Summer 2018

Potential Interaction Analysis of Offshore Wind Energy Areas and Breeding Avian Species on the US Mid-Atlantic Coast

Jeri Lynn Wisman
Old Dominion University, jlwisman@gmail.com

Recommended Citation

POTENTIAL INTERACTION ANALYSIS OF OFFSHORE WIND ENERGY AREAS

AND BREEDING AVIAN SPECIES ON THE US MID-ATLANTIC COAST

by

Jeri Lynn Wisman
B.S. May 2015, Old Dominion University

A Thesis Submitted to the Faculty of
Old Dominion University in Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

BIOLOGY

OLD DOMINION UNIVERSITY
August 2018

Approved by:

Sara M. Maxwell (Director)

Helen Bailey (Member)

Kent Carpenter (Member)

ABSTRACT

POTENTIAL INTERACTION ANALYSIS OF OFFSHORE WIND ENERGY AREAS AND
BREEDING AVIAN SPECIES ON THE US MID-ATLANTIC COAST

Jeri Lynn Wisman
Old Dominion University, 2018
Director: Dr. Sara Maxwell

Due to increasing US interest in developing wind energy sites in offshore waters, we synthesized existing data on colonial breeding seabird populations with the potential risk of interacting with lease areas in the mid-Atlantic. Previous efforts by BOEM and NOAA have predicted avian density using at-sea survey data; we seek to complement this work by focusing specifically on birds during the critical and energetically demanding breeding life history stage. We combined colony size and location for each species along the mid-Atlantic coast with buffers around the colonies that correlate with the species' foraging range. We integrated population size, vulnerability to offshore wind, and foraging areas to create a multi-species vulnerability model and overlaid this model onto current BOEM lease areas. Our model determined areas of high-predicted vulnerability in the northern and southern ends of the Eastern Shore of Virginia, southern to mid-areas of the New Jersey coastline, and western Long Island of New York. Out of the total study area, 31.73% of the high-predicted vulnerable areas overlapped with currently leased areas for offshore wind energy development. We also compared our model to NOAA's predicted density models and found they could be used together to identify areas with both high predicted density and high vulnerability as they overlapped 38.54% in our study area. The differences between these two models also suggest that simply relying on predicted density as a metric for determining impacts may miss areas that are critical for breeding birds.

We also collected GPS location data on common terns (*Sterna hirundo*) at Dawson Shoals, Virginia during their 2017 nesting season. We analyzed their movement and behavior in relation to offshore wind sites. We determined that common terns most often utilized an area roughly half the size of the suggested foraging range found in the literature, and that some traditional risk-models may be overestimating the potential impacts of offshore wind development on seabirds.

Tracking data should be integrated into methods used to minimize seabird impacts while developing an offshore wind energy industry in the mid-Atlantic.

This thesis is dedicated to my Mom and Dad, for inspiring, encouraging, and fostering my love of adventure and the ocean. Thank you for being constant rocks and providing support throughout graduate school. I love you to the moon and back. I also dedicate this thesis to Chris for his support and love throughout my graduate program and to Murphy for the thousands of puppy kisses.

ACKNOWLEDGMENTS

This work would not have been possible without a large community of people who have supported me throughout my graduate program through love, advice, and encouragement. First and foremost, thank you to my advisor Sara for being a constant source of help and support while working on my Master's. I am forever grateful for the lessons and experiences you have provided that have helped me to grow as a scientist and as a human since we began to work together. This degree has been an amazing experience, and it has been my greatest accomplishment to graduate from your lab. I look forward to future collaborations and laughs over tequila. I also owe many thanks to the other members of my committee, Helen Bailey and Kent Carpenter. Without you, this project would not have grown into what it is today.

I have been blessed with an incredibly talented and eager team of undergraduates who woke up at 3am countless mornings to make this field work possible. Endless thanks to Rachel Case, Emily Davis, Michael Marley, and Alexander Whatley and to ODU's Research for Undergraduates in Math and Science (RUMS) Program for providing the funding and opportunity for these individuals to join this project. More thanks to our amazing team of volunteers, Hannah Aichelman, Emily Anderson, Janelle Jilek, Amanda Larkin, Sarah Moore, Chelsea Putnick, and Nate Smith, for their help in the field. Thank you to Ruth Boettcher at the Department of Game and Inland Fisheries, Alexandra Wilke at the Nature Conservancy, and the Virginia Coastal Avian Partnership (VCAP) for help and knowledge of all things birds. Thank you to Eric Walters and Annie Coons for permitting and banding assistance. And finally, many thanks to our amazing boat captain Meriwether Payne at Seaside Ecotours for the all the smiles even in the early morning.

I owe an enormous thank you to my incredible friends and family. First, thank you Mom, Dad, Hallie, Max and King for being an unwavering source of support and love. This would not have been possible without you pushing me to achieve my dreams through dedication and hard work. Thank you to my lab mates and friends, Tiffany Dawson and Nick Sisson for answering all my questions and keeping me sane in the lab. Thank you to my boyfriend, Chris, for always being a source of encouragement and for the countless meals made and coffee brewed while working on my thesis. Thank you to my new team at the Bureau of Ocean Energy Management's Biological Sciences Unit for providing support in time and encouragement in the last two months of my thesis. Also, endless thanks to my crew of ODU grad student friends: Hannah, Jamie, and Emily. You've

showed me true friendship and I am forever grateful for you. You constantly inspire me, and I can't wait to see you continue to grow and conduct incredible science.

NOMENCLATURE

GW   gigawatts

BOEM   Bureau of Ocean Energy Management

US OCS   US Outer Continental Shelf

OREP   Office of Renewable Energy Programs

MDAT   Marine-Life Data Analysis Team

NOAA   National Oceanic and Atmospheric Administration

NCCOS   National Centers for Coastal Ocean Science

USFWS   US Fish and Wildlife Service

PP   proportion of population

FR   foraging range

VS   vulnerability score

CVspp   colony vulnerability

MSV   multi-species vulnerability

km   kilometers

BRPE   Brown pelican

COTE   Common tern

GBBG   Great black-backed gull

GBTE   Gull-billed tern

HERG   Herring gull

LAGU   Laughing gull

E   endangered

NL	not listed
P	protected
SC	special concern
GCN	greatest conservation need
T	threatened
IACUC	Institutional Animal Care and Use Committee
GPS	Global Positioning System
cm	centimeters
g	grams
mm	millimeters
KDE	kernel density estimation
KUD	kernel utilization distribution
UD	utilization distribution

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

POTENTIAL INTERACTION ANALYSIS OF OFFSHORE WIND ENERGY AREAS AND BREEDING AVIAN SPECIES ON THE US ATLANTIC COAST

INTRODUCTION

The need for renewable, clean energy is an increasingly pressing global issue. Renewable energy may be one of society's most promising opportunities to reduce excessive carbon dioxide emissions that have led to ongoing climate change (Dincer 2000, Panwar et al. 2011, Shahabuddin et al. 2016). Wind power is the fastest growing industry and source of renewable energy (Bastos et al. 2015). The European Union and China have led the world in planning, developing, and building wind energy sites (Drewitt & Langston 2006, Sun et al. 2012, Busch et al. 2013, Bailey et al. 2014). Offshore wind energy, where turbines are placed in marine environments, is now also on the rise, and promises to be an increasing source of renewable energy.

The first offshore wind turbines were built in Vindeby, Denmark in 1991 (Breton & Moe 2009), however the first commercial scale offshore wind farm was built in 2002 off the Denmark coast (Bailey et al. 2014). As of 2010, 45 European offshore wind energy sites had a power capacity of 2.9 gigawatts (GW) (Busch et al. 2013). One gigawatt can power between 225,000 to 300,000 homes, though this may be an underestimation[1]. In Portugal alone, there has been an increase in reliance on wind energy by 41% just in 2013, totaling 4.5 GW (Bastos et al. 2015). In China, offshore wind power resources have the potential to produce 750 GW whereas China's onshore wind power potential is 253 GW (Sun et al. 2012). China has set the highest pace for offshore wind energy site development and construction (Sun et al. 2012). Shanghai Donghai Bridge Wind Farm in China was the first offshore wind energy site demonstration project in Asia

---

[1] https://www.boem.gov/Offshore-Wind-Energy/

and is expected to power more than 200,000 city households (Sun et al. 2012). As of 2011, there are at least nine proposed offshore wind energy sites which could produce 2.35 GW of power total (Shiming et al. 2010, Jinjin 2011).

In the US, there is one commercial offshore wind site in operation consisting of five wind turbines off Block Island, Rhode Island. This site become operational in December 2016 and can produce 0.03 GW, powering 17,000 homes despite its small size[2,3] when compared to European and Chinese offshore facilities. The Bureau of Ocean Energy Management (BOEM) began overseeing renewable energy development in the US Outer Continental Shelf (OCS) in 2009. Since then, BOEM's Office of Renewable Energy Programs (OREP) has issued 13 commercial wind energy leases offshore[4] with the potential to produce at least 14.6 GW (Gilman et al. 2016). There are several other areas in the planning stages with BOEM (Gilman et al. 2016).

Though offshore wind energy seems to be a promising alternative to fossil fuels, there are key implications for marine species, especially for seabirds, that need to be considered (Drewitt and Langston 2006). As development of offshore wind energy expands, evaluations are needed to address how they will affect the marine environment and species. Though the environmental impacts of onshore wind energy development provide a starting point, offshore wind energy sites in the US are novel and their exact impacts are uncertain (Bailey et al. 2014). These environmental and biodiversity impacts include, but are not limited to: noise pollution, electromagnetic field disruption, entanglement risk, avoidance behaviors, collision risk, habitat change to both benthic and pelagic zones, food web changes, contaminant release from the seabed, and increased vessel traffic during construction (Boehlert & Gill 2010, Bailey et al. 2014). Wind energy sites could also affect human environments through visual impediment of oceans, potentially impact tourism, and could pose an obstruction to shipping lanes, among other impacts.

Of the many potential environmental impacts, seabirds are of particular concern, and effects on these species can include food web changes, collision, avoidance behavior, energetic costs, and migration route changes (Punt et al. 2009). Bird collision and displacement from important habitat areas may be the most frequent impacts (Gill 2005, Drewitt & Langston 2006,

---

[2] https://www.nytimes.com/2016/12/14/science/wind-power-block-island.html
[3] http://dwwind.com/project/block-island-wind-farm/
[4] https://www.boem.gov/BOEM-RE-Programs-Fact-Sheet/

Furness et al. 2013); therefore, they necessitate extensive assessments to propose areas for offshore wind energy development as well as mitigation plans for those in use. There have been many reviews and assessments of these marine avian risks to identify areas for offshore wind development that will minimize risk to seabirds (Curtice et al. 2016, Kinlan et al. 2016, Winship et al. personal communication). The Marine-Life Data Analysis Team (MDAT), a member of the National Oceanic and Atmospheric Administration (NOAA) National Centers for Coastal Ocean Science (NCCOS), produced long-term average predictive maps of relative abundance and relative occurrence probability using large datasets of at-sea transect surveys and environmental data (Curtice et al. 2016). The results of the abundance model are the long-term average relative abundance of individuals per strip transect segment while the occurrence probability model results are the long-term average relative occurrence probability per strip transect segment (Curtice et al. 2016). Species groups were developed including: regulated species, similar spatial patterns, similar taxonomic identification, common feeding strategies, common prey, how regions were utilized (breeding, feeding, migrating through, or resident), and stressor sensitivity-based (i.e. higher collision sensitivity, higher displacement) groups. Finally, total species richness maps were created by stacking each individual species' predicted presence and counting the total number of species present in each cell.

