	2
May	90.86	6.3	2
Jun	92.22	6.3	2
Jul	89.11	6.3	2
Aug	89.92	6.3	2
Sep	93.71	6.3	2
Oct	96.14	6.3	2
Nov	97.14	6.3	2
Dec	96.41	6.3	2

[1] Op: Wind availability, the maximum amount of time turbines can be operational/month depending on wind speeds and cut-in and cut-out speeds of the turbine.
[2] OpMean: Mean time that turbines will not be operational ("down time"), assumed to be independent of "MonthOp" – i.e., total operation = MonthOp*(1 – MonthOpMean).
[3] Standard deviation of mean operational time.

4.1 Roseate Terns

Collision risk for Roseate Terns was evaluated using default species input data in SCRAM. Movement data and flight height distributions were estimated from Roseate Terns tagged during the mid-incubation period and tracked during the post-breeding dispersal period (Figs. 10-11). Collision risk was only evaluated for months with sufficient movement data (June to September).

For each turbine model (8 MW and 15 MW), the probability of exceeding the specified threshold (1) in a single year was <0.001. This indicates that zero of the 1,000 model iterations estimated collisions equal to or greater than one bird annually over the months evaluated (June to September). For the 8 MW turbine model, total number of estimated annual collisions from June to September was 0.00012 to 0.00012 birds (95% prediction interval); with an estimated mean of 0.00012 birds. For the 15 MW turbine model, total number of estimated annual collisions from June to September was 0.00012 to 0.00012 birds (95% prediction interval); the mean estimate was 0.00012 birds. Across the 30-year operational lifespan of the facility, the total number of estimated collisions from June to September was between 0.0036 and 0.0036 birds (mean estimate of 0.0036 birds) for the 8 MW turbine model and between 0.0036 and 0.0036 birds (with a mean estimate of 0.0036 birds) for the 15 MW turbine model.

This hypothetical offshore wind facility had no collisions predicted for Roseate Terns during mid-incubation to post-breeding period (June to September) for either the 8 MW turbine model or the 15 MW turbine model (Fig 12). Collision risk during other portions of the annual cycle when Roseate Terns occur in the NES (e.g., fall migration and spring migration to the mid incubation period) was not evaluated due to lack of movement data collected during these time periods. Therefore, annual and operational collision risk estimates should be considered partial estimates. In addition, SCRAM assumes that each individual in a grid cell has one opportunity to collide with a turbine per day. For seabirds such as terns that spend a large proportion of their time in marine environments, this assumption could be inappropriate.

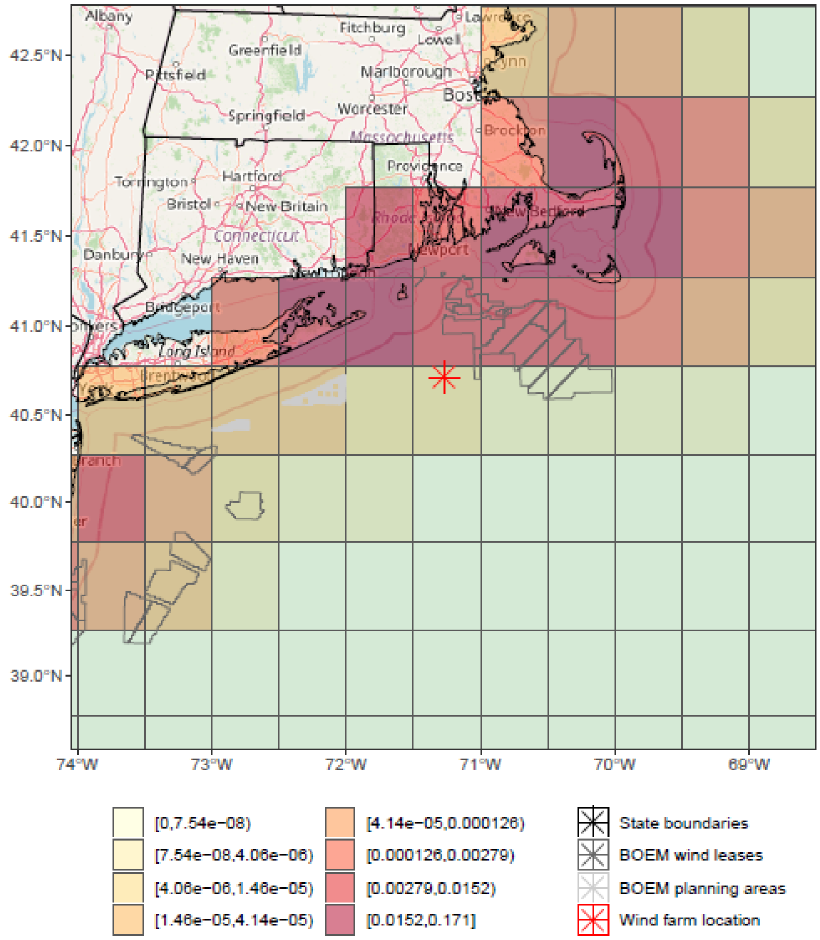

Figure 10. Roseate Tern mean summed monthly occurrence probability and wind farm location used in case study example.
Map from automated report generated by SCRAM.

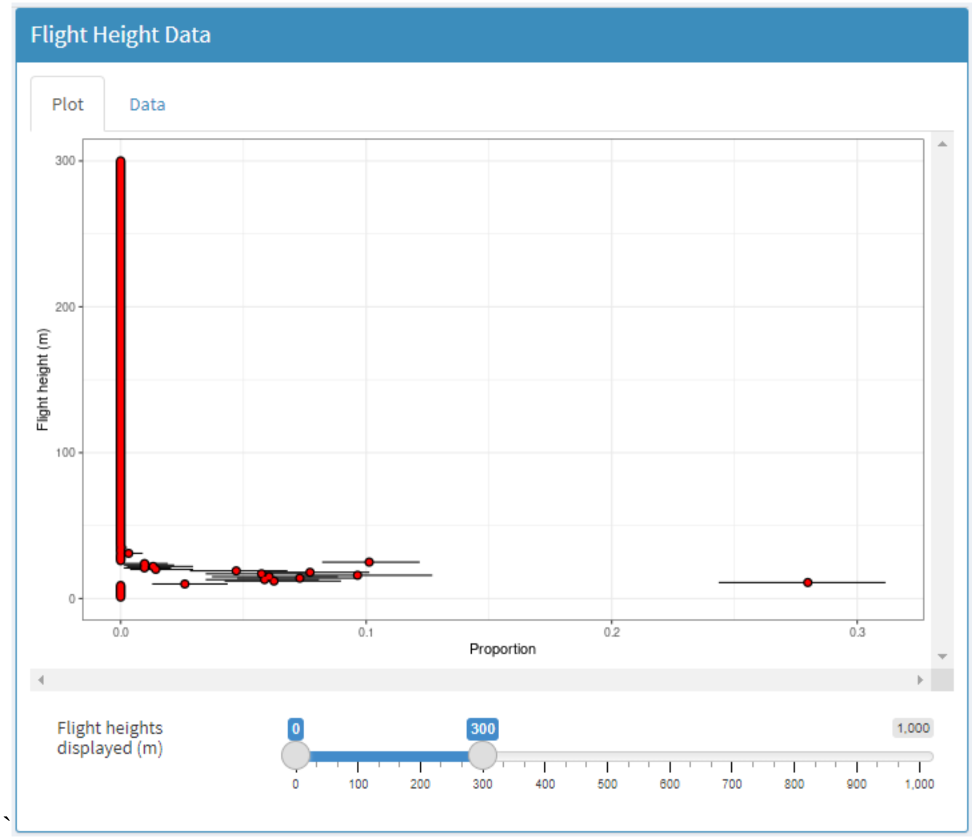

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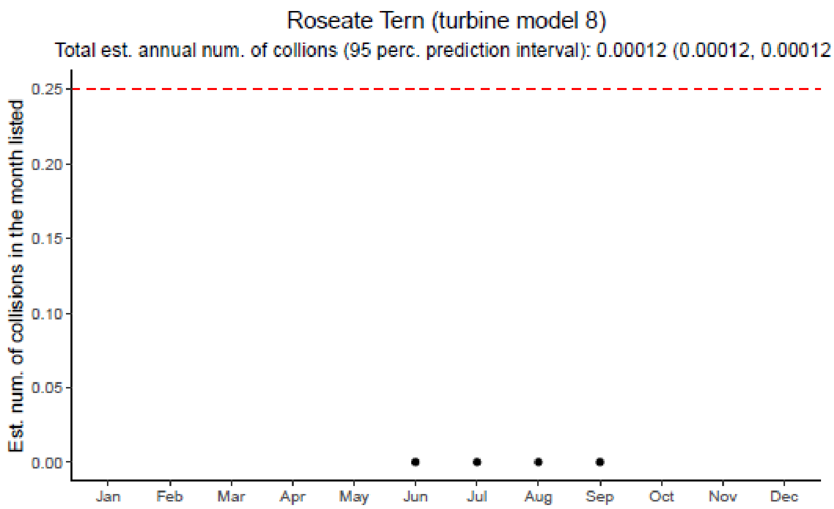
Figure 11. Roseate Tern flight height distribution relative to the rotor-swept zone of offshore wind turbines used in case study (RSZ min: 28 m asl, max: 270 m asl).
Data from SCRAM user interface.



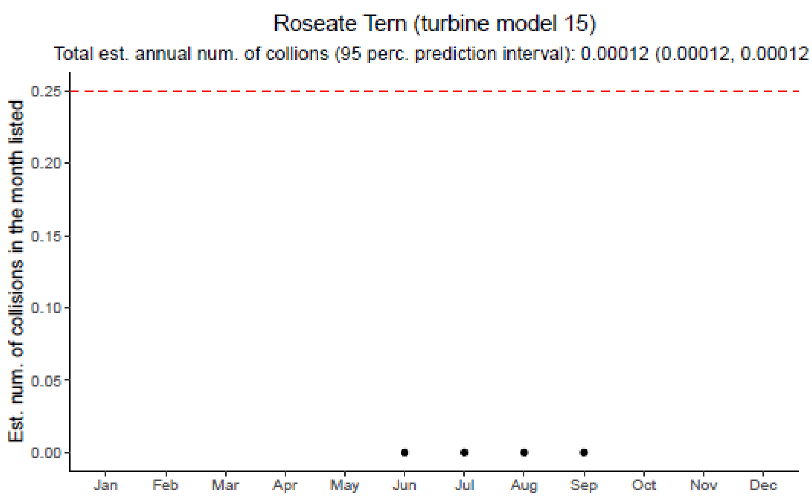


Figure 12. The predicted mean and 95% prediction intervals of the number of collisions per month for an 8 MW turbine (top) and a 15 MW turbine (bottom).
Results are not shown for months that do not have movement data. Total annual collision rate and 95% prediction interval are given at top. The threshold is shown divided by the number of months that movement data were available.

4.2 Piping Plovers

Collision risk for Piping Plovers was evaluated using default species input data in SCRAM. Movement data and flight height distributions were estimated from Piping Plovers tagged during the mid-incubation period and tracked during a portion of their fall migration (Figs. 13-14). Collision risk was only evaluated for months with movement data (May to September).