BOEM also funded NOAA's NCCOS' work to provide broad-scale avian spatial information to aid marine spatial planning in the mid-Atlantic region. Phase I of this project was published in 2016 (Kinlan et al. 2016) and phase II is currently underway (Winship et al. personal communication). Survey data on marine birds in the US Atlantic Coast was used to develop a statistical modeling framework to create avian relative occurrence and abundance models to estimate the relationship to temporal and spatial environmental predictor variables. These were also used to predict the spatial distribution of seabirds in the mid-Atlantic. Predictor variables are divided into six categories: survey, temporal, geographic, terrain, physical oceanographic and atmospheric, and biological. A fundamental assumption of this work is that all species were recorded when present; behavior was not considered as it is not possible through surveying methods. Breeding seabirds are inherently included in these predictive models, but the impacts to this critical life stage can be underestimated when combined with other life history stages. During the breeding season, seabirds are central place foragers, meaning that they are tied to the breeding colony and only forage in limited ranges for limited lengths of time before

returning to the nest to feed chicks or relieve their mates. Seabirds can be even more sensitive to avoidance and displacement of turbines and increased energy expenditures during this energetically demanding time, and as a result, impacts on breeding colonies from offshore wind energy should be critically assessed individually.

To assess the potential interaction risk, we created a model that incorporates colonial nesting data for breeding seabirds in the mid-Atlantic, and the vulnerability of these species to wind energy. Six seabird species were included in this model: brown pelican (*Pelecanus occidentalis*), common tern (*Sterna hirundo*), great black-backed gull (*Larus marinus*), gull-billed tern (*Gelochelidon nilotica*), herring gull (*Larus argentatus*), and laughing gull (*Leucophaeus atricilla*). All six species have a breeding season and spatial range within the mid-Atlantic region (Table 1) and are hypothesized to have high risk to offshore wind energy impacts based on previous studies (Willmott et al. 2013). Some of these seabirds are also listed as species of concern in various mid-Atlantic States (Table 2). This research aims to assess potential interaction of breeding seabird populations with offshore wind sites during the breeding season. Offshore wind energy in the US is a unique opportunity to evaluate and estimate impacts of wind turbines on the environment prior to construction. This study aims to inform environmental assessments to aide decision-makers in determining areas with minimal impact on seabirds.

Table 1. Breeding season timeline by species

Species	Arrive	Mate	Incubation	Brooding	Departure
Brown pelican	Apr – May	7-10 d	30-35.5 d	3 weeks	September
Common tern	May – June	not known	21.7-23.1 d	<12 days	mid-July
Great black-backed gull	Mar – Apr	Mar – Apr 5-6 d to lay eggs	27-28 d	7-10 days	August
Gull-billed tern	mid-Apr	monogamous nest bldg. 5-25 d after nest arrival	22-23 d	not known	mid-August
Herring gull	mid-May	pair formation occurs before arrival or right at arrival	22-27 d	8-10 days	August – September
Laughing gull	Mar-Apr	pair formation occurs before arrival	27-29 d	both day and night for 3-4 d and only at night for 10 d	July – September

Table 2. Species conservation status by state							
Species	VA	MD	DE	NJ	NY	CT	RI
Brown pelican	Not listed	Not listed	Not listed	Not listed	Not listed	Not listed	Not listed
Common tern	Greatest conservation need with very high conservation need	Endangered	Endangered – breeding	Special concern – breeding	Threatened	Special concern	Not listed
Great black-backed gull	Not listed	Not listed	Not listed	Not listed	Not listed	Not listed	Not listed
Gull-billed tern	Threatened	Endangered	Not listed	Special concern – breeding	Not listed	Not listed	Not listed
Herring gull	Not listed	Not listed	Not listed	Not listed	Not listed	Not listed	Not listed
Laughing gull	Greatest conservation need with moderated conservation need	Not listed	Not listed	Not listed	Protected	Not listed	Not listed

METHODS

DATA COLLECTION

Data on currently active renewable energy lease areas in the mid-Atlantic were downloaded as georeferenced shapefiles from BOEM and NOAA's Data Registry (MarineCadastre.gov). Colonial seabird data was provided from the USGS Colonial Waterbird Monitoring Database. This database is a collaborative effort between various partners who conduct waterbird nesting surveys and is funded by the US Fish and Wildlife Service (USFWS). The database extends from Maine to Georgia. The most recent survey was conducted in 2013 and was used in this analysis. From the 2013 survey, data from states in the mid-Atlantic region (Virginia, New Jersey, New York, and Connecticut) were included in our analysis; note that data was not available for Maryland, Delaware and Rhode Island. The data used were locations of coastal colonial sites and included the number of adult breeding pairs. All data were manipulated using ArcMap v10.5.1 (ESRI). Data were filtered by selecting only coastal colonies within the study region. Data were further filtered down to individual species identified as at-risk for impacts with offshore wind development (Willmott et al. 2013) and had a breeding range within the mid-Atlantic. Only species that have a documented foraging range during breeding that is greater than 10 km were further considered, as these species were most likely to forage within the current lease areas of offshore wind energy sites. The final species included in the potential interaction analyses were: brown pelicans (*Pelecanus occidnetalis*), common terns (*Sterna hirundo*), great black-backed gulls (*Larus marinus*), gull billed terns (*Gelochelidon nilotica*), herring gulls (*Larus argentatus*), and laughing gulls (*Leucophaeus atricilla*) (Erwin 1977, Morris & Black 1980, Briggs et al. 1981, Fritts et al. 1983, Fasola & Bogliani 1990, Rome & Ellis 2004).

MODEL DEVELOPMENT

A multi-species vulnerability model was created through a series of model steps (Fig. 1). First, for each of the six species, we used the colony location data in the mid-Atlantic region to split the nesting areas into natural 'colony groups' (Fig. 2); these groups were determined by identifying natural breaks in groupings of nesting sites, for example the break between Assateague island and Assawoman island in Virginia. Eight colony groups were identified, and

the number of pairs for each species in each colony group were summed to determine the proportion of population (PP). The proportion of the population within study area at each colony group was determined:

$$\text{(1) For each species: Proportion of Population (PP)} = \frac{\text{colony population}}{\text{spp population (in study area)}}$$

Second, potential foraging ranges (FR) were created to encompass possible areas where breeding seabirds could travel to forage based on information found in the literature (Table 3). As few of these species have been individually tracked using satellite telemetry, neither the most heavily used areas nor direction (along shore, offshore) could be included, as this information was not found in the literature (Table 3). Some generalizations, however, were found in the literature and areas where individuals are likely to forage more ('common' foraging zone) were weighted with a value of '1' and areas where the foraging range likely extended to but are less commonly found foraging ('uncommon' foraging zone) were weighted with a value of '0.5'.

Third, each species was given an offshore wind impact value ('individual species vulnerability score'). Using Wilmott et al. (2013), each species was given a value in the following categories: displacement risk, disturbance risk, threat ranking, population sensitivity, collision sensitivity, nocturnal flight, diurnal flight, macro avoidance of wind turbines, breeding, habitat flexibility, and percent of time spent in the rotor swept zone (Table 4). These values were summed for each species to create the individual species vulnerability scores used in this analysis. Individual vulnerability scores were then weighted based on its score relative to the other five species. The scores were weighted by dividing by the maximum score across all species' scores (Equation 2):

$$\text{(2) Individual Species Vulnerability Score (VS)} = \frac{\text{species vulnerability}}{\text{maximum vulnerability of all species}}$$

The above metrics were combined for each species, with the proportion of the population and vulnerability scores spatially incorporated into the foraging ranges for each colony:

(3) For each species at each colony: Colony vulnerability (CVspp) = PP x VS x FR

Finally, these individual species models were summed across the study area to create a multi-species vulnerability model with the following equation:

$$\text{(4) Multi-species vulnerability (MSV)} = \sum CV_{spp}$$

Using the multi-species vulnerability model, areas that have a heightened importance for surveying and monitoring impacts of offshore wind energy sites were identified.
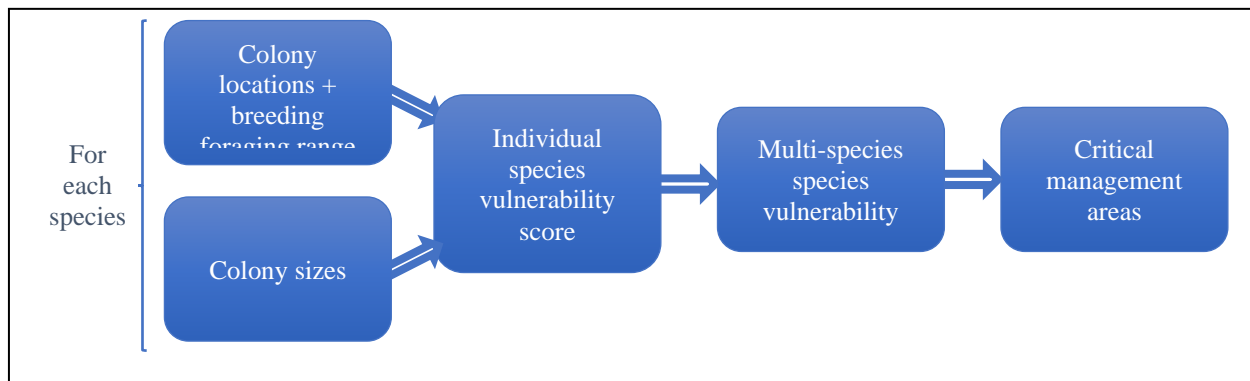

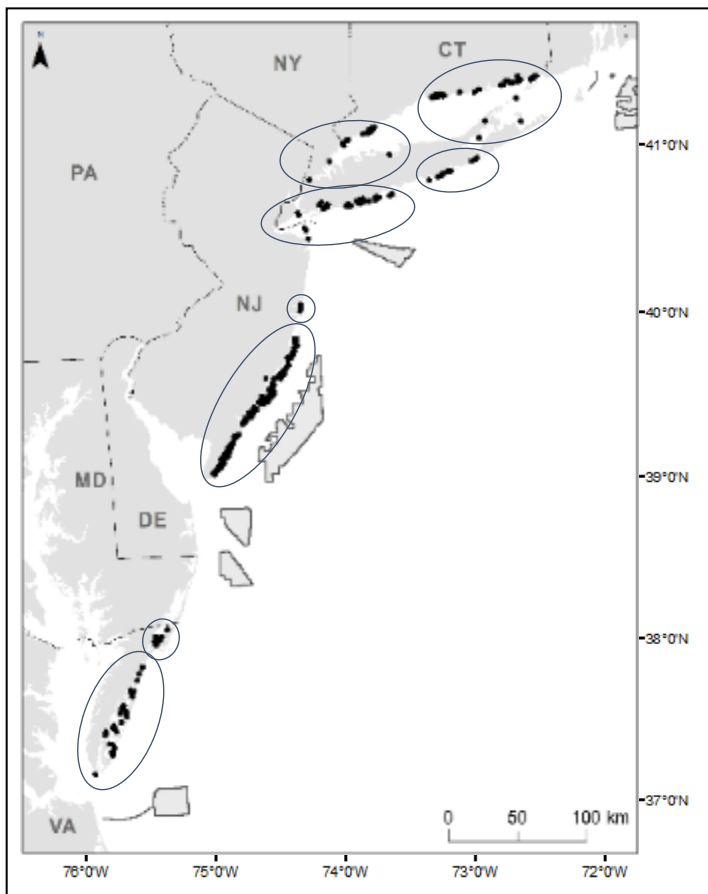Fig. 1. Flowchart of methods used to create the multi-species vulnerability model

Fig. 2. Natural colony groups of nesting colonies in the 2013 breeding season along the US mid-Atlantic coast

Table 3. 'Common' and 'uncommon' foraging ranges by species. 'Uncommon' foraging ranges are those determined through a literature search of the species' greatest distance travelled for foraging from their nest during the breeding season. 'Common' foraging ranges are determined through a literature search as the distance more commonly travelled from the nest during the breeding season (FR = foraging range)

Common name	Common FR (km)	Uncommon FR (km)	Common FR Information	Methodology	Data source
Brown pelican	10	20	Most abundant within 20 km of nesting islands during main breeding season	Beach censuses; ship and aerial surveys	(Briggs et al. 1981)
Common tern	13	20	Equally found in: open bay (13 and 21 km away); inlets/ beach; tidal creeks (1.5-2.5 km away); and marsh/ tidal pools (next to colony)	Field surveys	(Erwin 1977)
Great black-backed gull	10	15	N and SE direction 20m from nest site	Field surveys	(Rome and Ellis 2004)
Gull-billed tern	5	10	Densities decreased as the distance from colony increased	Field surveys	(Fasola and Bogliani 1990)
Herring gull	Not known	15	Occurred equally in all directions 20m from nest site	Field surveys	(Rome and Ellis 2004)
Laughing gull	20	45	May forage up to 45 km from colony sites	Field surveys	(Fritts et al. 1983)

Table 4. Values from Wilmott et al. (2013) used to determine the individual species vulnerability score

Category	Brown pelican	Common tern	Great black-backed gull	Gull-billed tern	Herring gull	Laughing gull
Displacement risk	4.54	8.03	8.37	0	6.55	5.74
Disturbance risk	3	1	2	2	2	2
Protected species	1	1	1	1	1	1
Population sensitivity	2.50	2.25	2.50	2.75	2.50	2.25
Collision sensitivity	8.83	9.16	9.81	4.62	9.81	8.98
Nocturnal flight	1	1	3	5	3	3
Diurnal flight	3	5	2	5	2	3
Macro avoidance	10	6	6	6	6	6
Breeding	1.5	2	2	1	2	1.5
Habitat flexibility	1	3	2	0	1	1
Rotor swept zone	3	1	1	1	1	3
TOTAL	39.37	39.44	39.86	28.37	36.86	37.47

MODEL COMPARISON

Data were downloaded from BOEM and NOAA's Data Registry (MarineCadastre.gov). We also compared our produced models to NOAA's avian predicted density model (Fig. 3) to determine spatial distribution of birds and highlight areas of high occurrence of at-risk seabird species (Kinlan et al. 2016). To compare our multi-species vulnerability model to NOAA's predicted density model, we acquired the predicted density raster layers for the same six seabird species (brown pelican, common tern, great black-backed gull, gull-billed tern, herring gull, laughing gull) (Winship et al. personal communication). We used the raster layers that represented the summer season (June to August) to attempt to relate breeding predicted density to vulnerability risk during the breeding season. Once the individual species' density raster layers were summed together, we normalized the model by using a 'rescaleLayer' function in R. This was to create a model that had a predicted density value range from 0 to 1. To compare our multi-species vulnerability model to NOAA's predicted avian density model, we calculated the percent overlap for the top quartile of model results when individual layers for all six species were combined (0.75-1.0).

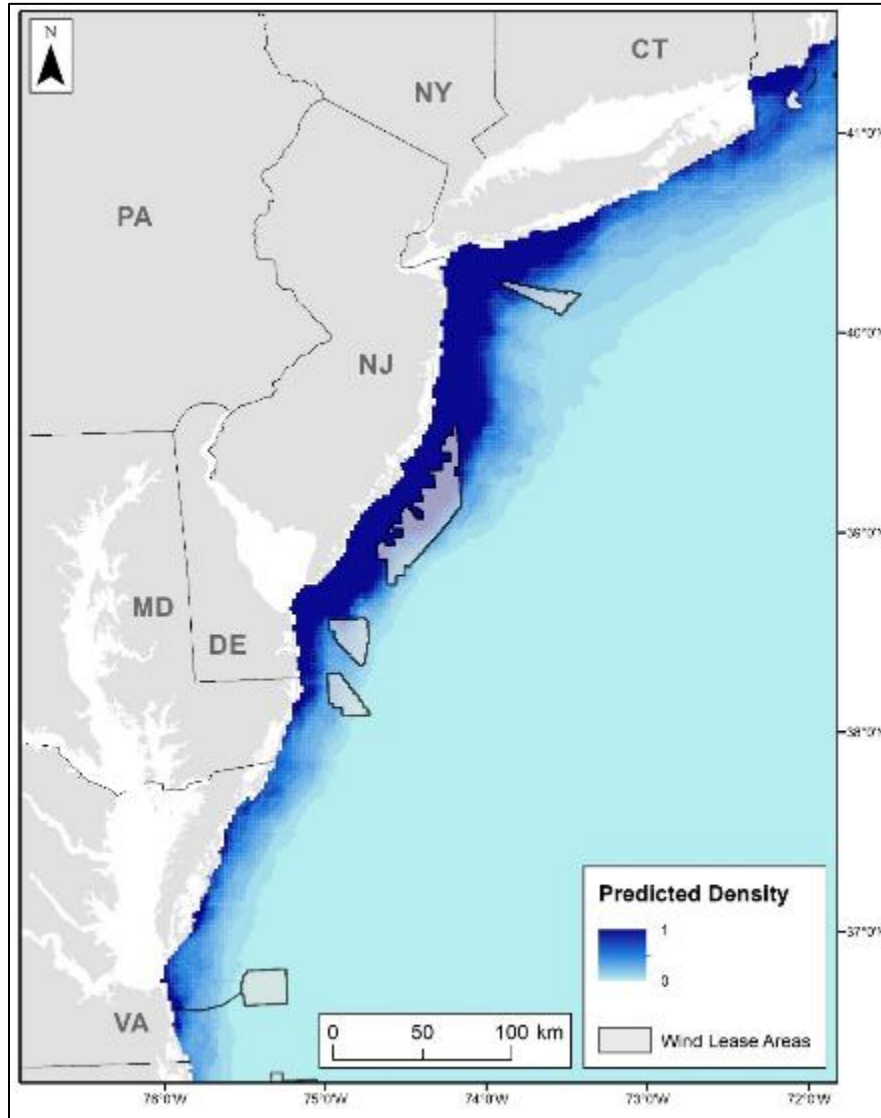Fig. 3. NOAA's predicted density model. Includes our selected six species (brown pelican, common tern, great black-backed gull, gull-billed tern, herring gull, laughing gull) along the US mid-Atlantic coast during the summer period (June to August) derived from a statistical modeling framework that related historical survey data to temporal and spatial environmental predictor variables (Winship et al. personal communication)

RESULTS

Approximately 700 colonies of our six species were observed in the 2013 Colonial Waterbird Survey, including three brown pelican colonies, 141 common tern colonies, 191 great black-backed gulls colonies, 22 gull-billed tern colonies, 180 herring gull colonies, and 156 laughing gull colonies (Fig. 4). This culminated in 61,725 pairs observed in 2013 in the mid-Atlantic region. When comparing the 'uncommon' outer foraging ranges of the six species, laughing gulls are expected to travel the furthest (45km) followed by brown pelicans and common terns (20km) (Fig. 5; Table 3). According to the literature, the most 'common' foraging range for assessed species were about the same distance (around 10 km) from their nest (Fig. 5; Table 3). Herring gulls did not have a common foraging range value, as it could not be determined from the literature. The greatest density of seabird colonies was found near southern to mid-New Jersey's coastline followed by the northern Eastern Shore of Virginia (Fig. 4). It should be noted that laughing gulls greatly influenced the southern New Jersey population numbers as 81.3% of the population was laughing gulls. Using the individual species vulnerability score assessment, we found that great black-backed gulls face the highest potential impact risk (39.68) followed by common terns (39.44) and brown pelicans (39.37; Table 4). The vulnerability score range was small, from 28.37-39.68 (difference of 11.31).

The multi-species vulnerability model indicates multiple areas of high vulnerability. These areas are a result of regions with high seabird populations, species with high vulnerability to offshore wind, high use foraging areas, or a combination of these three elements (Fig. 6). Our model results indicate higher variation in vulnerability when assessing areas closer to the coastline when compared to NOAA's predicted density model (Fig. 3). The NOAA predicted density model shows more variation in density in areas further offshore as the distance increases further offshore. Our multi-species vulnerability model shows more variation in vulnerability along the coast (Fig. 6). The top quartiles (values 0.75 – 1) of the two models overlapped 38.54% of the total study area for the multi-species vulnerability model (Fig. 7). Both models indicate that the southern New Jersey and western Long Island coast are higher vulnerable areas. Our multi-species vulnerability model also indicates that the Eastern Shore of Virginia coast is a higher vulnerable area along the coast but becomes less vulnerable more than 15 – 20km