For each turbine model (8 MW and 15 MW) the probability of exceeding the specified threshold (1) in a single year was <0.001. This indicates that zero of the 1,000 model iterations estimated collisions equal to or greater than one bird annually over the months evaluated (May to September). For the 8 MW turbine model, total number of estimated annual collisions from May to September was between 0.00015 and

0.0325 birds (95% prediction interval), with a mean of 0.0076 birds. For the 15 MW turbine model, total number of estimated annual collisions from May to September was 0.00015 to 0.0299 birds (95% prediction interval), with a mean of 0.00742 birds. Across the 30-year operational lifespan of the facility, the total number of estimated collisions from May to September for the 8 MW turbine model was between 0.0045 and 0.975 birds (95% prediction interval), with a mean estimate of 0.228 birds, and for the 15 MW turbine model was between 0.0045 and 0.897 birds (95% prediction interval) with a mean estimate of 0.2226 birds. This hypothetical offshore wind facility had a non-zero annual risk of collisions for Piping Plovers during the mid-incubation period through a portion of their fall migration (May to September). There was similar estimated collision risk associated with 8 MW turbine models relative to 15 MW turbine models during the months at which collision risk was assessed. Across the months and turbine models evaluated, collision risk was slightly higher during June and July but remained low overall (Fig. 15). Collision risk during other portions of the annual cycle when Piping Plovers occur in the NES (e.g., latter portion of fall migratory flights, spring migration and staging) was not evaluated due to lack of movement data collected during these time periods. Therefore, annual and operational collision risk estimates should be considered partial estimates.

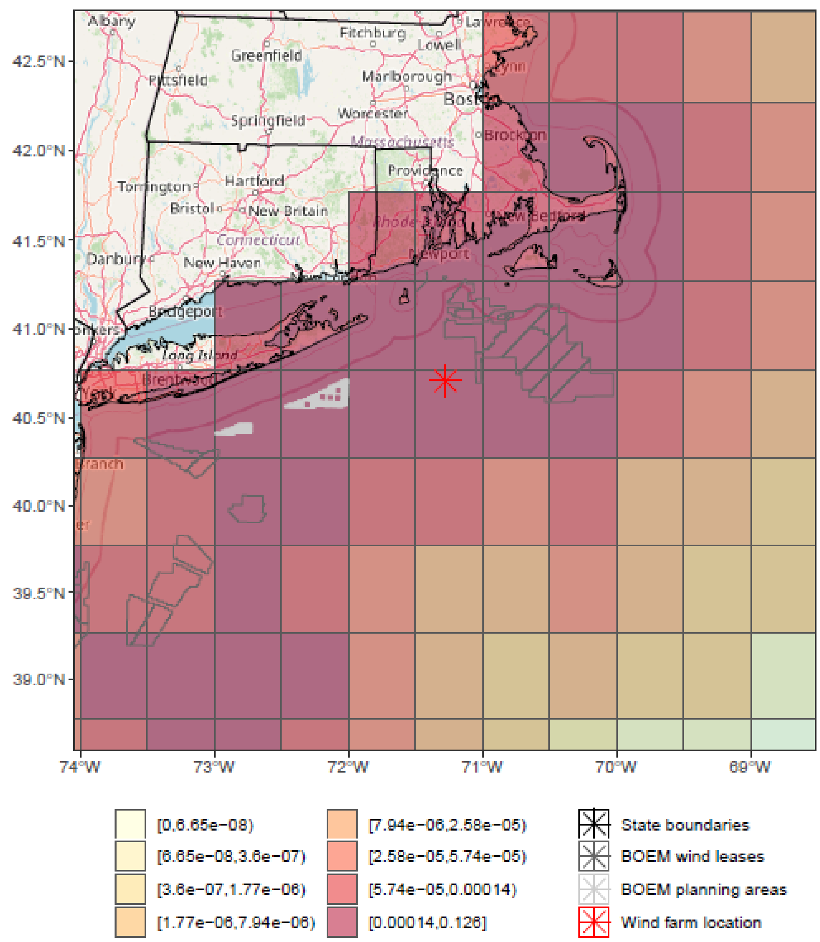


Figure 13. Piping Plover mean summed monthly occurrence probability and wind farm location used in case study example.
Map from automated report generated by SCRAM.

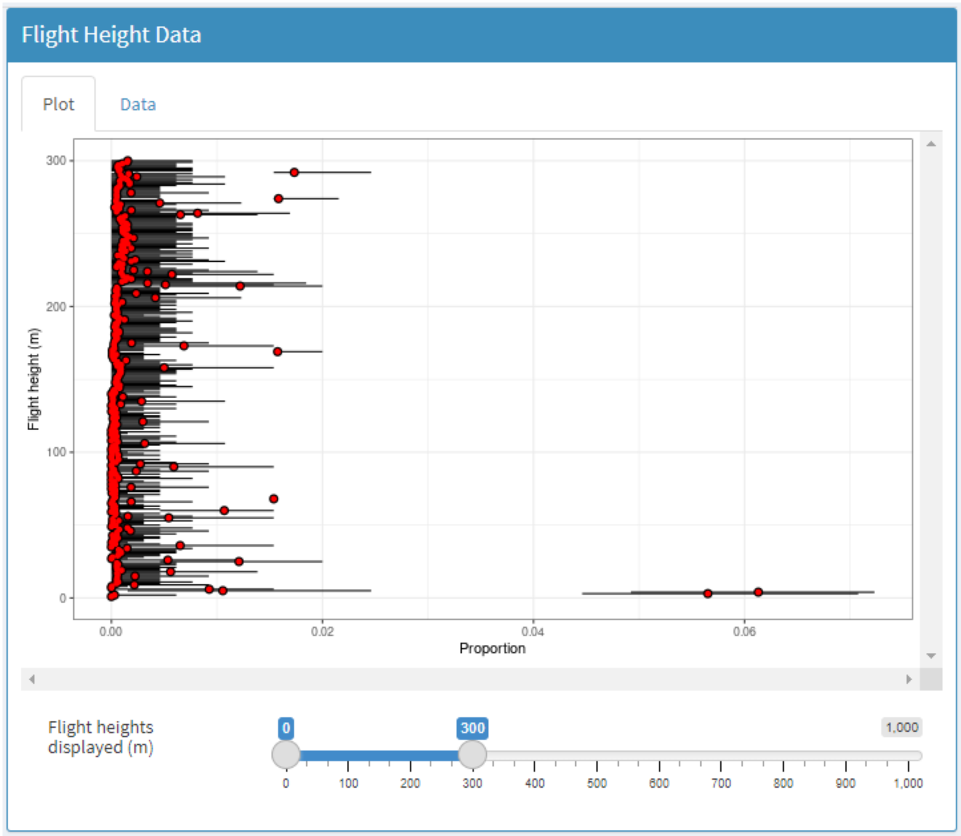


Figure 14. Piping Plover flight height distribution relative to the rotor-swept zone of offshore wind turbines used in case study (RSZ min: 28 m asl, max: 270 m asl).
Data from SCRAM user interface.

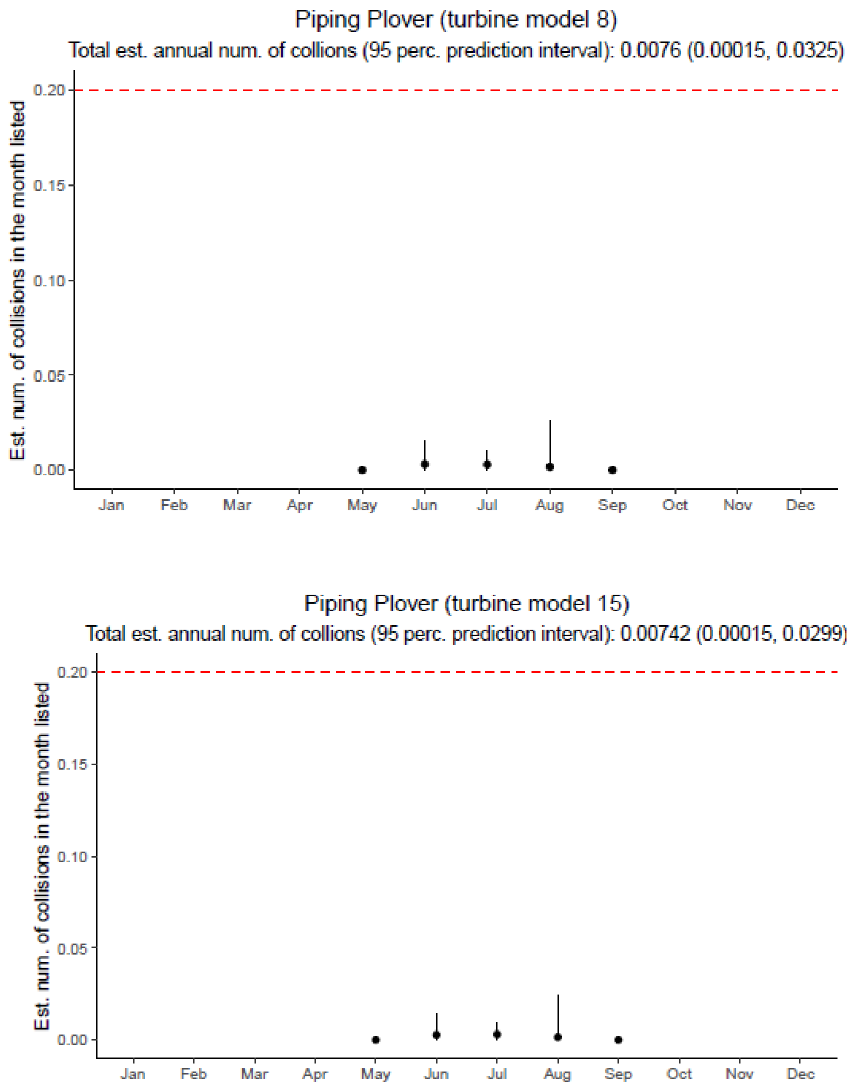


Figure 15. The predicted mean and 95% prediction intervals of the number of collisions per month for an 8 MW turbine (top) and a 15 MW turbine (bottom).
Results are not shown for months that do not have movement data. Total annual collision rate and 95% prediction interval are given at top. The threshold is shown divided by the number of months that movement data were available.

4.3 Red Knots

Collision risk for Red Knots was evaluated using default species input data in SCRAM. Movement data and flight height distributions were estimated from Red Knots tagged during the fall staging period and tracked during a portion of their fall migration (Figs. 16-17). Collision risk was only evaluated for months with movement data (August to November).

For each turbine model (8 MW and 15 MW) the probability of exceeding the specified threshold (1) in a single year was < 0.001. This indicates that zero of the 1,000 model iterations estimated collisions equal to or greater than one bird annually over the months evaluated (August to November). For the 8 MW turbine model, total number of estimated annual collisions from August to November was 0.00012 to 0.577 birds (95% prediction interval), with a mean estimate of 0.102 birds. For the 15 MW turbine model, total number of estimated annual collisions from August to November was 0.00012 to 0.529 birds (95% prediction interval), with a mean estimate of 0.093 birds. Across the 30-year operational lifespan of the facility, the total number of estimated collisions from August to November was between 0.0036 to 17.31 birds for an 8 MW turbine model (with a mean estimate of 3.06 birds) and between 0.0036 and 15.87 birds for a 15 MW turbine model (with a mean estimate of 2.79 birds).

This hypothetical offshore wind facility had a non-zero annual risk of collisions for Red Knots during the fall staging period through a portion of their fall migration (August to November). There was slightly higher estimated collision risk associated with 8 MW turbine models relative to 15 MW turbine models during the months at which collision risk was assessed. Across the months and turbine models evaluated, collision risk was highest during August and November (Fig. 18). Collision risk during other portions of the annual cycle when Red Knots occur in the NES (e.g., latter portion of fall migratory flights, spring migration and staging) was not evaluated due to lack of movement data collected during these time periods. Therefore, annual and operational collision risk estimates should be considered partial estimates.