offshore (Fig. 6). The multi-species vulnerability model shows that 31.73% of the top quartile areas overlap with the current offshore wind energy lease areas.
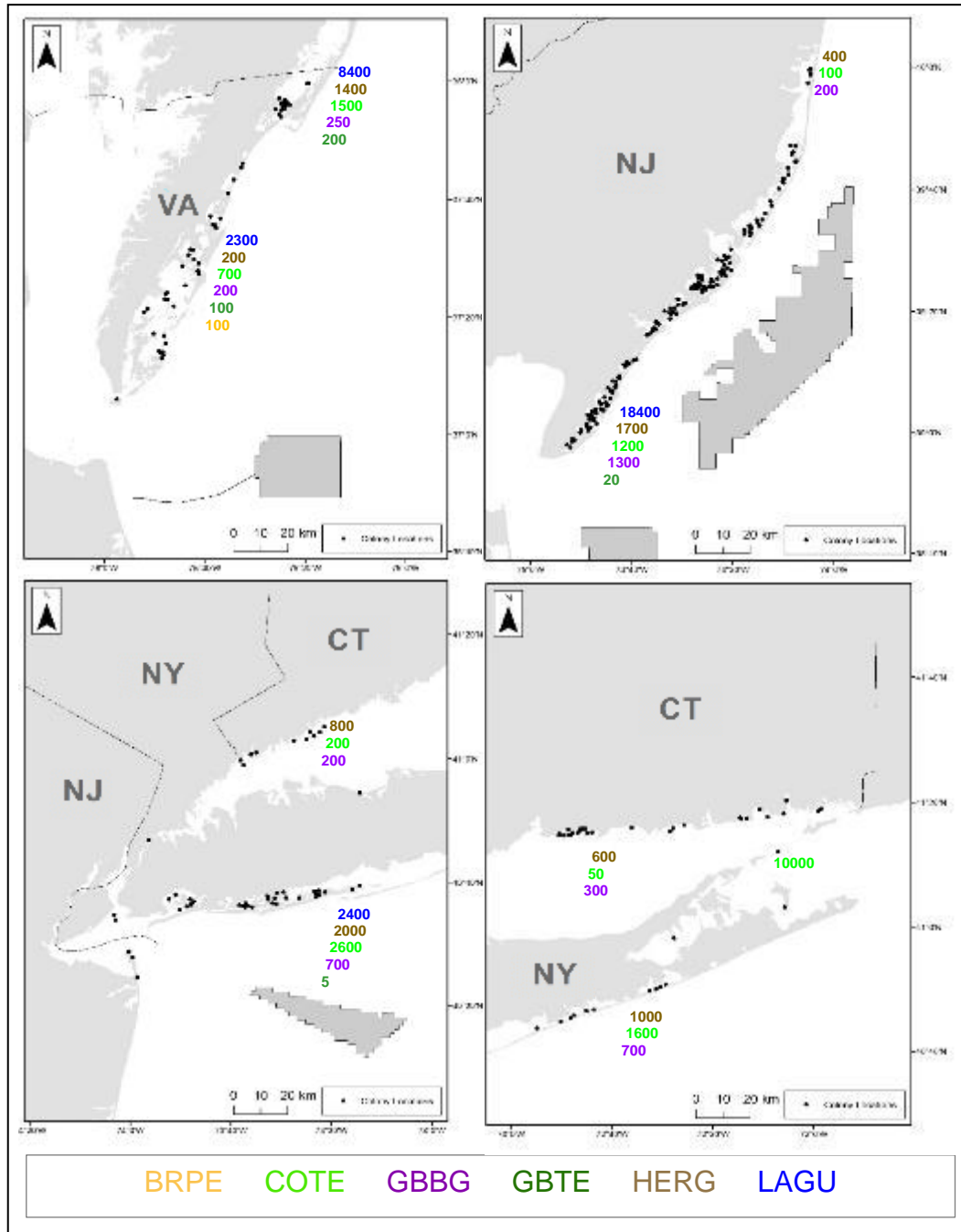
Fig. 4. Population size of nesting colonies in the 2013 breeding season along the US mid-Atlantic coast. Figure includes: brown pelicans (BRPE), common terns (COTE), great black-backed gulls (GBBG), gull-billed terns (GBTE), herring gulls (HERG), and laughing gulls (LAGU)
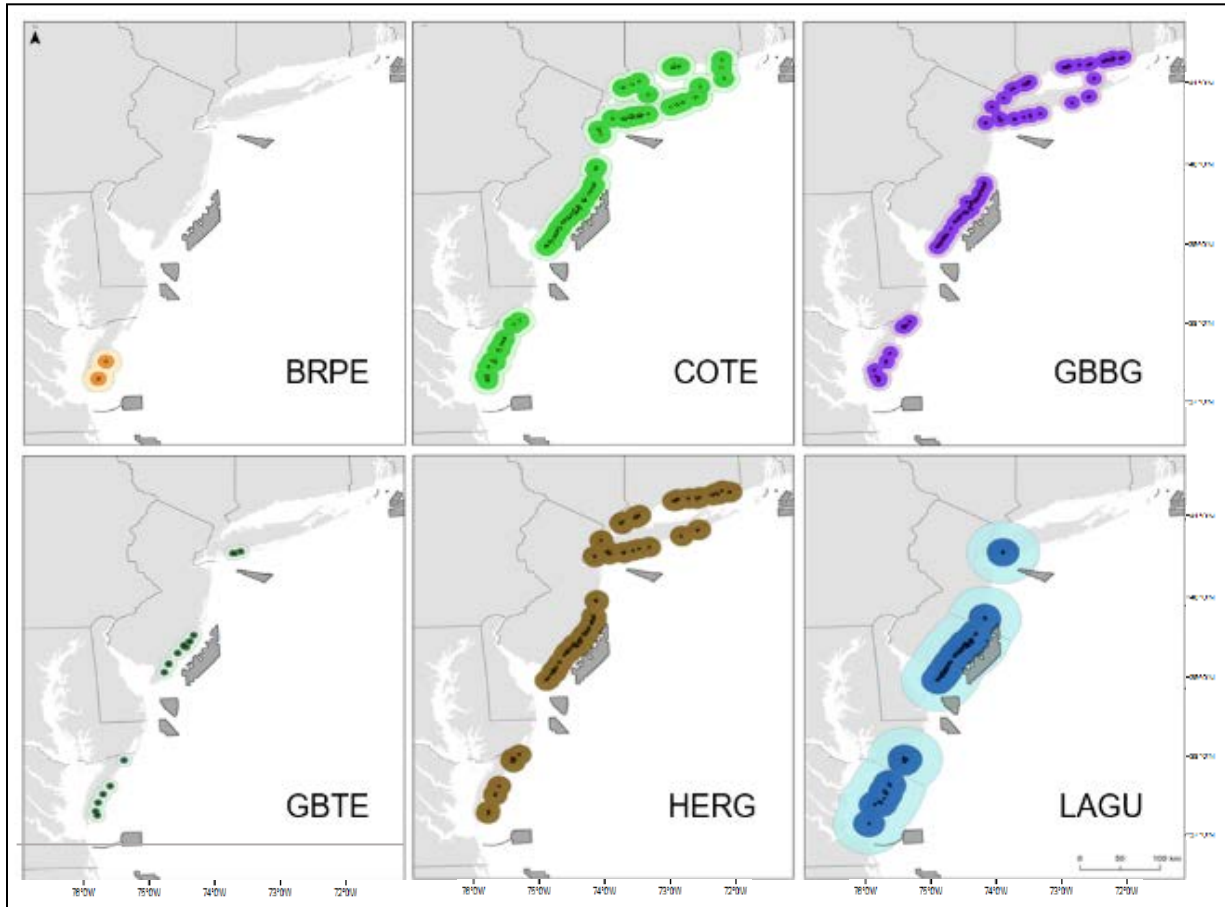
Fig. 5. 'Common' and 'uncommon' foraging ranges of nesting colonies in the 2013 breeding season along the US mid-Atlantic coast, including: brown pelicans (BRPE), common terns, (COTE), great black-backed gulls (GBBG), gull-billed terns (GBTE), herring gulls (HERG), and laughing gulls (LAGU)
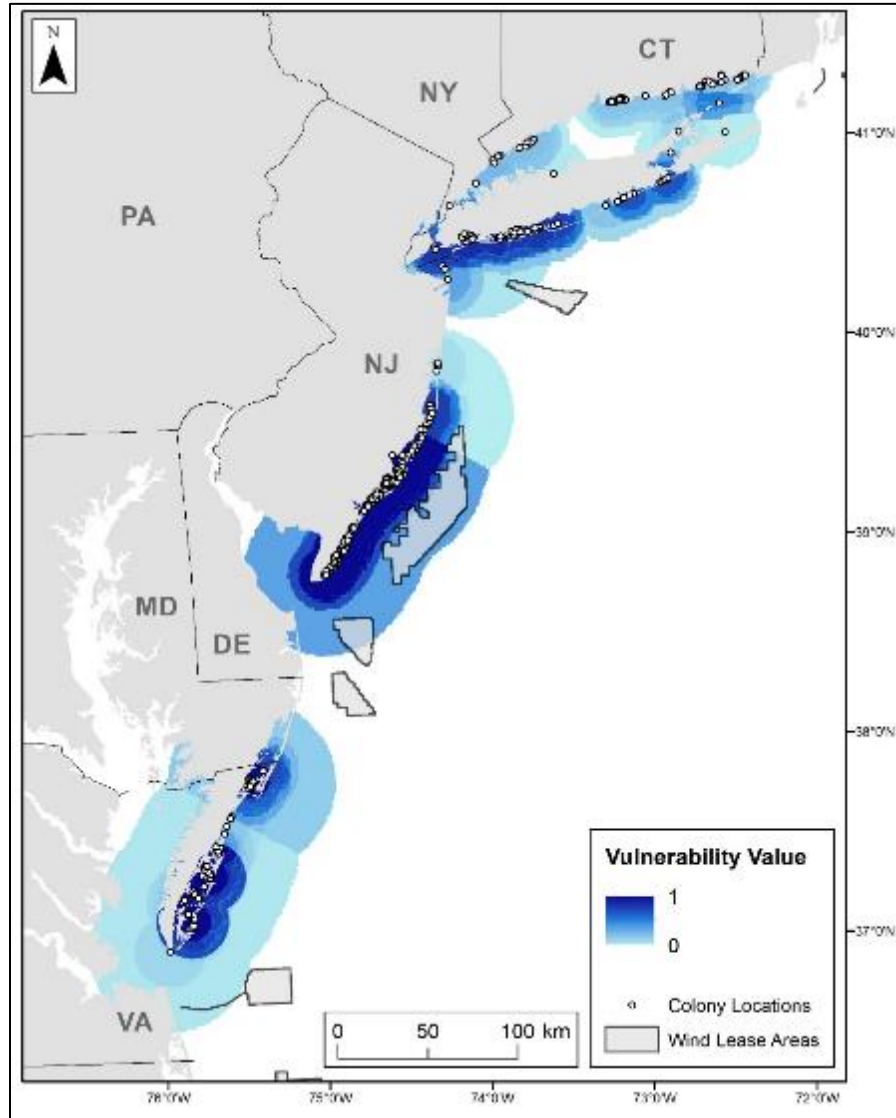
Fig. 6. Multi-species vulnerability model. Includes our selected six species (brown pelican, common tern, great black-backed gull, gull-billed tern, herring gull, laughing gull), which indicates areas of heightened importance for surveying and monitoring impacts of offshore wind energy sites
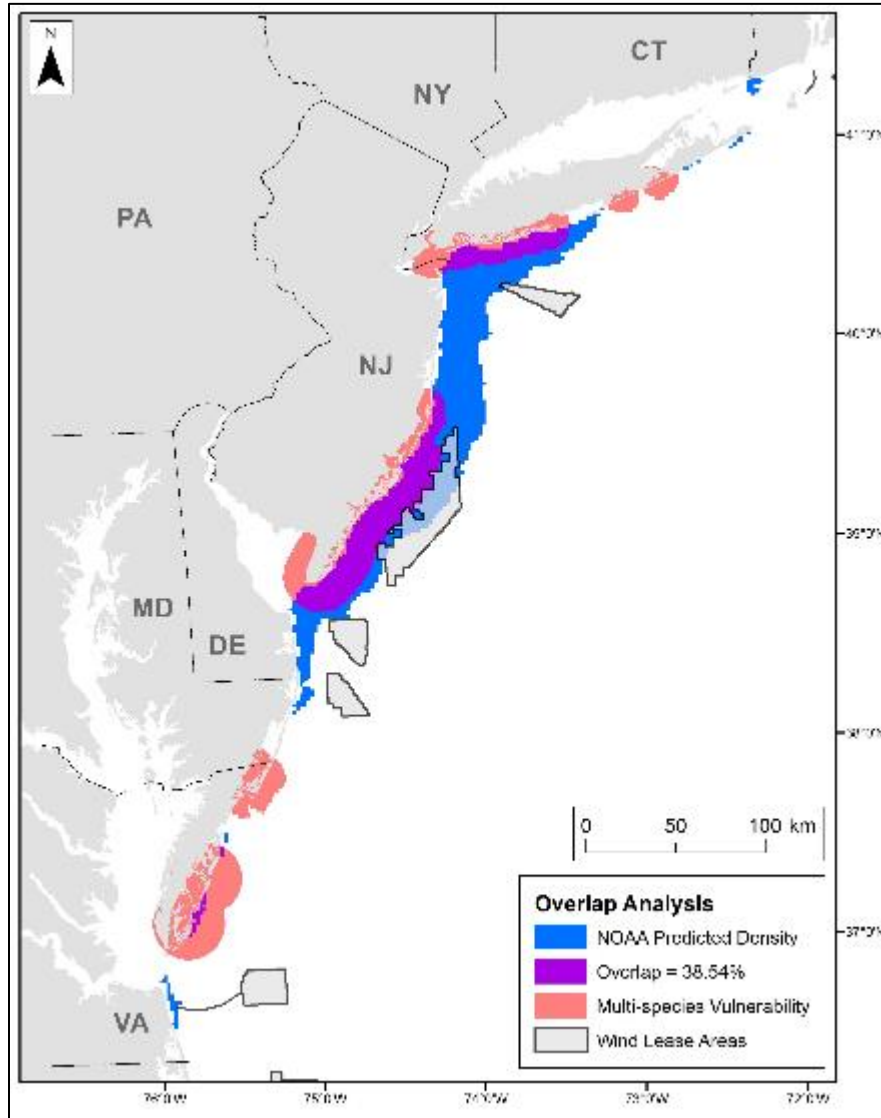
Fig. 7. Overlap analysis of our multi-species vulnerability model and NOAA's predicted density model. Both models include our selected six species (brown pelican, common tern, great black-backed gull, gull-billed tern, herring gull, laughing gull)

DISCUSSION

This study found that when assessing the breeding season individually, the potential for overlap and impacts from offshore wind energy differs from when breeding is included with several other parameters (Fig. 7). Using survey data of nesting pairs in conjunction with range data and species-specific vulnerability to wind energy, we were able to see finer-scale differences in vulnerability than previous studies. Focusing on specific, targeted species during the highly critical life history stage of breeding is a key component of assessing how offshore wind sites could affect seabird populations. Furthermore, our model allows users to see that areas commonly used for foraging (<10km offshore) may have potentially less impacts than the outer range of seabird foraging ranges (10 – 45km offshore; Fig. 6). For example, the literature suggests that common terns may forage up to 20km from their nests during breeding which would result in higher potential overlap with offshore wind lease areas. If the 'common' foraging area (13 km from nest) is weighted, as was in our model, then it displays lower potential overlap and vulnerability scores in the areas that do overlap with offshore wind lease areas. This suggests that the impact risk from offshore wind energy would be lower than previously expected and indicating the potential for lower ecological impacts from this renewable energy source.

COMPARISON TO PREDICTED DENSITY

We also compared our multi-species vulnerability model (Fig. 6) to NOAA's predicted density model (Fig. 3) for several seabird species (Kinlan et al. 2016, Winship et al. personal communication). The NOAA predicted density model shows consistently high-density values along the New Jersey coastline. Our multi-species vulnerability model shows that the vulnerability in this area ranges widely, with values ranging from 0.004 – 0.855. There are also similar differences in results between the two models when analyzing them throughout the Virginia coast. In western Long Island, the models are more similar than along New Jersey and Virginia, but again our multi-species vulnerability model shows more variability compared to the consistently high-density values. This suggests it is important to consider offshore wind vary when accounting for population density, vulnerability, and the foraging range during the breeding season. These two models should be used together to find areas with heightened vulnerability to impacts from offshore wind by first determining areas of high predicted density

using resources like NOAA's predicted density models (Kinlan et al. 2016, Winship et al. personal communication) followed by the application of the multi-species vulnerability model to determine areas within high avian predicted density that also have high predicted vulnerability values as well. This can focus conservation and mitigation efforts to areas with both high density and high vulnerability, with an increased focus on the breeding season when birds are most vulnerable.

Our multi-species vulnerability model overlapped with the NOAA predicted density model 38.4% when considering the top quartile of each models results (Fig. 7). One explanation for the relatively low similarity between the two models could be the lack of colonial data from Maryland, Delaware and Rhode Island in the multi-species vulnerability model. Furthermore, the multi-species vulnerability model only extends up to 45km from the shoreline as this is the furthest foraging range distance, whereas the predicted density model extends up to 475km offshore. Despite the differences between these models, energy site managers and developers can still evaluate important impact risk information. Our model is an important management tool as it assesses impacts to hypothesized at-risk seabirds during a known critical life history stage and fills a critical data gap in assessing offshore wind site risk on breeding seabirds. Furthermore, we suggest that conservation efforts focused on monitoring population-level impacts posed by offshore wind should be targeted in areas along the southern and northern ends of the Virginia Eastern Shore, the coast of New Jersey and the western area of Long Island.

MODEL LIMITATIONS

Our multi-species vulnerability model is not predictive and relies on nesting survey data that is collected every five years and does not consider flight behavior. It takes a conservative approach in identifying high vulnerability areas for seabirds from offshore wind energy development. The foraging ranges are large and rely on the literature. Additionally, our model currently only includes six at-risk seabird species (Willmott et al. 2013). NOAA's predicted density model can include up to 40 species (Kinlan et al. 2016, Winship et al. personal communication). However, for comparison purposes, the predicted density model used in this study assessed only the same six species as our vulnerability model. More species should be considered in the future when evaluating overlap and risk posed by offshore wind energy sites, if

additional species are found to extend offshore or wind energy areas or impacts are determined to be closer to shore.

Updated and new technologies should also be considered when identifying foraging ranges as they can provide more detailed and exact information regarding the common foraging areas and the direction of travel from the nests. Our model is spatially limited because some states in the mid-Atlantic region (Maryland, Delaware and Rhode Island) were not included in the USGS Colonial Waterbird Database. Our multi-species vulnerability model methods should be continued and expanded to include updated colonial data, improved spatial information on foraging ranges, and more seabird species that are at-risk from impacts to better assess and identify key areas to monitor for population impacts from offshore wind.

IMPORTANCE OF CONSIDERING BREEDING

As evident in the differences between our multi-species vulnerability model and survey-based species richness and predicted density models (Kinlan et al. 2016, Winship et al. personal communication), considering only breeding seabirds allows users to identify smaller, possibly more critical management areas. These areas can be targeted for management and conservation purposes in the event of nearby offshore wind energy development. These areas can be monitored for changes in breeding population numbers to assess changes possibly due to offshore wind development. We suggest considering the critical life history stage breeding separately as well as included in multi-variate models when evaluating population impacts of offshore wind energy development on marine avian species.

CONCLUSIONS

Our multi-species vulnerability model determined that impact risk from wind energy is different when solely assessing breeding data with foraging ranges and species-specific vulnerability. The results display finer-scale differences in vulnerability than previous studies that included breeding with several other parameters. Furthermore, considering specific species during the breeding season is a key component of assessing how offshore wind energy sites could affect seabird populations. Also considering foraging ranges during the breeding season found that 'common' foraging ranges may face potentially less impacts than the 'uncommon' foraging range found in the literature. Using our multi-species vulnerability model, we suggest that the southern and northern ends of the Virginia Eastern Shore, the southern to mid-New Jersey coast, and western Long Island of New York could face higher levels of vulnerability to offshore wind energy and should be monitored if development begins.

CHAPTER 2

COMMON TERN MOVEMENT ECOLOGY DURING THE BREEDING SEASON AND IMPLICATIONS FOR OFFSHORE WIND ENERGY DEVELOPMENT

INTRODUCTION

There are several methods of using tags to track individual animals that ecologists can use to assess movement and behavior of many animal species. However, the technology has been limited for which species can be assessed. Until recently, satellite tags have been too large for many avian species which rely on flight. As this technology has improved, size and costs of tracking devices have both decreased. These improvements allow for a better understanding of fine-scale movements and behaviors of smaller avian species that could not previously support larger tags (Maxwell et al. 2016). These newer and smaller tags have allowed researchers to study fine-scale seabird movements, behavior, and habitat use (Burger & Shaffer 2008, Hazen et al. 2012, Montevecchi et al. 2012).

The greatest asset of satellite tracking studies is the potential to contribute to conservation and management decision-making (Burger & Shaffer 2008). There are numerous advantages of animal-borne tracking; multiple individuals from established populations can be tracked, individual behaviors can be determined through time and key habitat areas can be identified. Unlike surveying efforts, satellite telemetry is a good method for encompassing wider geographic and temporal coverage (Williams et al. 2015). Studies using satellite tags on seabirds have revealed long-range movements of many seabird species (Burger & Shaffer 2008). Long-term datasets from tracking data can be vital for understanding the impacts of anthropogenic activity, such as offshore wind energy development, on seabirds (Williams et al. 2015).

Birds have often been used as environmental indicators and to study the anthropogenic impacts on ecosystems. Birds are sensitive to environmental changes, respond predictably, and data can be easy to compile and interpret (Butler et al. 2012). Birds have been used to learn more about habitat quality (O'Connell et al. 2000, Stolen et al. 2005, Frederick et al. 2009), impacts of pollution (Bouwman et al. 2013, Balmford 2013, Pilastro et al. 1993), disease outbreaks (Eidson et al. 2001, Rochlin et al. 2011, Suarex & Tsutsui 2004), and are indicators of biodiversity (Mikusiński et al. 2001, Kati et al. 2004). Birds have also been useful subjects for conservation planning and informing policy as they allow researchers to study ecosystem health.

One such species of seabirds that could be used as environmental indicators from anthropogenic impacts are common terns (*Sterna hirundo*). This is an avian species that have previously been difficult to track due to their small body mass; however, several conservation concerns exist for this species that would be aided through tracking. Common terns are migratory, colonial seabirds that are long-lived, lay small clutches, and do not begin breeding until around 4 years old (Erwin 1977, Ezard et al. 2007, Palestis 2014). Common terns are generalist foragers, meaning they will feed both inshore and offshore. During the nesting season they become central place forages, meaning they only forage centrally around the nest (Erwin 1977). They feed on small fish (i.e. silversides, killifish, sandeels, bay anchovies) while diving and breed on barrier islands in the Eastern Shore of Virginia from late May to early July (Erwin 1977, Safina & Burger 1985). Common terns are listed globally as "least concern" by the IUCN Red List (International 2016), however the coastal Virginia population has declined 70.7% between 1993 and 2013 (Watts & Paxton 2014). This decline was mostly due to the invasion of laughing gulls within the Hampton Roads Tunnel Island, which was habitat for the largest common tern colony in Virginia and had compensated for common tern population numbers in the past (Watts & Paxton 2014). The common tern population in Maryland has also declined 86% since the early 1990s[5]. Common terns are listed as a species of greatest conservation need in Virginia[6] and endangered in Maryland[7].

Common terns are hypothesized to have a high risk of collision and displacement from offshore wind energy (Willmott et al. 2013) and have been sited during ship-based surveys

---

[5] http://md.audubon.org/conservation/tern-island-birds
[6] https://www.dgif.virginia.gov/wp-content/uploads/virginia-threatened-endangered-species.pdf
[7] http://dnr.maryland.gov/wildlife/Documents/rte_Animal_List.pdf

conducted at Virginia's offshore wind energy lease site (Tetra Tech 2014). This species also displays high foraging habitat fidelity which leads researchers to believe that they will have a high sensitivity to displacement by wind turbines (González-Solís et al. 1999). Despite being agile flyers, terns could still face the risk of bird strikes if turbines are established in areas where they aggregate in large groups or if they are built within regular flight paths (Palestis 2014). The extent of collision and disturbance risk has been hard to determine with survey data. Surveys are limiting for assessing collision risk as it is a poor method of documenting seabird movement patterns, is costly, is unable to accurately collect behavioral data (e.g. foraging and transiting) and is difficult to compare importance of different areas (Drewitt & Langston 2006, Williams et al. 2015). Surveying also suffers from large inter-observer differences (Camphuysen et al. 2004) and cannot suffice for small-scale, individual temporal coverage, as they are costly to conduct and thus are usually limited in both duration and area surveyed (Drewitt & Langston 2006). These limitations may have contributed to an under- or over-estimation of wind energy risk to seabird populations as regulators assessed risk in a very conservative manner due to the uncertainties involved (Bailey et al. 2014).