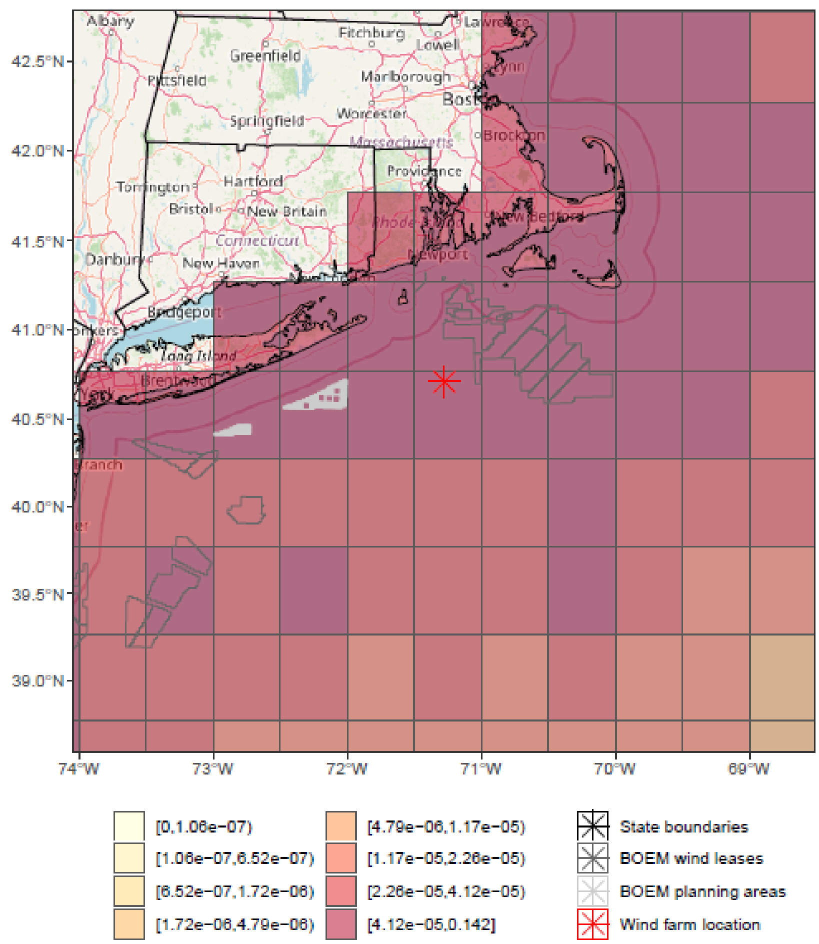


Figure 16. Red Knot mean summed monthly occurrence probability and wind farm location used in case study example.
Map from automated report generated by SCRAM.

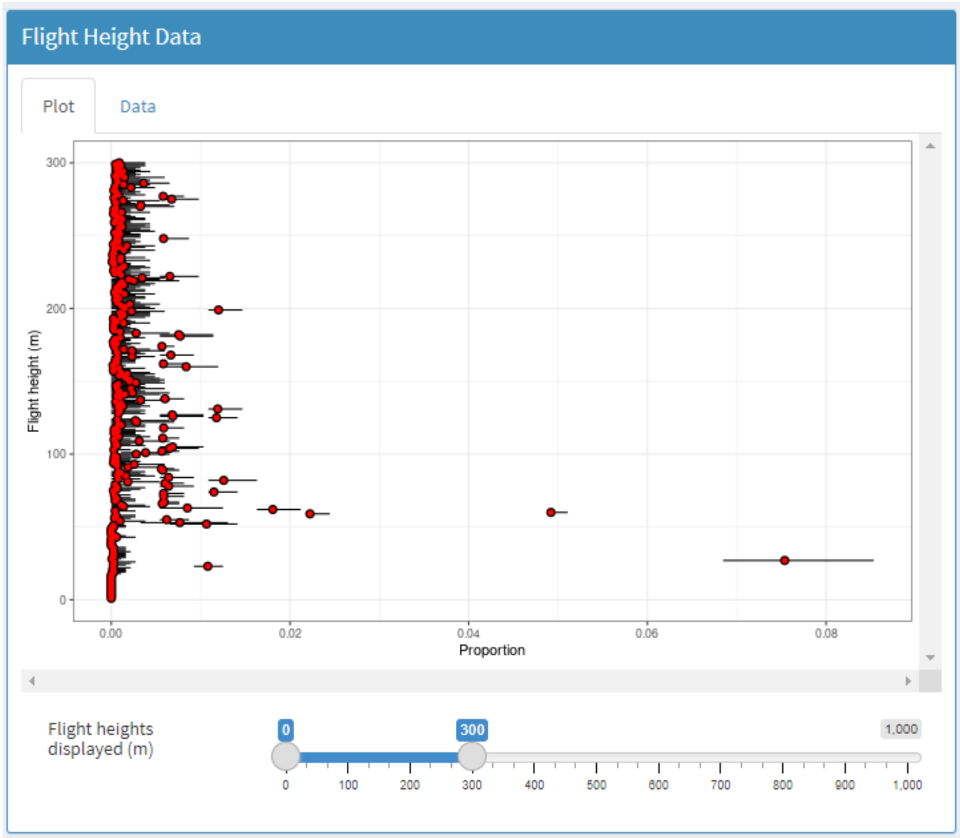
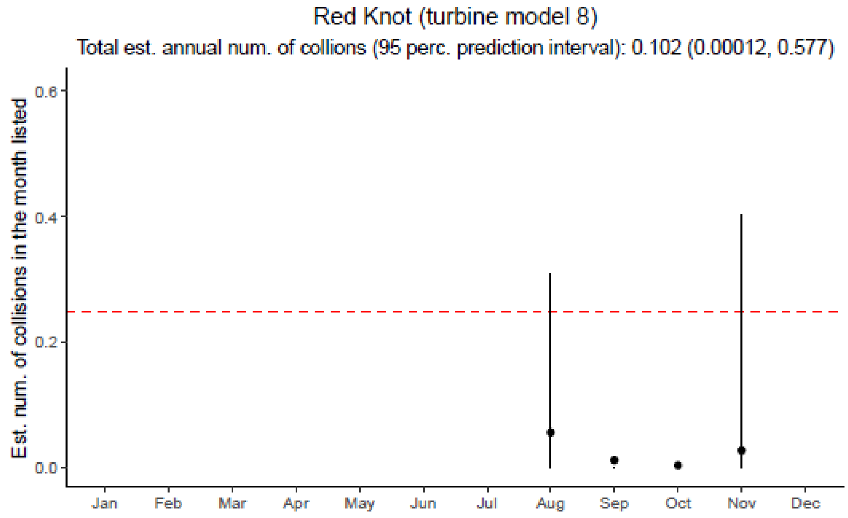


Figure 17. Red Knot flight height distribution relative to the rotor-swept zone of offshore wind turbines used in case study (RSZ min: 28 m asl, max: 270 m asl).
Data from SCRAM user interface.



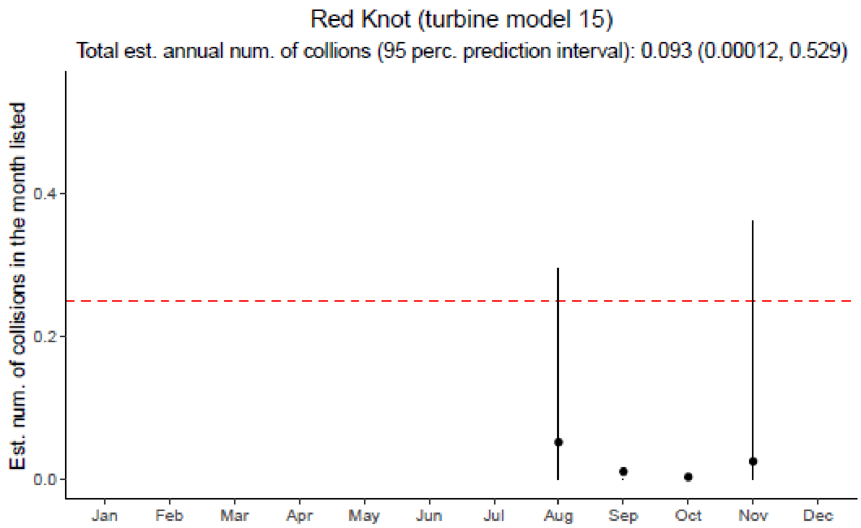


Figure 18. The predicted mean and 95% prediction intervals of the number of collisions per month for an 8 MW turbine (top) and a 15 MW turbine (bottom).
Results are not shown for months that do not have movement data. Total annual collision rate and 95% prediction interval are given at top. The threshold is shown divided by the number of months that movement data were available.

4.4 Recommendations for Implementing SCRAM for Risk Assessments

The case studies above provide a general template for implementing SCRAM for risk assessments. Due to the challenges of tracking small-bodied birds offshore, the species data in SCRAM have several notable limitations that should be clearly identified in assessments. Birds were tagged at a limited number of sites throughout their migratory range and tracked by land-based Motus stations with limited offshore detection range and geographic coverage, so the movement data may not be representative of the broader populations using the NES. Estimates of the size of the population present in the NES study area (Appendix B) are approximations. Flight height data were estimated from Motus data with high uncertainty. Estimates of avoidance rates are approximations based on data collected on gulls and terns in

Europe (Cook 2021) and do not account for variations in weather or lighting conditions that may affect responses of birds to wind turbines. Thirty-year risk assessments were made via extrapolation from a single year's collision estimates and do not account for potential changes in population size, distribution, or behavior over time. And as noted above, collision risk was not evaluated in SCRAM during portions of the annual cycle due to lack of movement data collected during these time periods. A description of these limitations should be included when implementing SCRAM for effects analyses so that the results can be interpreted in the context of the input data. Limitations are discussed in additional detail in Section 6.

To improve accuracy of risk assessments, we recommend that developers provide complete information on all turbine input parameters (Table 4) for their intended turbine models. If multiple options are being considered (e.g., project envelope), developers should provide complete information for all input values for the minimum-sized turbines and maximum-sized turbines being considered. For newer turbine models, detailed specifications may not be available. Therefore, the best available information should be used. For example, specifications for a 15 MW reference turbine can be found in Gaertner (2020). In addition, we recommend that developers provide the best available information on all operational parameters (Table 5) for their project area.

For consistency and transparency, all Construction and Operations Plans should include complete information on turbine input parameters following the format in Table 4 and complete information on operational parameters following the format in Table 5. Templates for these data may be found in Appendix C.

5 Initial Framework for Using SCRAM to Estimate Cumulative Impacts of Offshore Wind Development to Federally Protected Species

To address short-term needs for applying SCRAM in a cumulative effects context, we have developed an initial framework that makes use of the existing version of SCRAM to estimate collision risk across multiple offshore wind energy projects. Although cumulative effects analyses are an important component of risk assessments in the U.S. and Europe, there is currently no standardized approach for conducting these analyses (Masden 2009, Goodale and Milman 2016).

In this framework, we demonstrate an additive method that is consistent with current approaches used to assess potential cumulative effects of offshore wind energy development in Europe (e.g., Brabant et al. 2015, Busch and Garthe 2018). This method involves running SCRAM for each project site individually and summing site-specific results outside of the tool to estimate total collisions across multiple sites and years. Other anthropogenic stressors that may also affect populations of interest are not included in this assessment. This framework is intended to be a starting place for implementing CRMs in a cumulative effects context that could be improved upon in future model development efforts.

Below, we present an example that combines results for Red Knots from two hypothetical offshore wind facilities: the case study presented above, as well as estimated risk from a second hypothetical offshore wind facility in the NES.

5.1 Cumulative Risk Assessment Example - Red Knots

We demonstrate this framework using results from our case study on Red Knots for a wind farm located in the mid-Atlantic portion of the NES region, and by running SCRAM using the same input parameters as the case study for an additional hypothetical wind farm. This additional wind farm covers an area of 24 km^2 with a centroid at 37.956, -74.181. As with the case study in southern New England, this project footprint can accommodate 150 8-MW turbines spaced at approximately 1 nautical mile (1.852 km) or 80 15-MW turbines spaced at 1.44 nautical miles (2.67 km) for a total wind farm capacity of 1.2 GW. For the cumulative risk assessment, both wind farms are assumed to have a 30-year operational lifespan.