Here, we determine the movement and behavior of common terns using GPS tracking devices. Our primary aims are to: (1) determine home range and distribution of common terns during the breeding season, (2) determine if movements are impacted by environmental influences such as weather or diurnal patterns, (3) aid decision-makers in minimizing the impact of offshore wind turbines on seabird populations. This goal is to inform environmental assessments that can contribute to establishing an offshore wind energy industry in Virginia and Maryland that will have minimal ecological impact with maximum human and ecosystem health and clean energy benefits. We hypothesize that the common tern study population will rarely enter the current Virginia and Maryland offshore wind lease areas (Fig. 8) during their breeding season. We also aim to establish more precise foraging range information for common terns and discuss how this can be applied to other common tern colonies that are closer to offshore wind lease areas.
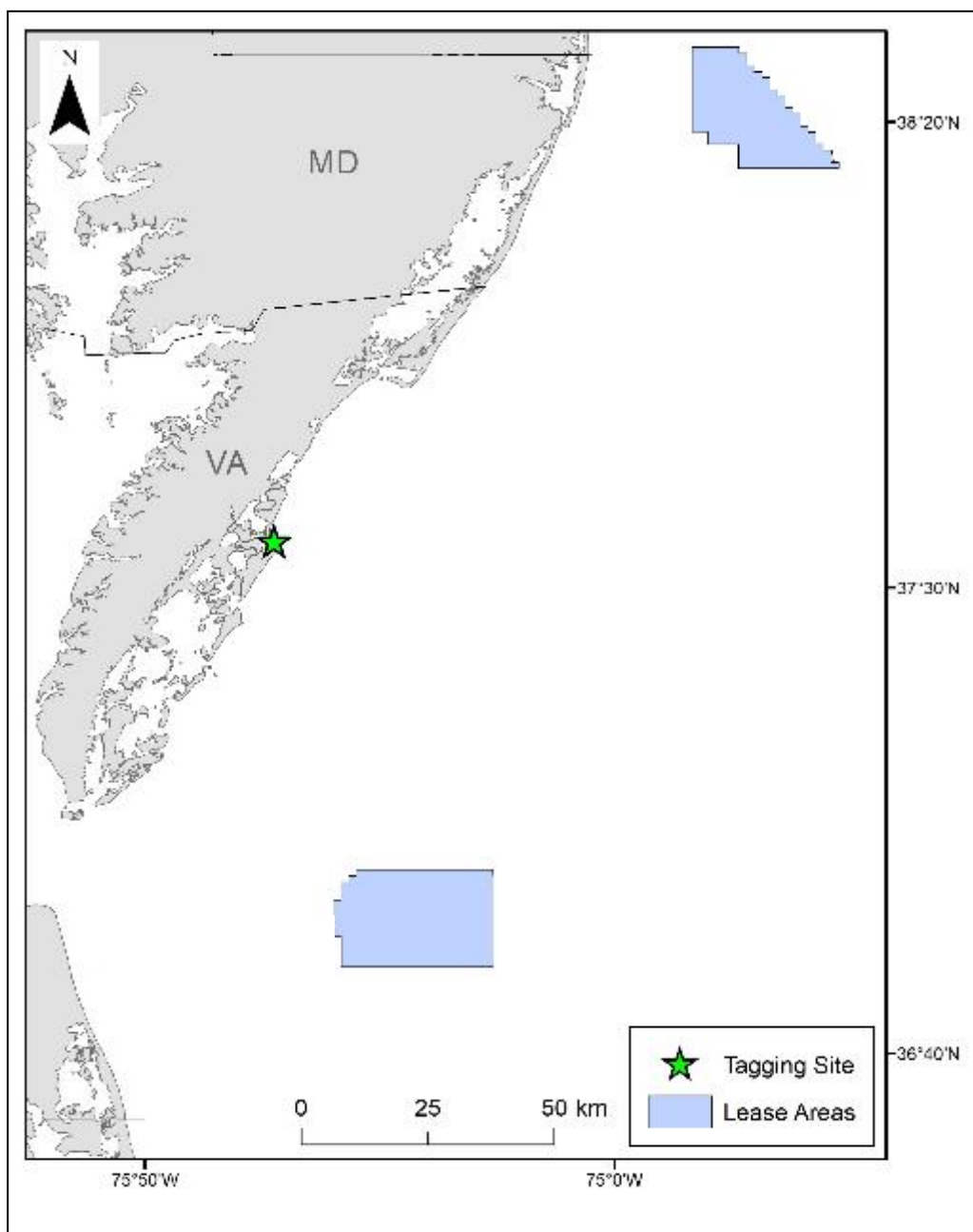
Fig. 8. Maryland and Virginia lease areas for offshore wind energy development (current as of May 2018)

METHODS

ETHICS STATEMENT

      All state, federal and institutional guidelines were followed, and this study was approved by and carried out in accordance with the recommendations of the Institutional Animal Care and Use Committee at Old Dominion University (IACUC Permit 17-007). Permission to work with Federal Bird Banding was issued by the US Department of the Interior (Bird Banding Permit 23803 under Dr. Eric Walters). Permissions to work within the state of Virginia were issued by the Virginia Department of Game and Inland Fisheries (Scientific Collection and Bird Banding Permit 059952).

SATELLITE TRACKING

      We used animal-borne telemetry technology to track the movements of common terns from late May to early June of 2017. Tags used the Global Positioning System (GPS) to record locations (latitude and longitude) of the individuals to track animal movement and determine animal behaviors and habitat usage (Hazen et al. 2012; Fig. 2). Common terns were captured in situ at their breeding grounds using methods demonstrated by Burger and Shaffer (2008) and Maxwell et al. (2016).

      This study was conducted at Dawson Shoals (37.6° N, 75.6° W), a barrier island off the coast of the Virginia Eastern Shore, where common terns nest during the early summer. The lagoon and barrier island system of the Eastern Shore are critical areas for colonial seabird nesting and accounted for 54.7% of all breeding pairs surveyed in the coastal plain region of Virginia (Watts & Paxton 2014). Dawson Shoals is located between both the Maryland and Virginia offshore wind energy lease sites (Fig. 9); the construction of the Virginia demonstration site is scheduled to begin by 2020 at the earliest[8].

      We captured adult individuals at their nests during incubation using a treadle trap and then recaptured with either a treadle trap or bow net. Waterproof GPS transmitters (Pathtrack

---

[8] http://pilotonline.com/news/local/environment/dominion-loses-million-federal-grant-for-virginia-offshore-wind-project/article_5e69e24a-bb41-57b3-b582-a411d12c352b.html

Ltd, Otley, West Yorkshire, UK; nanoFix-GPS+) were attached to individuals to collect movement and behavior data. Tags were attached using waterproof Tesa tape (Tesa Tape Inc., Charlotte, NC) to the back two tail feathers, 1–2cm behind the uropygial or preening gland. Tags were 2.4 x 1.1 x 0.5cm with a thin antenna extending 4.8cm and weigh 1.4g, approximately 1.14% of the average body weight of the tagged birds (122.7g, 102-157g). There were no visible signs of discomfort from the tags as there were no observed bite marks on the tape or tags nor were birds ever observed to attempt contact with the tags (pecking at them, etc.) during our monitoring after tag deployment. The location data was stored on the devices and required recapture of the individual to download the information. Twenty-six GPS tags were deployed and 15 were recovered resulting in a 58% success rate of recapture. Recapture was possible as common terns are central foragers during the breeding season and return frequently to nests to incubate eggs and/or bring food to their mate. Tags are also capable of being reused once the data is downloaded and removed. Tags were deployed on an average of five days and collected a data point every 10 minutes. This allowed the tags to capture a minimum of four foraging trips which has been shown to produce reliable estimates of animal ranges and sufficient evidence for individual behaviors (Soanes et al. 2013).

Tag deployments were conducted in two batches. The first round was deployed from 6/9/17 to 6/13/17 and the second round was deployed from 6/16/17 to 6/26/17 (Table 5). Other information was collected on the individuals as we handled and attached the tags to them, including: weight (g), wing length (mm), tarsus length (mm), the maximum and minimum length (mm), fork length (mm), and the head to bill length (mm). All handled birds were banded with permissions and protocol from the USGS Bird Banding Lab. Regurgitation samples were collected opportunistically and feather samples were collected from all individuals to analyze in future studies to tie stable isotope and diet information to the habitat distribution determined in this project.
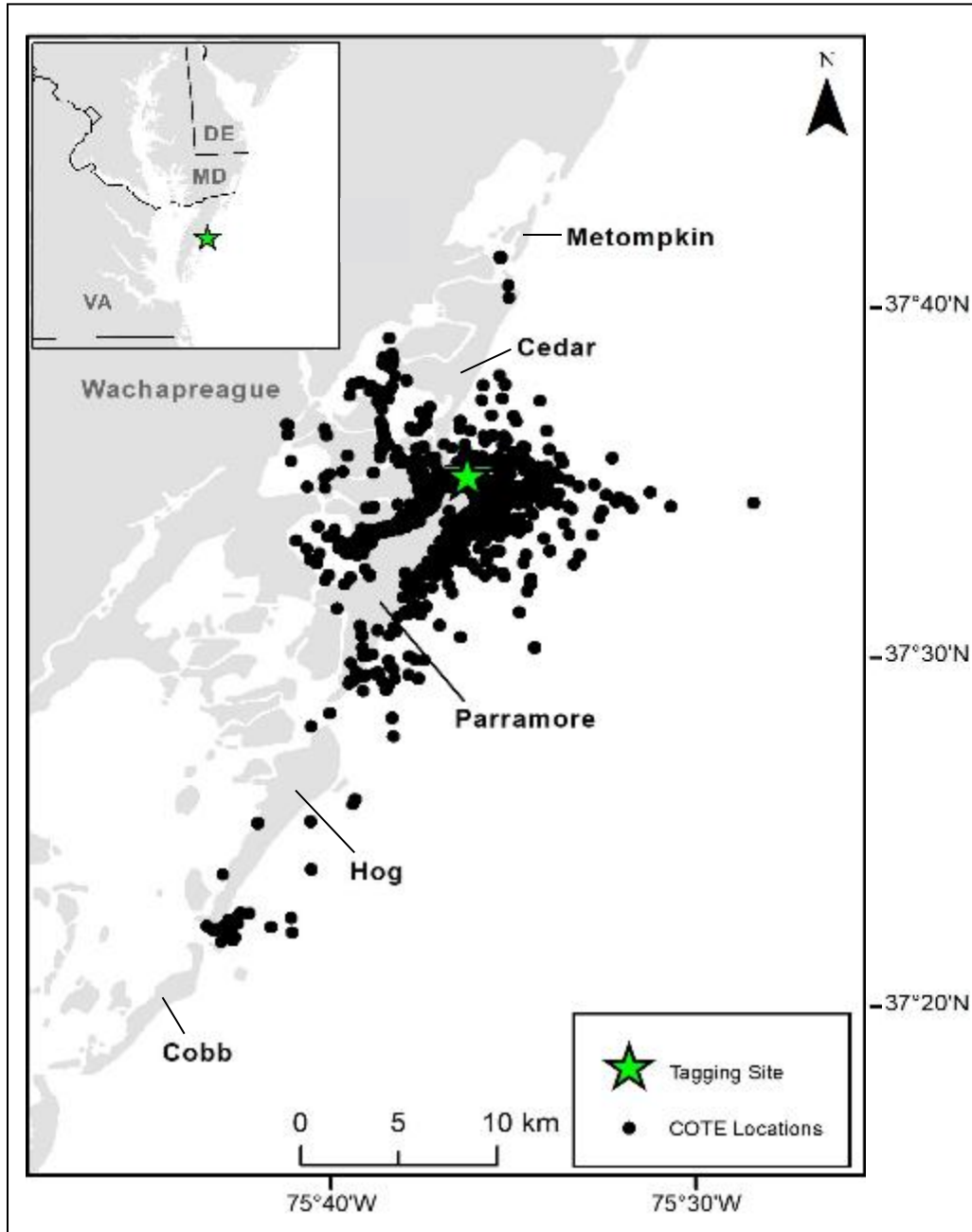
Fig. 9. Location data points of the tagged common tern population during breeding season of 2017

Table 5. Tag deployment summary

Individual	Deployment date	Recapture date	Length of tag attachment (days)
1A	9 June 2017	10 June 2017	1
1B	10 June 2017	12 June 2017	3
2A	9 June 2017	12 June 2017	4
2B	12 June 2017	18 June 2017	7
3A	13 June 2017	16 June 2017	4
3B	13 June 2017	NA	NA
5A	13 June 2017	16 June 2017	4
5B	13 June 2017	16 June 2017	4
6A	13 June 2017	16 June 2017	4
8A	17 June 2017	26 June 2017	10
8B	22 June 2017	NA	NA
12A	18 June 2017	25 June 2017	8
13A	17 June 2017	23 June 2017	7
13B	18 June 2017	25 June 2017	8
14A	18 June 2017	25 June 2017	8
14B	22 June 2017	NA	NA
15A	17 June 2017	22 June 2017	6
15B	18 June 2017	22 June 2017	5
16A	18 June 2017	NA	NA
18A	18 June 2017	22 June 2017	5
18B	18 June 2017	22 June 2017	5
21A	18 June 2017	22 June 2017	5
21B	17 June 2017	22 June 2017	6
23A	17 June 2017	22 June 2017	6
23B	18 June 2017	26 June 2017	9
24A	16 June 2017	22 June 2017	7
24B	18 June 2017	25 June 2017	8
25A	16 June 2017	22 June 2017	7
25B	22 June 2017	NA	NA

FLIGHT METRICS

The GPS location data were used to create flight tracks of the foraging trips taken by the tagged individual birds (Fig. 10). These tracks were then used to calculate the average distances traveled. We used ArcMap 10.5.1. (ESRI) software to calculate the cumulative distances for each flight that the recaptured birds took. To avoid an individual bird bias while producing the averages, flight distances were first averaged on an individual basis. These averages produced an overall average of the distance travelled by the tagged population. We also divided the tracks into two categories: nocturnal and diurnal flights. Diurnal flights were considered from times 06:00 to 20:00 and nocturnal flights were considered from times 20:01 to 05:59, based average sunrise-sunset times for the time of year. A paired student t-test determined if there was a statistical difference between the distance travelled nocturnally versus diurnally.
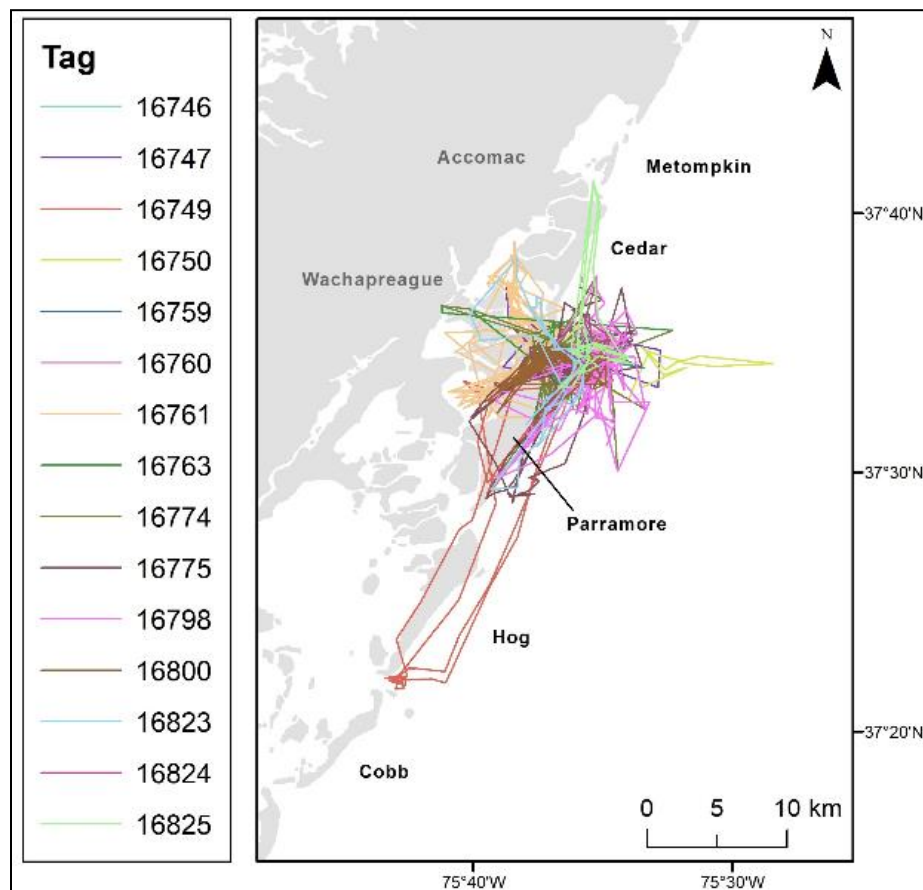

Fig. 10. Trajectories of the movements tracked using GPS satellite transmitters on breeding common tern individuals in June of 2017

ANALYTICAL TECHNIQUES

All analyses and map-building were conducted using R (R Core Team) and ArcMap 10.5.1 (ESRI) programming. First, animal movement and behavior were determined through a residence time analysis. Second, home range and animal distribution estimates were produced through a kernel density estimation analysis (Kernohan et al. 2001). These analyses allowed us to determine where critical foraging and transiting habitat occurs and whether this overlapped with either the Maryland or Virginia offshore wind energy lease areas. Data for the wind energy lease areas were obtained from the Bureau of Ocean Energy Management's (BOEM) Marine Cadastre database.

I.   ANIMAL MOVEMENT AND BEHAVIOR

A residence time analysis was conducted to determine areas of greatest use (high residence time) by the common tern individuals. Methods employed by Barraquand and Benhamou (2008) are commonly used to classify foraging behaviors and is based on time spent near successive path locations. Using this method, we imposed a circle over each consecutive location and the time spent within the circle was summed. The size of the circle is user-defined and dependent on the biology and foraging behavior of the study species (Maxwell et al. 2016). For this project, we used a small circle radius - of 1.11×10^{-3} km (or 1×10^{-4} degree decimals) - as the common terns tended to stay close to their nest (within 13 km). Locations with high residence time were defined as the top 25% quartile of all residence time values (Torres et al. 2011, Maxwell et al. 2016).

II.   HOME RANGE AND ANIMAL DISTRIBUTION

A kernel density estimation (KDE) analysis results in kernel utilization distributions (KUDs), the number of locations per user-defined grid cells, by taking the weighted sums of normal distributions centered on each point within the dataset (Maxwell et al. 2011). This was done by creating individual KUDs for each tagged seabird at UD levels of 90%, 75%, 50%, and 25%. For all KUDs in this study, a 1 km buffer was created around the tag deployment site/ nesting site to eliminate data points within the buffer so that the KDE focused only on habitats not being used for nesting. The KDE also requires a minimum of five location data points to calculate the distribution so any individual in the following scenarios studied that had less than

five points did not have a KUD created. To minimize bias towards individual that collected more locations, the individual KUD values were summed for all birds in each raster cell. The summed layer was then 'normalized' by dividing the sum raster layer by the maximum value in the layer. This created an overall KUD for the study population.

Furthermore, environmental factors were examined using home range estimation. We subset and compared distribution on days where weather events occurred ('weather' days) versus days where no weather events occurred ('clear' days) as well as compared diurnal versus nocturnal flights. Weather data was collected from Weather Underground (the Weather Company) and days when rain, thunderstorms, and/ or fog occurred were considered 'weather' days compared to days 'clear' days, resulting in 8 days with weather events and 10 days without. Diurnal flights were considered from times 06:00 to 20:00 and nocturnal flights were considered from times 20:01 to 05:59, based on average sunrise-sunset times for the time of year. The KUDs for these environmental factors were created using the same methods as above for the overall population KUD.

To determine if the collected dataset contained an adequate number of individuals to represent most of the home range (90% utilization distribution) for the entire population, we created a kernel density utilization distribution home range, iteratively adding individuals to determine how many is needed to reach a home range size asymptote, indicating a sufficient sample size (Soanes et al. 2013, Maxwell et al. 2016).

RESULTS

FLIGHT METRICS

The data collected shows that the average flight distance of the tagged common tern population was 12.01 km (6.20 – 20.87 km; Table 6). Flights were mostly to nearby barrier islands and inshore towards Wachapreague, Virginia. The average flight distance during the day was 11.00 km (4.72 – 21.36 km) and during the night was 16.98 km (6.60 – 52.97 km). The common terns took longer, single nocturnal flight trips, but there was on average more diurnal flights per bird. We found a statistically significant difference between nocturnal and diurnal flight distances (t = 2.2855; df = 24; p = 0.0314).

Table 6. Flight track metrics

Individual	Avg flight (km)	Avg flight per day (km)	Avg flight per night (km)	Avg flight duration (mins)
1A	6.20	4.72	12.13	18.00
1B	11.95	5.45	30.00	67.50
2A	7.60	5.75	17.82	46.15
2B	2.20	2.20	NA	20.00
3A	9.73	9.95	10.82	30.00
5A	20.03	21.36	9.36	56.11
6A	17.54	16.65	20.18	45.00
8A	15.75	14.53	20.18	46.22
13A	9.32	9.27	10.08	35.33
14A	8.88	8.34	13.42	36.60
15B	9.69	9.54	11.40	20.71
18B	12.62	12.44	14.92	32.41
23A	20.87	17.88	52.97	82.34
24B	9.44	9.63	7.86	33.61
25A	8.48	8.53	6.60	36.39
Mean (Max-Min)	11.35 (2.20-20.87)	10.42 (2.20-21.36)	16.98 (6.60-52.97)	40.42 (18.00-82.34)