As with the case study, collision risk for Red Knots at the additional wind farm was evaluated using default species input data in SCRAM. Movement data and flight height distributions were estimated from Red Knots tagged during the fall staging period and tracked during a portion of their fall migration (Fig. 19). Collision risk was only evaluated for months with movement data (August to November). The probability of exceeding the specified threshold (1) in a single year was 0.001 for the 15 MW model and 0.002 for the 8 MW model. This indicates that a small number of the 1,000 model iterations estimated collisions equal to or greater than one bird annually over the months evaluated (August to November). For the 8 MW turbine model, total number of estimated annual collisions from August to November was between 0.00012 and 0.664 birds (95% prediction interval) with a mean estimate of 0.0703 birds. For the 15 MW turbine model, total number of estimated annual collisions from August to November was between 0.00012 and 0.572 birds (95% prediction interval) with a mean estimate of 0.064 birds. Across the 30-year operational lifespan of the facility, the total number of estimated collisions from August to November for the 8 MW turbine model was 0.0036 to 19.92 birds (95% prediction interval), with a mean estimate of 2.109 birds. For the 15 MW turbine model, the total number of estimated collisions from August to November across the 30-year operational lifespan of the facility was between 0.0036 and 17.16 birds (95% prediction interval), with a mean estimate of 1.92 birds. Across the months and turbine models evaluated, collision risk was highest during November (Fig. 20).

We evaluated cumulative risk for Red Knots from 1) the case study wind farm located offshore of Rhode Island Sound, and 2) the additional wind farm in the mid-Atlantic, using an additive approach annually and across the 30-year operational lifespan of the facilities (Table 6). For the 8 MW turbine model, total number of estimated annual collisions from August to November for both facilities combined was 0.00024 to 1.241 birds (95% prediction interval), with a mean estimate of 0.1723 birds. For the 15 MW turbine model, total number of estimated annual collisions from August to November for both facilities combined was 0.00024 to 1.101 birds (95% prediction interval), with a mean estimate of 0.157 birds. For both facilities combined, across the 30-year operational lifespan, the total number of estimated collisions from August to November for the 8 MW turbine model was 0.0072 to 37.23 birds (95% prediction interval), with a mean estimate of 5.169 birds. For both facilities combined, across the 30-year operational lifespan, the total number of estimated collisions from August to November for the 15 MW turbine model was 0.0072 to 33.03 birds (95% prediction interval), with a mean estimate of 4.71 birds.

Across both wind farms evaluated, there was slightly higher estimated collision risk associated with 8 MW turbine models relative to 15 MW turbine models during the months at which collision risk was assessed. Cumulative collision risk during other portions of the annual cycle when Red Knots occur in the NES (e.g., latter portion of fall migratory flights, spring migration and staging) was not evaluated due to lack of movement data collected during these time periods. Therefore, cumulative estimates of annual and operational collision risk should be considered partial estimates.

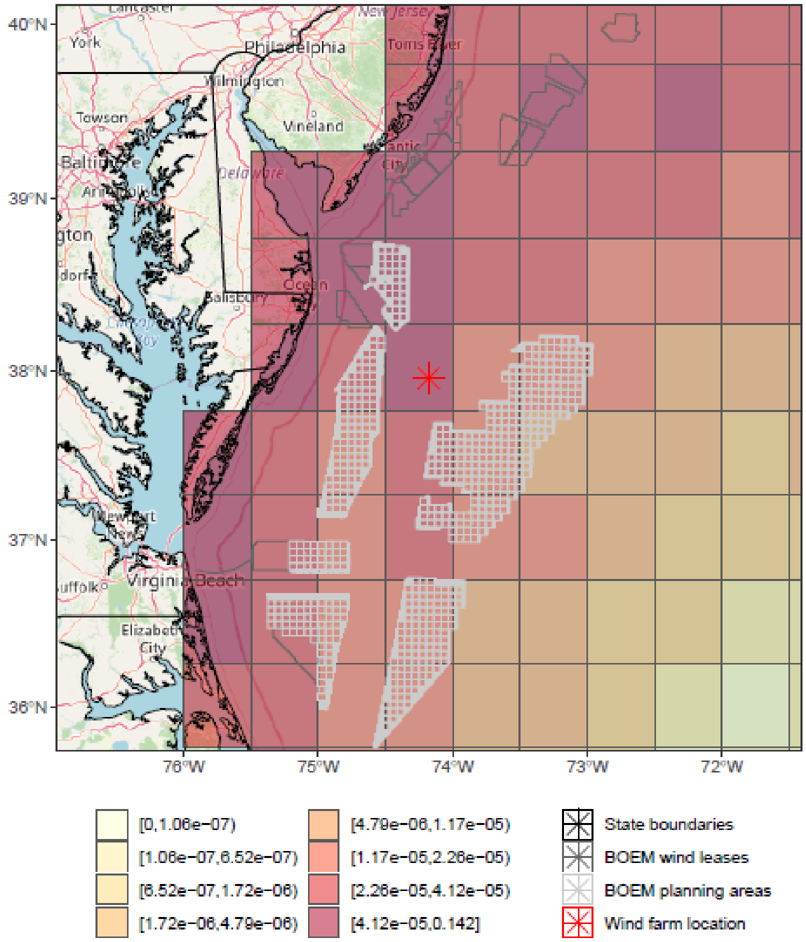
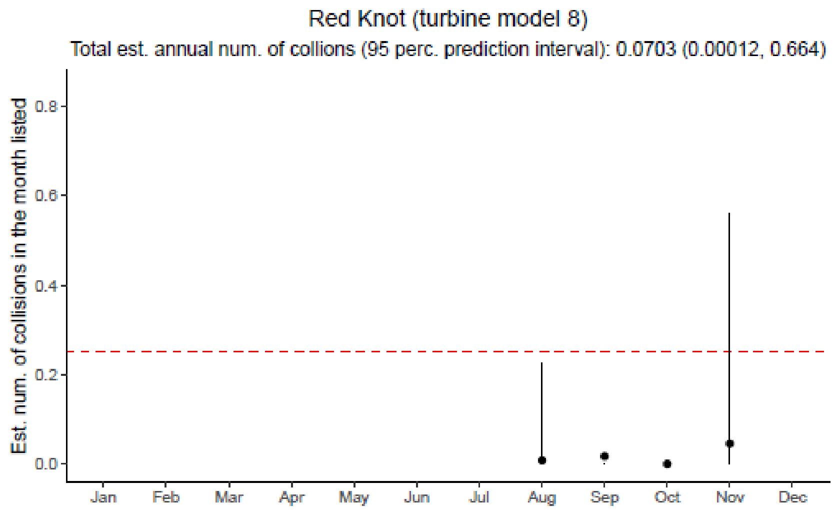


Figure 19. Red Knot summed monthly occurrence probability and location of wind farm in the mid-Atlantic used for cumulative risk assessment example.
Map from automated report generated by SCRAM.



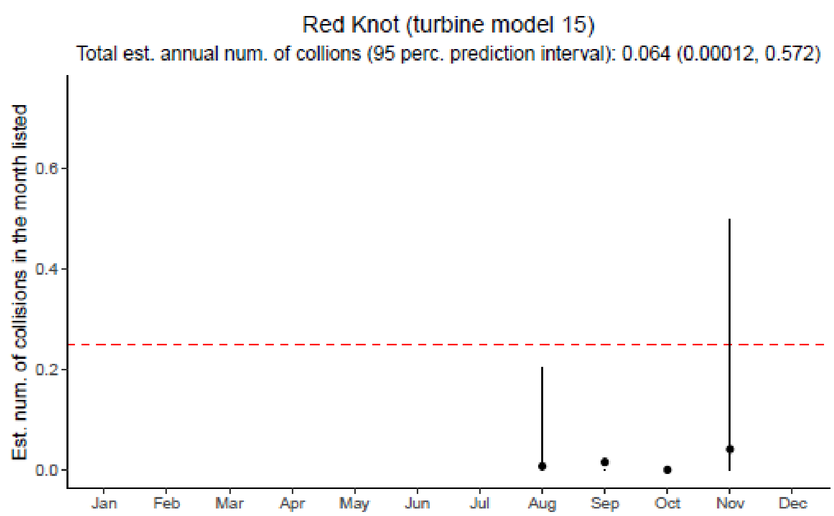


Figure 20. The predicted mean and 95% prediction intervals of the number of collisions per month at the mid-Atlantic wind farm for an 8 MW turbine (top) and a 15 MW turbine (bottom).
Results are not shown for months that do not have movement data. Total annual collision rate and 95% prediction interval are given at top. The threshold is shown divided by the number of months that movement data were available.

Table 6. Assessment of annual, operational, and cumulative risk (number of collisions) for Red Knots at the case study wind farm south of Rhode Island Sound and additional wind farm in the mid-Atlantic U.S.

Mean and 95% prediction intervals (lower and upper bounds) are shown for each turbine model evaluated (8 MW and 15 MW).

	Turbine Model	Annual Risk		Operational (30 year) Risk		Annual Risk	Operational Risk
		Case Study	Mid Atlantic	Case Study	Mid Atlantic	Cumulative	Cumulative
Lower 95% bound	8 MW	0.00012	0.00012	0.0036	0.0036	0.00024	0.0072
Upper 95% bound	8 MW	0.577	0.664	17.31	19.92	1.241	37.23
Mean collision estimate	8 MW	0.102	0.0703	3.06	2.109	0.1723	5.169
Lower 95% bound	15 MW	0.00012	0.00012	0.0036	0.0036	0.00024	0.0072
Upper 95% bound	15 MW	0.529	0.572	15.87	17.16	1.101	33.03
Mean collision estimate	15 MW	0.093	0.064	2.79	1.92	0.157	4.71

5.2 Assumptions and Limitations of the Current Process for Estimating Cumulative Risk

The movement model in SCRAM predicts density of animals per ½ degree grid cell,[2] so if a wind farm spans multiple model grid cells, the model will use the density estimate from the centroid grid cell location. As a result, estimates of collision risk do not account for potential variation in estimated density across wind farm footprints. This may be a particular issue for large wind farms that span multiple model grid cells and for wind farms located on a density gradient, where estimated density for the species of interest may vary substantially between adjacent cells. Because of this limitation, cumulative risk assessments should not combine multiple offshore wind farms into a single shapefile to run SCRAM. Apart from likely differences in turbine models by lease area, if turbines in an uploaded shapefile span multiple cells, the density value will only be drawn from the single centroid cell and the cell-level variation in density values provided by the movement model will be lost.

As a result of running SCRAM for each lease area independently and using an additive approach to estimate cumulative impacts across wind farms, the total number of collisions is likely overestimated. For example. if an animal on southbound migration collides with a turbine in Maine, it is not “removed” from the regional population size estimate and density estimates for grid cells located south of that location during that autumn, even though the animal clearly is no longer available to collide with additional turbines.

More broadly, a spatially and temporally explicit cumulative impact framework would allow for the incorporation of population-level stochasticity and population trends over time. Regional population size estimates and other species data are baked into current models so there is no flexibility to change regional

[2] Grid cells are based on BOEM lease blocks, which are approximately 55 x 60-75 km depending on their specific latitude and longitude.

population size over a 30-year project lifespan. As noted below, this limitation is expected to be addressed in Phase 2 of SCRAM development (2023-2024) to facilitate future cumulative effects analyses.

6 Conclusions and Next Steps

The goal of SCRAM is to help transparently estimate collision risk to birds from offshore wind farms in the U.S. Atlantic. The Motus movement models, species data, flight height distributions, and sCRM model are all publicly accessible via the SCRAM online web application and accompanying user manual and GitHub repository. This report further documents the published model, presents associated case study data to demonstrate evaluation of collision risk of Roseate Tern, Piping Plover, and Red Knot at offshore wind energy areas in the U.S. Atlantic, and includes an initial framework for using site-specific data to estimate cumulative collision risk across spatiotemporal scales.

6.1 Limitations

As noted in Section 3 of this report, SCRAM (and indeed, collision risk models in general) have several limitations in their model structure as well as in the data available to parameterize models and validate model predictions. These limitations may bias estimates of collision risk and lead to either over- or under-estimates of risk (Table 7). Though there are further model development approaches we can undertake to address some of these limitations, **it is impossible to fully assess the degree of bias in collision risk estimates without empirical validation of model predictions**. We have recommended a variety of steps, below, to advance these models and improve the resulting accuracy of collision risk estimates, including 1) the collection of additional tracking data and other empirical information to inform model parameterization, and 2) field validation of collision risk estimates via the deployment of collision detection systems on offshore wind turbines. In the meantime, **it is recommended that SCRAM be used to assess relative risk of collisions (e.g., between different locations, turbine models and wind farm configurations, etc.) rather than absolute risk of collisions.** Responses to questions about the appropriate use of SCRAM in a permitting context are included in Appendix D.

Table 7. Factors that could limit the accuracy and precision of our collision estimates.
For each limitation the direction of potential bias is indicated (e.g., whether it may be expected to bias estimates higher or lower than reality), along with a brief explanation and potential solutions. This table includes several major limitations but is not an exhaustive list; additional limitations are noted in Section 3, above.

Limitation	Direction of Potential Bias	Reasoning	Potential Solution
Collision risk estimates are only available for part of the year	↓	Current "annual" estimates only include part of the annual cycle. Periods of missing data are not evaluated and cannot be included in the annual collision risk estimate (see Section 3.1.6).	Gather additional tracking data from other parts of the life cycle for focal species
Collision risk model does not incorporate estimates of macro-avoidance	↑	Many birds are known to avoid turbines and wind farms at larger spatial scales than the meso-scale (avoidance of turbines) to micro-scale (last-minute avoidance of turbine blades in the RSZ). This larger-scale macro-avoidance presumably reduces collision risk but is not currently incorporated into collision risk models.	Develop taxonomically specific evidence of macro-avoidance of wind farms (e.g., through additional tracking studies in the offshore environment) and integrate this information into collision risk models via adjustments in density estimates (e.g., Skov et al. 2018, Cook 2021).
Collision risk estimates do not consider the effects of lighting-related attraction or other environmental conditions	↓	Artificial lights can attract and disorient birds, potentially leading to increased collisions. It is currently unclear how much lighting-related attraction will occur given expected turbine lighting regimes (BOEM 2021). Likewise, weather conditions such as windspeed/direction and visibility likely affect collision risk, but this effect is currently unknown and is not included in the model.	Conduct studies at operational offshore wind farms to assess the degree of lighting-related attraction that occurs, and to measure avoidance behaviors and collisions under different environmental conditions
Monthly occupancy estimates assume that all tags detected within a given month are active for the entire month	↓	Tag retention times were fairly short in some cases, particularly for Piping Plovers. Thus, the model may underestimate occupancy for this species by assuming that all tags (even those that are dropped) are active for the entire month in which they are detected.	Assess options for changing the model's time window for occupancy estimates to a sub-monthly scale, and/or obtain additional tagging data with longer retention times
Motus stations are currently all coastally located and thus provide more limited, less accurate offshore detection data	↓	Offshore movements, and thus offshore occupancy, may be underestimated given the current distribution of Motus stations, which are exclusively located along the coast.	Erect Motus stations in the offshore environment (e.g., on wind turbines and other offshore structures) to provide more offshore detection data
Monthly regional population sizes assume perfect availability of the population in the study area/period	↑	The regional population sizes for fall months include birds that may not be available to collide (for example, regional population size estimates for Piping Plovers and Roseate Terns assume all breeding and hatch year birds remain in the NES until the end of October, though some individuals will leave the NES earlier).	Conduct additional tracking studies or synthesize data from existing studies to better understand migratory and nonbreeding movements and the proportion of regional populations present in the NES by month

Limitation	Direction of Potential Bias	Reasoning	Potential Solution
Birds in collision risk model are only allowed to interact with (i.e., potentially collide with) turbines once per day	↔	The assumption that birds within a given grid cell are available to collide with turbines once per day could bias results estimates in a variety of ways. For migrants flying through a cell once per season, assuming they are available to collide on a daily basis for a given month is probably an overestimate. For birds that are moving through a wind farm repeatedly over the course of their daily movements, assuming they are only available to collide once per day may be an underestimate. Additionally, as only the first detection of each day was retained for modeling, some proportion of detections are excluded from the modeling dataset.	Update movement models to incorporate multiple daily detections (below); collect additional tracking data to further inform model parameterization
Limited information on meso/micro-avoidance rate for species of interest (avoidance rate used in current version of SCRAM for all three focal species is the combined gull/tern estimate from Cook 2021)	↔	Collision risk models are sensitive to changes in estimated avoidance rate (Masden et al. 2021). The Cook (2021) combined gull/tern avoidance rate estimate is similar to other values that have been used in the literature for the three focal species (e.g., Hatch and Brault 2007, Stantial 2014, Gordon and Nations 2016), and we feel it to be the best-supported avoidance rate estimate currently available, but we have limited to validate this assumption for our three case study species. Moreover, avoidance rates likely vary with weather conditions, life history stage (Henderson et al. 1996), and other factors, but we have limited or no empirical data to inform understanding of how rates may vary with environmental conditions.	Empirical validation of avoidance rate estimates for focal species under varying conditions and life history stages
Limited information on flight height distributions for species of interest	↔	For the current version of SCRAM, we used Motus data to derive flight height estimates. These estimates may represent a biased sample of flight heights relative to the total population and probably overestimate true variance in flight height values.	Better describe model-predicted variance and/or use flight height data from multiple sources (e.g., GPS tracking data for Red Knots) to clarify the best processes for error propagation in these models

6.2 Next Steps

SCRAM will continue to be updated with model improvements, bug fixes, and additional functionality in the coming years; future changes will be documented in the GitHub repository and on the SCRAM webpage at briwildlife.org/SCRAM. Addenda to this report may also be produced if major changes are made to underlying models, and likewise will be published at the above webpage.

Several immediate next steps have been identified for the application under the current funding support mechanism, which extends until September 1, 2024. These include:

- Maintain the web application, user manual, and code repository. This includes publishing periodic updates via the GitHub repository, managing a feedback/support system for users of the app where users can send suggestions for improving the application, and fixing any bugs that occur as a result of updates or as discovered by users.

- Maintain a project webpage that includes links to updates (or plain-language description of changes) to the following products as they are released: web app, user manual, final report and addenda, and model code.
- Work with European stochCRM experts to conduct an external technical review of the movement, flight height, and CRM models and web application. Relatively simple fixes suggested by external reviewers will be addressed with current funding; recommended longer-term updates will be documented for future updates.
- Reexamine how uncertainty flows through the models and conduct sensitivity testing in order to more clearly specify the assumptions baked into the SCRAM framework. This is expected to include:
    - Examination of the sensitivity of the models to the population size parameter (and uncertainty in that parameter), and
    - Examination of the sensitivity of the models to the assumption that the movements of tracked animals are representative of the movements of the entire population for the time period of interest.
- Update movement models to better account for daily variation in detection rates and movements.
- Update SCRAM to include a parameter for uncertainty in the regional population size parameter, if the above sensitivity analysis suggests this is important.
- Update SCRAM to allow users to provide their own species input parameter for regional population size. This would facilitate cumulative effects analyses (for example, if a user wants to develop an estimate of effect over a 30-year project lifespan, and current best available data suggests a population is shrinking at a rate of 2% per year, then ideally there would be flexibility for user-input changes in regional population size values such that the model could be rerun with this gradually decreasing population size over time to get a more accurate estimate of cumulative effect over the wind energy project's lifetime).
- Explore model sensitivity to other species input parameters such as flight speed and avoidance rate, and model assumptions like number of daily turbine interactions. After, we will update SCRAM to allow users to provide their own species input data for parameters that most strongly influence model outcomes.
- Update SCRAM to allow both basic and extended avoidance values to be used in models, so that the user can select the appropriate value based on whether they are running the basic or extended version.
- Explore approaches to incorporate data from other sources into flight height models (specifically, newly collected data from Argos- and/or GPS-tagged Red Knots).

6.3 Recommendations for Future Work

The above plans will improve the current version of SCRAM and continue to make it more flexible and user-friendly. We have also identified a range of recommendations that would require a longer time horizon and/or additional funding support, but that would further improve the ability of SCRAM to support risk assessments and decision making. In general, these recommendations fall into the following categories: 1) collecting additional field data to inform model structure and parameterization; 2) updating movement models and flight height distribution models; 3) updating CRM models (including the species data feeding into these models); 4) further updates to the web application; and 5) additional theoretical development and consideration of processes for estimating cumulative impacts. The recommendations below are listed in no particular order and are not prioritized.

6.3.1 Collect additional field data to inform model structure and parameterization

Individual tracking remains one of the best available methods to obtain additional data for the three case study species in the current implementation of SCRAM. Other methods should be explored to improve estimates of specific model parameters, as well as the data feeding into flight height distribution models.

And there remains limited validation of flight height models to assess their real-world accuracy in predicting collision risk, a gap that must be addressed via technological development of improved monitoring systems for offshore wind farms.

- **Motus tracking in new locations.** Current Motus data used in the movement and flight height models are limited to specific populations and times of year. Expanding future telemetry data collection to other geographic areas and life history stages (including new nesting or wintering populations and staging populations) would expand the sample represented in the current dataset. Incorporating data from offshore Motus stations into SCRAM (as more offshore stations are established) will also help improve the sample used in models.
- **Use of alternative telemetry methods, particularly to obtain data on spring migration.** Other types of tracking data could supplement the gaps in Motus data. GPS and satellite telemetry approaches, while limited by the body size of target species, are beginning to be used to assess movements for these species and can provide movement and location information even in areas lacking Motus station coverage. In particular, we would recommend targeting deployments of such tags during the nonbreeding season in order to obtain movement data from spring migration that is lacking in our current dataset. Satellite- or GPS-derived fall migration data for Roseate Terns would also be informative.
- **Improve parameter estimates for flight behaviors.** Additional field research is needed to inform model parameterization (particularly at-sea flight height and flight speed distributions for species of interest, and data on avoidance rates at macro-, meso-, and micro-scales for species of interest).
- **Improve parameter estimates for morphometric parameters.** Field researchers typically do not collect body length and wingspan measurements. Inclusion of these measurements (e.g., Liddy 1990) in handling processes for captured individuals would help to validate the morphometric values used in the current model. Additionally, measuring wingspan and wing cord on the same individuals may allow for the identification of a correlation between these values such that the range/variance from existing large wing cord datasets can be used to inform estimates of wingspan.
- **Validate model predictions.** While it is quite difficult to monitor collisions at offshore wind farms directly, particularly for small-bodied species, such efforts are necessary to validate the collision estimates arising from CRMs. Given the rarity with which collisions are generally expected to occur, technological advancements in camera systems, radar, and other technologies are needed for long-term, multi-year deployments.

6.3.2 Update movement models

- **Update structure of movement models.** Movement models are currently broken out into multiple compartments/steps. It would be more coherent to restructure these, run the movement models on three chains rather than one, and recreate the baked products that are feeding into SCRAM.
- **Update movement models to account for multiple sources of uncertainty.** Currently movement models assume there is no measurement uncertainty. By incorporating multiple daily detections, we can estimate daily uncertainty in location from both daily movements and measurement precision.
- **Update movement models to determine position estimates for individual detections.** Past efforts have attempted to estimate 3D position of animals using Motus data, but results lacked precision and accuracy based on calibration data. By using signal strength, multi-antenna detections and detection time we are planning on building new models that provide fast and accurate estimates of 3D position for discrete detections on the network. Currently, we are planning on developing these models in collaboration with the University of Rhode Island as part

of Project WOW (Wildlife and Offshore Wind; https://offshorewind.env.duke.edu/), and hope to apply these efforts to update the movement and flight height models in SCRAM in future.

- **Incorporation of alternative tracking data into SCRAM.** Update movement models to integrate movement data from satellite (Argos) and GPS tags as well as Motus.
- **Inclusion of additional species.** Assess data availability for other species of interest in the U.S. Atlantic, and for selected species, parameterize models to assess collision risk. This effort is likely to focus initially on Common Terns, for which substantial information is already available in the formats required for SCRAM.

6.3.3 Update CRM models

- **Include additional data on wind speed.** CRMs can be sensitive to bird flight speed, which is heavily influenced by wind speed (Masden et al. 2021). It may be helpful to include more detailed wind speed data for each site of interest (for example, by accessing ocean wind speed data from the National Oceanic and Atmospheric Administration) and using these data to inform predicted flight speed ranges, the prevalence of head/tailwinds and variation in daily estimates of collision.
- **Use new sources of telemetry data to inform estimates of flight speed.** Newly collected Red Knot GPS data from current studies could be used to inform estimates of flight speed for this species.
- **Allow user-specified species data as inputs in SCRAM.** Currently, users can specify wind farm data, but species data are "baked in" to the models. Allowing users to modify default values could facilitate incorporation of newer data.

6.3.4 Update web application and user interface

- **Create an R package to pre-process data for SCRAM.** If CRM models are updated to allow users to provide their own species data (above), those data will need to be formatted correctly for uploads to function properly. A data preprocessor that helps users get data into the correct format could help facilitate this process.
- Create an R package for easy simulation and manipulation of SCRAM for other expert users. The developers of StochCRM recently created the stochLAB R package (https://cran.r-project.org/web/packages/stochLAB/index.html) for a similar purpose; replicating this effort would likewise be useful for SCRAM.

6.3.5 Further consideration of cumulative impacts

- **Continue to iterate on the above initial framework for assessing cumulative effects.** The purely additive framework described in this report lacks several nuances that may influence cumulative effects in a real-world scenario. For example, the effects of multiple offshore wind projects should interact in a cumulative effects scenario; a collision "upstream" (such as during migration) should reduce estimates of density/flux for locations downstream, as that animal has been removed from the population. Macro-avoidance and displacement from offshore wind farms will also affect the behaviors and movements of many species, and these large-scale changes are not currently incorporated into estimates of collision exposure/risk. Seabirds also use the marine environment in a more complicated way than migrants, such that movements cannot simply be considered "flux" in densities as birds move north or south, but also must incorporate roosting, foraging, and a range of other behaviors that could affect cumulative risk. All of these factors, and others, should be considered in a more inclusive framework for estimating cumulative effects.
- **Update movement model to an individual-based model structure.** This change would allow SCRAM to better account for cumulative effects and address interactive issues such as those noted above.

- **Change the structure of the web application to run multiple offshore wind projects** through SCRAM at the same time, rather than exporting individual outputs. This change would allow SCRAM to better estimate cumulative effects and address interactive issues such as those noted above.
- **Develop a common approach for obtaining biologically defensible cumulative effects estimates to meet regulatory needs.** We recommend the formation of a cross-Atlantic collaboration with scientists in the UK and elsewhere who are working on sCRMs and develop cumulative effects estimates in relation to offshore wind energy development. Such collaboration would allow us to avoid duplication of effort and jointly develop an approach that could be used on both sides of the Atlantic. This could include the formation of a cross-Atlantic working group and/or a stakeholder engagement process with workshops to help formulate a detailed framework for estimating cumulative effects.

6.4 Conclusions

Stochastic collision risk modeling attempts to estimate avian collision risk at offshore wind farms, which is often difficult to measure directly. Model results can inform risk assessments, but limited validation of CRM model structure, as well as limited data to inform the estimation of specific model parameters, ensure substantial uncertainty in model results. In the SCRAM collision risk model for three species of interest (Red Knot, Piping Plover, and Roseate Tern) in the U.S. Atlantic, there are several limitations specific to the Motus dataset currently used to parameterize the model. At the time the dataset was produced, all Motus stations were land-based, for example, and thus offshore movements were interpolated rather than measured directly. Estimates of flight altitude from Motus data are currently rather coarse, and both movement and flight height data were limited to specific tagged populations and times of year, resulting in “annual” estimates of collision risk that do not include potentially important time periods such as spring migration.

SCRAM is a significant step forward for transparent, data-driven collision risk estimation for three listed bird species in the U.S. Atlantic. Further advances (noted as immediate next steps and recommendations, above) will continue to increase its utility for estimating risk at U.S. offshore wind farms. However, the gaps and uncertainties in available data, as well as uncertainty in model implementation, suggest that a long-term, adaptive monitoring and management framework is needed to further improve and validate model estimates and ensure that risk to important bird species is minimized as the offshore wind industry progresses. As such, SCRAM and this report will continue to be updated in future years. Addenda to this report will be posted on the project webpage at https://briwildlife.org/SCRAM.

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A Appendix: Differences between SCRAM and previous implementations of the Band model

SCRAM makes full use of recent advancements in quantifying the potential impacts of offshore wind energy development from Band (2012) and adaptions of the Band framework (Masden 2015, Trinder 2017, McGregor et al. 2018). We aimed to advance the implementation of this framework in the western Atlantic by 1) contributing updates to the primary model script and 2) developing an online interface that best addresses the specific needs of users and stakeholders in the eastern U.S. While there is significant overlap in the model description between our version and previous iterations, there are several important differences. All of the changes to the underlying model code are tracked on GitHub.

Major differences in primary computational script:

- SCRAM uses spatially explicit occupancy derived from correlated random walk models using Motus data, rather than density estimates derived through surveys. To appropriately scale occupancy to the entire population, an estimate of population size (and uncertainty if available) is used (Appendix B).
- The primary computational script was revised to include a preamble that conducts a set of checks on the input data sources to ensure they are uploaded correctly.
- SCRAM's calculation of bird passage rates is similar to the Band (2012) Annex 6 approach but defines the migratory corridor width, required in the Band single transit model, as the width of the grid cell where the wind farm is located. It also includes a correction for the proportion of transient vs. stationary behavioral states the model predicts for a given grid cell. Finally, instead of allowing monthly interactions between a migrant and the wind farm, SCRAM allows daily interactions.
- SCRAM integrates the flight height distributions with risk along the rotor blade using cell-wise instead of point-wise probabilities. We modified this component to treat flight heights as a

statistical distribution, as opposed to point-wise sampling along the range of flight heights. The consequence of this change is that the first probability of the flight height distribution (labeled as 1 m) corresponds to the band that is 0 – 1 m above sea level.

- SCRAM allows the user to conduct an approximated global sensitivity analysis to quantify the contribution of input data to the uncertainty bounds of the results.
- SCRAM allows for missing values (specified as NA) in the input data. This is useful, for example, when movement data are not available for every month. Missing values are automatically propagated through the model and displayed in the results accordingly.
- SCRAM calculates total operation time as wind availability*(1 – down time) to avoid the fact that negative values can theoretically happen with the original formulation (wind availability – down time).
- SCRAM estimates rotor speed using the relationship between tip speed ratio (TSR), wind speed (S), and rotor diameter (r): w = (TSR * S)/r * pi (in radians/s), which is converted to rpm.
- SCRAM fixes an error in the Riemann sum for rotor risk (used for the "extended" version of Band [2012]) that was causing a redundant loop.
- The primary computational script is run asynchronously, using the framework of making "promises" with the 'promises' and 'future' R packages (Bengtsson 2020, Cheng 2020), to allow multiple users simultaneously and allow the ability to cancel computational tasks.
- SCRAM allows the user to download inputs and outputs from every iteration of the model run.
- Tidal offset and nocturnal activity are no longer user-specified parameters.
- Inputs were simplified so that a global avoidance is used instead of option-specific rates.

Major differences in online interface:

- SCRAM's interface was built from the ground up, focusing on simplicity and encouraging a linear path through the tool.
- Only the most appropriate options in SCRAM are available to the user, depending on the input data and model specifications, to minimize the chance of running the model in a way the user did not intend. Most data inputs being embedded in the app or accomplished using .csv files that the user can store locally, as opposed to requiring the user to input data on the interface itself.
- SCRAM provides the take-home results on the application interface, but the majority of SCRAM's results are provided via either 1) downloads of the raw results, or 2) a downloadable report that contains visualizations and input and output data tables.

B Appendix: Derivation of Regional Population Size Estimates for Case Study Species

Estimates of regional population size were developed for the three case study species (see main text), and a maximum number of individuals in the study area was estimated for each month. The monthly estimation process was built entirely on expert opinion and species monitoring, there is no model development or creation. Monthly population sizes vary by migration to or through the NES and annual breeding ground productivity. The most recent available data was used for these estimates. These regional populations estimates were specifically focused on the U.S. Atlantic study region (Fig. 2). If no birds of a species were assumed to fly through the U.S. Atlantic study region for a given month, it was assigned a population size of zero. If there were no available data to estimate the standard deviation (SD) of a population estimate, the SD was assigned a value of zero. Collision risk estimates were not generated by SCRAM for months in which there were no data from the movement model; thus, in the tables below, the "SCRAM estimates collision risk?" field indicates which monthly population values were used in the development of collision risk estimates.

The below regional population size estimates have a number of limitations and uncertainties, as discussed in Section 3.2.1.1 and Section 6.1 of the main text.

B.1 Red Knots

Estimates of regional population size for Red Knots are presented in Table B1. Values were derived from a combination of wintering population size estimates for various locations (Table B2) and estimated numbers of hatch-year (HY) birds produced per year. The following assumptions were used to develop these estimates (U.S. Fish & Wildlife Service 2020, Lyons et al. 2017, W. Walsh pers. comm Jul. 2022):

- Winter populations include the total number of adults and sub-adults; they do not include hatch-year birds from the previous fall.
- Birds wintering in both southern and northern areas could be present in the study region during July – September; only northern-wintering birds could be present during October – November; and only southeast U.S. wintering populations could be present in the study region in December.
- Birds from the western Gulf of Mexico population do not use the U.S. Atlantic region.
- 90% of the total wintering population of 59,200 (Table B2) are breeders, equating to 26,640 breeding pairs, and we assume a 0.5 chick/pair fledge rate for 13,320 hatch-year birds produced per breeding season.

Table B 1. Estimates of regional population size for Red Knots by month (with standard deviation values in parentheses).

Sources: U.S. Fish & Wildlife Service 2020, Lyons et al. 2017, W. Walsh pers. comm Jul. 2022.

Month	Population Size Estimate	Justification	SCRAM estimates collision risk?
Jan	10,400 (±0)	Wintering population estimate for Southeast U.S.	No
Feb	10,400 (±0)	Wintering population estimate for Southeast U.S.	No
Mar	10,400 (±0)	Wintering population estimate for Southeast U.S.	No
Apr	10,400 (±0)	Wintering population estimate for Southeast U.S.	No
May	59,200 (±0)	Combined population estimate for Southern, Northern Brazil, Southeastern U.S., & Caribbean wintering populations	No
Jun	59,200 (±0)	Combined population estimate for Southern, Northern Brazil, Southeastern U.S., & Caribbean wintering populations	No
Jul	59,200 (±0)	Combined population estimate for Southern, Northern Brazil, Southeastern U.S., & Caribbean wintering populations	No
Aug	59,200 (±0)	Combined population estimate for Southern, Northern Brazil, Southeastern U.S., & Caribbean wintering populations	Yes
Sep	72,520 (±0)	Combined population estimate for Southern, Northern Brazil, Southeastern U.S., and Caribbean wintering populations, plus 13320 hatch-year birds produced across all breeding grounds	Yes
Oct	54,720 (±0)	Combined population estimate for Northern Brazil and Southeastern U.S. wintering populations, plus 13320 hatch-year birds produced across all breeding grounds	Yes
Nov	41,400 (±0)	Combined population estimate for Northern Brazil and Southeastern U.S. wintering populations	Yes
Dec	10,400 (±0)	Wintering population estimate for Southeast U.S.	Yes

Table B 2. Regional wintering population size estimates for Red Knots.

Sources: U.S. Fish & Wildlife Service 2020, Lyons et al. 2017, W. Walsh pers. comm Jul. 2022.

Wintering Population	Population size estimate
Southern	12,700
Northern Brazil	31,000
Southeast US	10,400
Caribbean	5,100
Total	**59,200**

B.2 Piping Plovers

Estimates of regional population size for Piping Plovers are presented in Table B3. Values were derived from a range of Atlantic coast-wide population parameters outlined in Table B4. The following assumptions were used to estimate these Piping Plover regional population size estimates (Source: U.S. Fish & Wildlife Service 2022):

- The entire Atlantic coast population could be present in the study region during non-winter months. Occurrence through October is still assumed to potentially include all birds in the population, via birds stopping over in the mid-Atlantic (e.g., North Carolina), though the number of birds truly still present in the U.S. Atlantic study region is likely lower by that point in the year.

- The 20-year (2002-2021) average productivity (unweighted) is a reasonable estimate of the number of hatch-year birds fledged per year.

Table B 3. Regional population estimates used in SCRAM for Piping Plovers.

Source: U.S. Fish & Wildlife Service 2022.

Month	Population Size Estimate	Justification	SCRAM estimates collision risk?
Jan	0 (±0)		No
Feb	0 (±0)		No
Mar	4,578 (±0)	Population estimate for U.S. and Eastern Canada (adults only)	No
Apr	4,578 (±0)	Population estimate for U.S. and Eastern Canada (adults only)	No
May	4,578 (±0)	Population estimate for U.S. and Eastern Canada (adults only)	Yes
Jun	4,578 (±0)	Population estimate for U.S. and Eastern Canada (adults only)	Yes
Jul	4,578 (±0)	Population estimate for U.S. and Eastern Canada (adults only)	Yes
Aug	7,423 (±0)	Population estimate for U.S. and Eastern Canada (adults plus hatch-year birds; see Table B4)	Yes
Sep	7,423 (±0)	Population estimate for U.S. and Eastern Canada (adults plus hatch-year birds; see Table B4)	Yes
Oct	7,423 (±0)	Population estimate for U.S. and Eastern Canada (adults plus hatch-year birds; see Table B4)	No
Nov	0 (±0)		No
Dec	0 (±0)		No

Table B 4. Atlantic Coast population data for Piping Plovers (2021 update).

Source: U.S. Fish & Wildlife Service 2022.

Parameter	Value
US pairs	2,109
US adults	4,218
Eastern Canada pairs	180
Eastern Canada adults	360
HY fledge per pair in US	1.22
HY fledge per pair in eastern Canada	1.51
HY fledge in US	2,573
HY fledge in Canada	272
Adults + HY	**7,423**

B.3 Roseate Terns

Estimates of regional population size for Roseate Terns are presented in Table B5. Values were derived from northwest Atlantic population parameters outlined in Table B6. The following assumptions were used to estimate these Roseate Tern regional population size estimates (Source: Mostello 2021, Gochfeld & Burger 2020):

- The entire Northwest Atlantic population could be present in the study region during the non-winter months. Occurrence through October is still assumed to potentially include all birds in the population, via birds stopping over in the mid-Atlantic (e.g., North Carolina), though the number of birds truly still present in the U.S. Atlantic study region is likely lower by that point in the year.
- Fledging and the post-breeding dispersal period occurs from July through September.
- There are no non-breeding adults or one- and two-year-old birds that return but do not breed.
- The average of the most recent (2018 and 2019) productivity data from the three largest colonies (representing >90% of the population) is representative of the entire population.

Table B 5. Regional population estimates used in SCRAM for Roseate Terns.

Source: Mostello 2021, Gochfeld & Burger 2020.

Month	Population Size Estimate	Justification	SCRAM estimates collision risk?
Jan	0 (±0)		No
Feb	0 (±0)		No
Mar	0 (±0)	Population estimate for U.S. and Eastern Canada (adults only)	No
Apr	10,916 (±0)	Population estimate for U.S. and Eastern Canada (adults only)	No
May	10,916 (±0)	Population estimate for U.S. and Eastern Canada (adults only)	No
Jun	10,916 (±0)	Population estimate for U.S. and Eastern Canada (adults only)	Yes
Jul	4,578 (±0)	Population estimate for U.S. and Eastern Canada (adults only)	Yes
Aug	16,251 (±0)	Population estimate for U.S. and Eastern Canada (adults plus hatch-year birds; see Table B6)	Yes
Sep	16,251 (±0)	Population estimate for U.S. and Eastern Canada (adults plus hatch-year birds; see Table B6)	Yes
Oct	16,251 (±0)	Population estimate for U.S. and Eastern Canada (adults plus hatch-year birds; see Table B6)	No
Nov	0 (±0)		No
Dec	0 (±0)		No

Table B 6. Northwest Atlantic population data for Roseate Terns.

Source: Mostello 2021.

Parameter	Value
Pairs	5,458
Adults	10,916
Average productivity (HY fledged per pair)	0.9775*
HY fledged	5,335
Adults + HY	**16,251**

*Average of 2018-2019 productivity for Bird (1.04 and 0.79 fledged/pair in 2018 and 2019, respectively), Ram (0.98 and 0.80), and Great Gull Island (1.48 and 0.775 fledged/pair) colonies.

C Appendix: Templates for wind farm data and operations data

The following wind farm data and operations data should be provided by developers in the Constructions and Operations Plan for each proposed wind energy project (Tables C1-C2). Additional details may be found in the case studies section of the report.

Table C 1. Wind farm data needed to run SCRAM.
In the case of a project design envelope, parameters for each turbine model under consideration should be provided in each Run column (e.g., Run 1, Run 2, add columns as needed).

Parameter	Parameter definitions	Run 1	Run 2
Num_Turbines	The number of installed turbines		
TurbineModel_MW	The turbine model option or MW rating of the turbine. In SCRAM, this is purely for labeling purposes only and does not affect the results.		
Num_Blades	The number of installed blades on each turbine		
RotorRadius_m	The radius (meters) of the rotor from blade tip to middle of the rotor nacelle (axis of rotation)		
RotorRadiusSD_m	The standard deviation of the rotor radius (meters). We recommend setting this value to 0.		
HubHeightAdd_m	The distance between sea level at highest astronomical tide and the lower blade tip (meters), also referred to as the air gap. From this value the hub height is calculated and presented in the output.		
HubHeightAddSD_m	The standard deviation of the air gap (meters). We recommend setting this value to 0.		
BladeWidth_m	The turbine blade width (meters).		
BladeWidthSD_m	The standard deviation of the turbine blade width (meters). We recommend setting this value to 0.		
WindSpeed_mps	Mean wind speed at the wind farm (meters per second) for the periods during which wind speeds are between cut-in and cut-out speeds of the turbine (i.e., turbines could be spinning); or if not available, the rated wind speed of the turbines. The turbine wind speed rating is the wind speed at which maximum power production occurs.		
WindSpeedSD_mps	The standard deviation in wind speeds or wind speed rating (meters per second). We recommend setting this value to 0 unless data can be obtained on the variation in wind speeds or wind speed rating relative to the model turbine.		
Pitch	The average angle of the blade (degrees) relative to the rotational plane of the blades while the turbine is spinning.		
PitchSD	The standard deviation in pitch (degrees).		
WFWidth_km	Wind farm width (km). If the wind farm is not square, use (length + width)/2 of the wind farm or total perimeter length/4 if an irregular shape.		
Latitude	Latitude (decimal degrees) of wind farm centroid		
Longitude	Longitude (decimal degrees) of wind farm centroid		

Table C 2. Wind Farm operations data needed to run SCRAM.

Op = Wind availability, the maximum amount of time turbines can be operational/month depending on wind speeds and cut-in and cut-out speeds of the turbine. OpMean = Mean time that turbines will not be operational ("down time"), assumed to be independent of "MonthOp" – i.e., total operation = MonthOp*(1 – MonthOpMean). OpSD = standard deviation of mean operational time.

Month	Op	OpMean	OpSD
Jan			
Feb			
Mar			
Apr			
May			
Jun			
Jul			
Aug			
Sep			
Oct			
Nov			
Dec			

D Appendix: Responses to questions about the use of SCRAM in environmental permitting

Questions were submitted to the SCRAM developers as part of a question-and-answer session with USFWS and BOEM environmental permitting staff. The original questions and the responses from USFWS and BRI are included below to provide additional context for readers of the final report.

1. Please explain the interaction between the monthly population size estimates and the modeled flight trajectories in SCRAM. Is this different for Piping Plovers (assuming only one southbound offshore flight per year per bird), Roseate Terns (with potential for flights to/from wintering, staging, and breeding sites), and Red Knots (where juveniles and nonbreeding adults remain resident in the mid-Atlantic for prolonged periods and may cross the migration front multiple times)?

This is the occupancy estimation process that we derive from the Motus data, and it's the same for all species during months where tracking data are available. We have discussed further refining this model in future versions of SCRAM, details to come. For this process, we run the Motus data through a movement model and then use the predicted locations from each track to estimate how many individuals were present in each grid cell each day (while accounting for uncertainty in the movement estimation process). Each day, we sum all the individuals in each cell and then divide by the total number of individuals with tags for a given month. That gives us the daily occupancy probability of that cell (in this case, defined as the proportion of tracked individuals present in that cell for a given day). We assume the monthly regional population is spread out across all cells as a function of that occupancy (i.e., if you have 1000 individuals and one cell has 10% occupancy, then 100 individuals are in that cell). We also assume that only "transient" (e.g., migrating) birds can transit through an offshore wind farm, so we multiply this daily population estimate by the proportion of animals in a transient state. The proportion of animals in the transient state is estimated via the state-switching correlated random walk model used to predict birds' locations – it determines whether a bird is likely in a transient state showing fast, directed movement, or in an "area-restricted" state such as staging, foraging, etc., that involves lingering in areas. Using this process, we calculate the number of transient birds in each grid cell on each day, and then add it all up within a month to give us the total number of expected transits in a given cell for that month. Note that because we assume that animals are present and can transit a turbine on a daily basis, the number of monthly transits can exceed the regional population size for that month. This assumption might be more appropriate for some species than others.

The ability for birds to transit more than one a month is one of the major differences between SCRAM and the Band 2012 model: the migratory collision risk model ("Annex 6") of Band 2012 assumes that each bird can only interact with a turbine once a month, while the regular Band model (which is appropriate for non-migratory species) assumes many potential passages a day through the wind farm. SCRAM assumes that each bird can only interact with a turbine once a day (so long as they are present in the grid cell on each day). As such, in areas with high occupancy rates, SCRAM is likely to provide higher collision risk estimates than the Band migrant model (because it gives the opportunity for more transits through a project per month) but lower collision risk estimates than the Band non-migrant model, which essentially assumes constant flux. Whether or not any of these assumptions is accurate for a given species is a function of that species' movement ecology.

In an example where the Motus dataset includes multiple flights over multiple days over the ocean for a single tagged individual, then the model structure would allow all of those flights to influence occupancy estimates. However, in the case that these multiple flights happen within the SAME day, or a bird passes through multiple offshore grid cells in a given day, the movement model only uses the first detection of each bird for each date and thus the remaining flight data within a day do NOT influence the movement model.

Regional population size estimates were developed independently of movement models and are based on literature and expert opinion regarding the number of adults in the relevant population, productivity per year, migration timing, and other factors (this is described in Appendix B). These monthly regional population size estimates are for the entire region (e.g., the Atlantic coast study area shown in Figure 2 of the report). The determination of how that regional population is distributed within the study area is based on the distribution of tagged birds in that month, as described above.

2. Which tracks inform the daily occupancy probability in a given grid cell? Is this total tracked individuals (or individuals with modeled tracks) within a particular grid cell? Or is it total tracked individuals in the entire study? How many months had >5 tracked transient plovers? Note that Loring et al. 2019 (page 109) states that exposure of Piping Plovers to the Wind Energy Areas (WEAs) occurred between 5 July and 14 August. How/why are there cells fairly far north of Monomoy (even east of New Hampshire) with estimated plover occupancy?

All animals being tracked at a given time inform the occupancy probability cells on that day. The occupancy probability is a function of the presence of birds in a given cell, along with the monthly number of active transmitters (see response to #1, above). There were more than 5 Piping Plovers tracked in the five months SCRAM uses for the species (May-September). This does not mean that all were necessarily in transient movement states in all months. The individuals in the sample population may be staging or doing other things besides migrating offshore.

There are plovers estimated to occur in areas north of the capture locations in summer/fall primarily because Motus data are highly uncertain and the movement model accounts for that. Essentially, the model predicts how animals are moving around at the daily scale (as estimated via the data themselves) and adds uncertainty into our position estimation process as a function of that movement. This uncertainty can be particularly high when we lack detections for the species across multiple days. In the case mentioned in this question, the uncertainty in those movements suggests they could be moving North along the coast. It doesn't seem biologically likely for this particular species, but the uncertainty in the estimation process is happening throughout their range with SCRAM. It's more obvious how uncertain the movement model is near the northern edge of the study area because we don't expect many southern New England Piping Plovers to be moving in that direction in summer/fall.

3. Does the movement model account for cells where detection was unlikely, given receiver locations and the flight height distribution for a given species? As more Motus tracks are added to the model in the future and the number of receivers changes, will the movement model account for variable probability of detections across years?

Yes and no. Right now, the movement model doesn't know where Motus towers are. All it knows is where we are detecting animals each day and if there are gaps in the daily detection pattern. So variable Motus station coverage across years is not currently factored in. One of our biggest priorities moving forward for SCRAM is to improve the movement modeling process and continue developing these approaches to better account for uncertainties in the Motus data.

Right now, we use the movement model to limit the area of inference for the study. We calculate the coefficient of variation for our occupancy estimates and when that value passes a key threshold, indicating that the model is very uncertain about the predictions we are making, we do not provide SCRAM estimates for those species/locations. These areas strongly (negatively) correspond with the areas of coastal/offshore coverage by Motus stations.

4. Please explain how many empirically derived and interpolated flight height samples were available/used for each species and the number of tagged birds from which they came so that we can better characterize how robust they are.

We used all the Motus flight height estimates for each species from the Loring et al. (2018) and the Loring et al. (2019) studies. Data from Piping Plovers consisted of 10,359 data points from 68 birds. Data from Roseate Terns consisted of 4,272 data points from 85 birds. Data from Red Knots consisted of 12,044 data points from 118 birds. A non-parametric Monte Carlo process was used to bootstrap flight heights to account for flight height variance across individuals. Individual flight heights were sampled 10 times per individual with replacement. Then each replicate of that individual-balanced simulation was resampled 1000 times. After the bootstrap process, the probability density of flight for each 1m interval was calculated. These estimates are based on Motus movement modeling data that have low precision; as such, we advise caution in how these data are interpreted, but they were the best estimates available for these species.

5. Are you aware of any studies to inform avoidance rates for any shorebird species?

We are not aware of any reliable avoidance estimates for shorebirds at offshore wind turbines. Studies that have assessed risk for shorebirds and offshore wind to date have ignored the avoidance issue altogether (e.g., Schwemmer et al. 2022) or used numbers from other species (e.g., Gordon and Nations 2016). We do the latter and use the 0.9295 ±0.0047 gull/tern avoidance estimate from Cook 2021 for all three of our focal species. In the case of Red Knot and Piping Plover the estimate is not from particularly similar species, but it's a well-supported estimate of avoidance rates derived from multiple studies, and there is an estimate of uncertainty to accompany the value itself, which is important for developing an accurate collision prediction interval.

The Cook 2021 value we used is similar to avoidance rates that have been posited for Red Knot in the literature; Gordon and Nations (2016) suggested a 0.93 micro-avoidance probability for Red Knot at actively rotating turbines in good weather (e.g., tailwinds). This was based on the "average of Petersen et al.'s (2006) average micro-avoidance value for sea ducks at the Nysted Wind Project in Denmark (0.886) and the overall average micro-avoidance probability for all birds (0.976) in the studies reviewed by Cook et al. (2012), which is heavily weighted toward highly maneuverable species, such as gulls and terns." They suggested that in poor weather (e.g., headwinds of >5 m/s) micro-avoidance could drop to 0.75 "to account for the relatively high wing-loading in Red Knots (Harrington 1996) and assumed lower maneuverability when flying into a headwind." However, even if this value had been empirically supported, SCRAM does not currently produce condition-specific estimates of collision risk.

6. Are SCRAM collision risk estimates always higher than those from the Band migrant model, given that birds are allowed to pass a turbine rotor-swept zone (RSZ) daily rather than once per month?

SCRAM collision risk estimates may be either higher or lower than the Band migrant model for a grid cell of interest. This is because migrant flux (birds/day/km) is estimated differently between the two models.

In Band 2012, you estimate the width of a migratory corridor (migratory front) that all birds in your population pass through, and then the model assumes a uniform distribution of birds across the migratory front. There are three key issues with this approach: 1) it's very difficult to accurately estimate this corridor width, 2) it's likely that offshore migration activity is not uniformly distributed within a designated migration corridor, and 3) individuals of some species could interact with turbines multiple times per month. It seems much more likely, based on what we know about patterns of avian migration generally, that offshore migration happens in some offshore cells more often than others. Patterns of activity likely relate to each cell's position along the coast, proximity to breeding or stopover locations, and other factors.

So instead of using a uniform distribution across the migratory front, in SCRAM we use Motus movement data to help inform our estimate of migrant flux on a per-grid cell basis. We estimate occupancy of each grid cell using movement data, and then assume a uniform distribution of birds within that grid cell. This means that if there are spatial distribution patterns of migration offshore, that will hopefully show up in the movement dataset, and thus allow us to develop a better localized flux estimate for each location of interest.

It follows then that if the estimated flux for a given grid cell (based on estimated occupancy from the movement data) is lower in SCRAM than in the Band migrant model (which has the assumption of uniform distribution across the migratory front), then you can get lower collision risk estimates for that cell in SCRAM than you would with Band 2012 migratory collision risk estimates. This can occur even though we're allowing birds to pass through the RSZ multiple times a month by assessing occupancy on a daily rather than a monthly scale. This may be particularly true for cells located farther away from Motus stations and tag deployment locations. At the time that the Motus dataset was produced, Motus stations and tagging efforts were all land-based, so there is a bias towards coastal locations, and specifically the locations along the coast in which stations were located and tags were deployed. We don't know how large this bias is, but regardless, there is a large amount of uncertainty in our estimates of movement farther away from these station/deployment locations, and our estimates of occupancy for locations farther from Motus deployments are more likely to be lower than what would be predicted by the uniform distribution used in the Band model.

To summarize, in grid cells with low occupancy rates, SCRAM can produce collision risk estimates that are substantially lower than estimates by Band 2012 migratory collision risk model. In grid cells that are very close to Motus station and tagging locations, there is likely to be high estimated occupancy, and this can translate to high estimates of collision risk in SCRAM. Given that Motus tagging and receiving stations were concentrated in locations that were known important habitat use areas for the species of interest, it is difficult to know if this is leading to actual overestimates of collision risk in SCRAM. But at a minimum, SCRAM estimates for these locations will often be higher than the collision risk estimates derived using the assumption of a uniform distribution in the Band 2012 migrant model.

7. What about grid cells where SCRAM's monthly exposure estimates are larger than the regional population size for that month? That's got to produce unreasonably high estimates of collision risk, right?

Areas with high occupancy probabilities can achieve higher than the monthly regional population size estimates of flux because we calculate flux on the daily scale. The Band 2012 migrant model assumes that each bird can only interact with a turbine once a month and SCRAM assumes that it can happen once a day. As such, SCRAM is likely going to be higher than Band in many areas with high occupancy rates because it gives the opportunity for many transits through a project per month. This can be true even though we are correcting for movement state (stopovers vs. migrants).

Whether or not it is accurate to assume that birds could interact with turbines multiple times per month is really a function of that species' movement ecology, and possibly also the specific location of interest. It seems unlikely that shorebird migrants like Red Knots would regularly have multiple transits per month in a location far offshore. However, the Band 2012 migrant model only allows a single transit per month, which is arbitrary and also has biological problems. We know birds don't always fly in a direct route or have a clean delineation between staging/foraging activity and migration, so there definitely can be opportunities for birds to pass the same location multiple times during a migration season.

In the long term, we will consider implementing an approach for SCRAM where we have species-specific transit models that are using the Motus data in different ways, so that we can make different assumptions about how often we think birds might have the potential to pass through a wind farm.

Currently, we're limited by a lack of empirical data to achieve such model specificity. Keep in mind that these estimates are based on limited movement data and we lack a way to ground truth the estimates of collision risk that any collision model produces. Our suggestion for next steps is to improve the underlying movement models by incorporating GPS tracking data where available, so we're not relying solely on Motus data that 1) has very high uncertainty, and 2) has known biases towards locations where Motus stations are available to detect tags. GPS data can still be biased towards tag deployment locations, but they remove the station location bias and also provide much more precise location information, especially offshore where very few Motus receiving stations currently occur.

8. Do avoidance and collision risk estimates include mortality caused by collisions with the monopiles and vortex/turbulence effects of the rotors, or do they only include collisions with the turbine blades?

The short answer is that the physical collision risk model developed in Band 2012, and modified for use by others, including in SCRAM, only includes collisions with the rotors and does NOT consider vortex/turbulence effects, but avoidance rates are partially based on datasets that may include other sources of mortality at turbines. Some nocturnal migrants, like songbirds, are known to collide with stationary towers, but collisions are mediated by environmental conditions, lighting, and the presence of guy wires (Gehring et al. 2009). It is unclear how frequent collisions with stationary objects will be for species currently modeled in SCRAM.

There used to be much greater concern about turbulence and changes in air pressure around blades and the potential for injury/mortality from wind turbines; however, recent studies have discounted this concern to a large extent (e.g., Lawson et al. 2020). For example, the accepted wisdom 10-15 years ago was that bat mortality at terrestrial wind farms was mostly caused by air pressure changes around the blades (“barotrauma”), rather than actual collisions (Baerwald et al. 2008). More recent studies concluded that this effect is rare (Rollins et al. 2012), and occurs so close to the blades that it is nearly impossible for bats to be affected by extreme pressure changes without also colliding with the turbine blades (Lawson et al. 2020). Turbulence alone is not likely to be a substantial contributor to mortality, though it is possible that it could prevent birds from enacting last-minute avoidance maneuvers (i.e., micro-avoidance); we know of no studies that have examined this question.

That being said, Cook (2021) aggregated results from multiple European studies, including coastal studies like Everaert and Stienen (2007), which used carcass collection to help retroactively estimate avoidance of terns. As such, the “all tern/gull” avoidance rate is at least somewhat influenced by mortality that may have occurred from collision with the monopile, not just the blades. However, most offshore projects cannot estimate mortality or avoidance via carcass collection, in which case assessments of avoidance (via cameras or other monitoring approaches) focus specifically on the turbine blades.

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