RESIDENCE TIME

We found high residence times throughout the entire area used by the birds, but most occurred close to the nesting area (Fig. 11). There were a few high residence locations inshore near the town of Wachapreague, the southern end of Hog Island, and north of Cedar Island. These high residence locations were attributed to individual birds, however, and did not reflect the trends of the entire tagged population. Other high residence areas occurred east of the nesting site in offshore waters up to about 10 km from the tagging site as well as the northern end of Parramore Island. Low residence locations occurred frequently throughout the entire study area near Dawson Shoals, Parramore Island, Hog Island, Cedar Island, and inshore between Dawson Shoals and Wachapreague (Fig. 11).
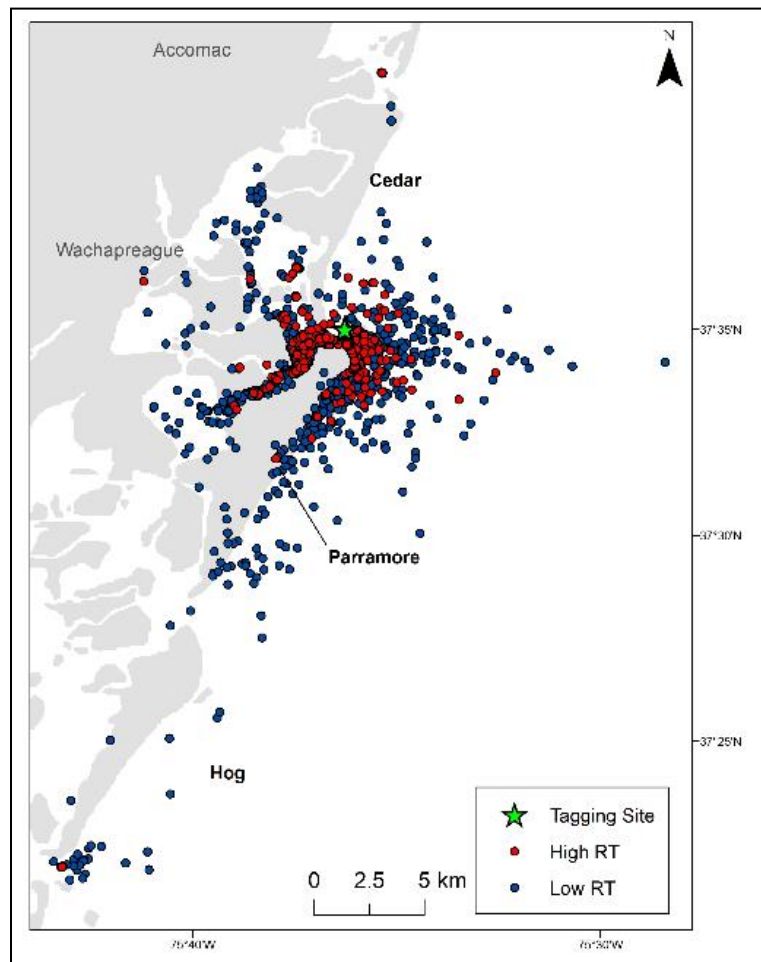
Fig. 11. Residence time analysis of common terns tracked during 2017 breeding season

KERNEL DENSITY ESTIMATION

The KUD of the overall habitat usage (Fig. 12) for the common tern population at the overall area (90% KUD) was 343.92 km^2 and the core use are 25% was 7.25 km^2 with the locations within 1 km of the tagging site removed (Table 7). Like the residence time analysis, we found that the areas heavily used (25% KUD) by the common tern individuals were close to the nesting area (Fig. 5). Less-used areas (90% KUD) occurred inshore towards Wachapreague, the northern end of Cedar Island, the southern end of Hog Island, and directly offshore from Dawson Shoals (roughly 10 km). However, the areas that were furthest from the nest were utilized by a single individual. Parramore Island is also an important area that the common terns utilize.

Fig. 12. KUD analysis of all common tern locations during the 2017 breeding season

Table 7. KUD areas of total common tern population, flights on 'clear' days and days with weather events (i.e. fog, rain, thunderstorm), and diurnal and nocturnal flights
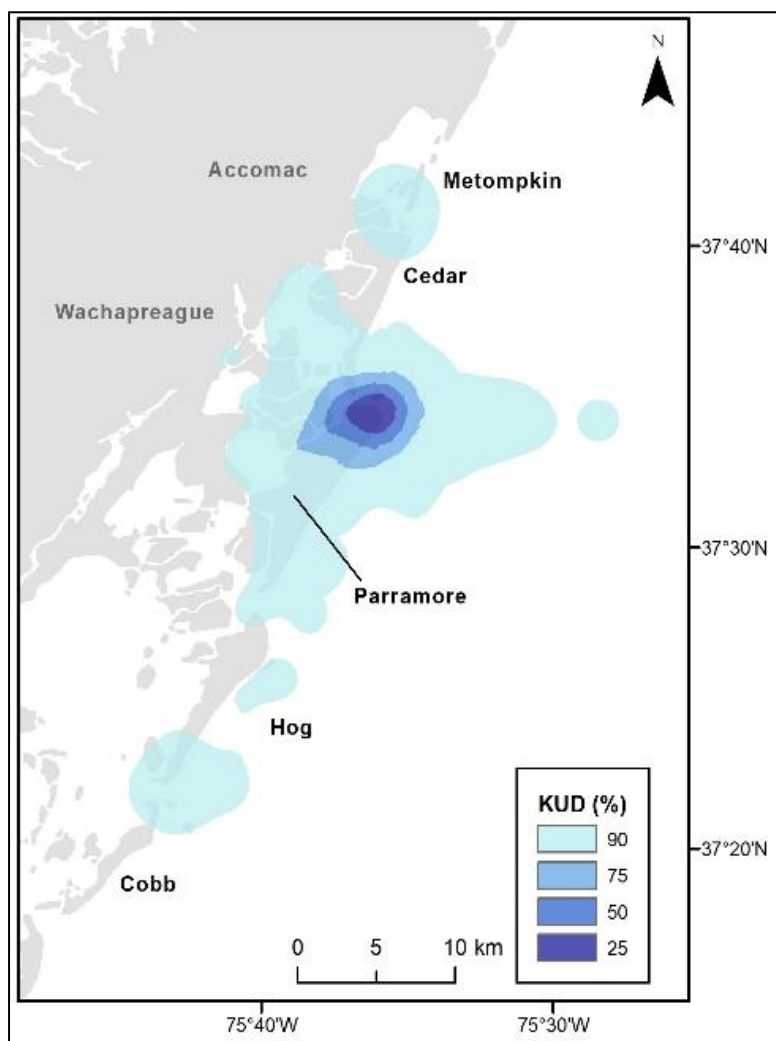
KUD (%)	Overall area (km²)	'Clear' days area (km²)	'Weather' days area (km²)	Diurnal flights area (km²)	Nocturnal flights area (km²)
25	7.25	13.35	13.70	7.10	8.75
50	12.48	15.75	16.85	12.10	14.90
75	24.73	36.50	29.06	24.55	28.71
90	343.92	357.61	232.49	315.94	192.50

ENVIRONMENTAL IMPACTS ON HOME RANGE

We found differences in the KUD on 'clear' days when compared to 'weather' days (rain, thunderstorm, and/or fog). The overall area (90% KUD) on 'clear' days was 357.61 km² and the core area (25% KUD) was 13.35 km² with the locations within 1 km of the tagging site removed. The overall area (90% KUD) on 'weather' days was 232.49 km² and the core area (25% KUD) was 13.70 km². On 'weather' days, the common terns utilized southern islands such as Parramore and Cedar Island and tended to stay inshore or along the coastline (Fig. 13). On 'clear' days, the utilization distribution was very similar to the overall habitat usage (Fig. 13). On 'clear' days, the KUD extends up to northern Cedar and Metompkin Island as well. For both 'clear' days and 'weather' days, the heavily used areas were both close to the tagging site and only had a 2.5% difference (the 25% KUD on days with weather events was larger). However, the 90% KUD of the 'clear' days was 35% larger than the 90% KUD of the 'weather' days.

We found differences in the KUD of nocturnal flights when compared to diurnal flights. The overall area (90% KUD) for diurnal flights was 315.94 km² and the core area (25% KUD) was 7.10 km². The overall area (90% KUD) for nocturnal flights was 192.50 km² and the core area (25% KUD) was 8.75 km². During the day, the KUD extends to southern Hog Island, about 10 km offshore from the nest site, and inshore towards Wachapreague (Fig. 14). The diurnal flight 90% KUD is like both the 'clear' days and the total population 90% KUD. At night, the KUD extends to northern Cedar Island but otherwise remains close to the tagging site (Fig. 14). The heavily used areas for both diurnal and nocturnal flights were both close to the tagging site, with the core area during nocturnal flights being slightly to the east of Dawson Shoals (~1 km). The heavily utilized area (25% KUD) of the nocturnal flights was 18.85% larger than the heavily utilized area of the diurnal flights. However, the 90% KUD of the diurnal flights was 39% larger than the 90% KUD of the nocturnal flight area.
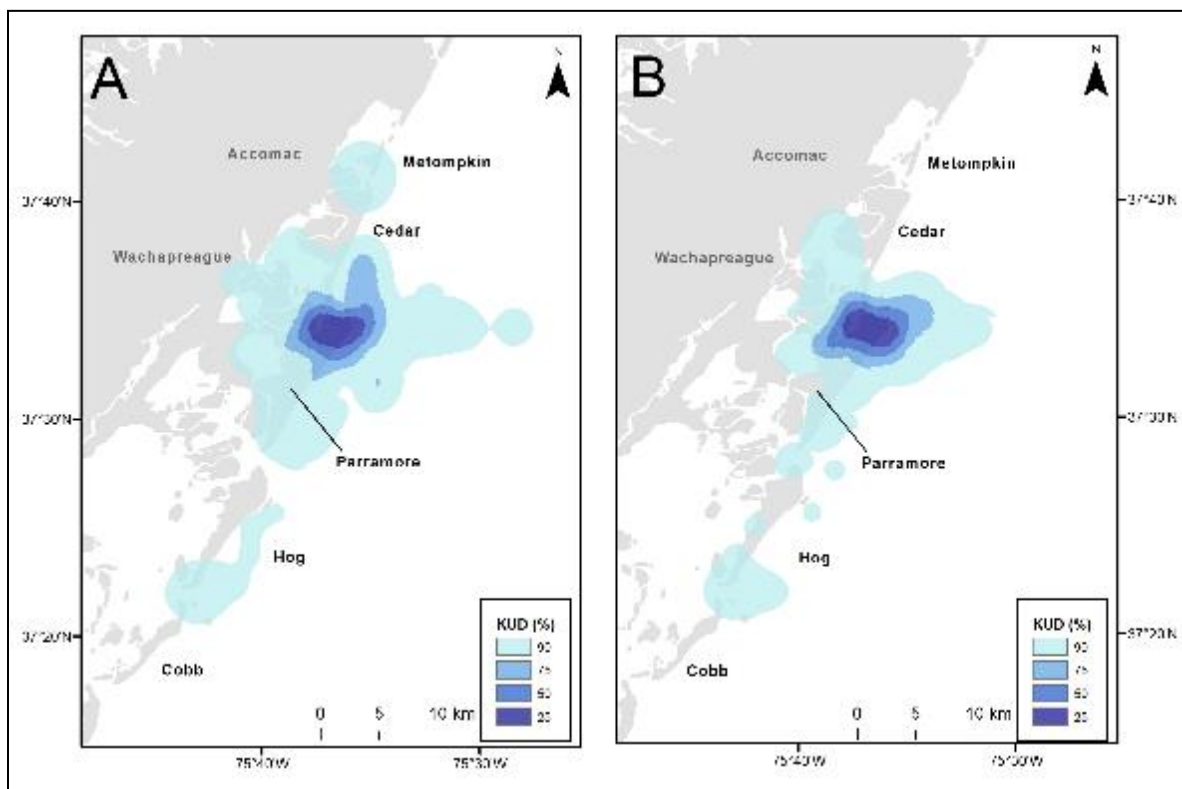
Fig. 13. (A) KUD analysis on 'clear' days and (B) KUD analysis on 'weather' days (i.e. fog, rain, thunderstorm)
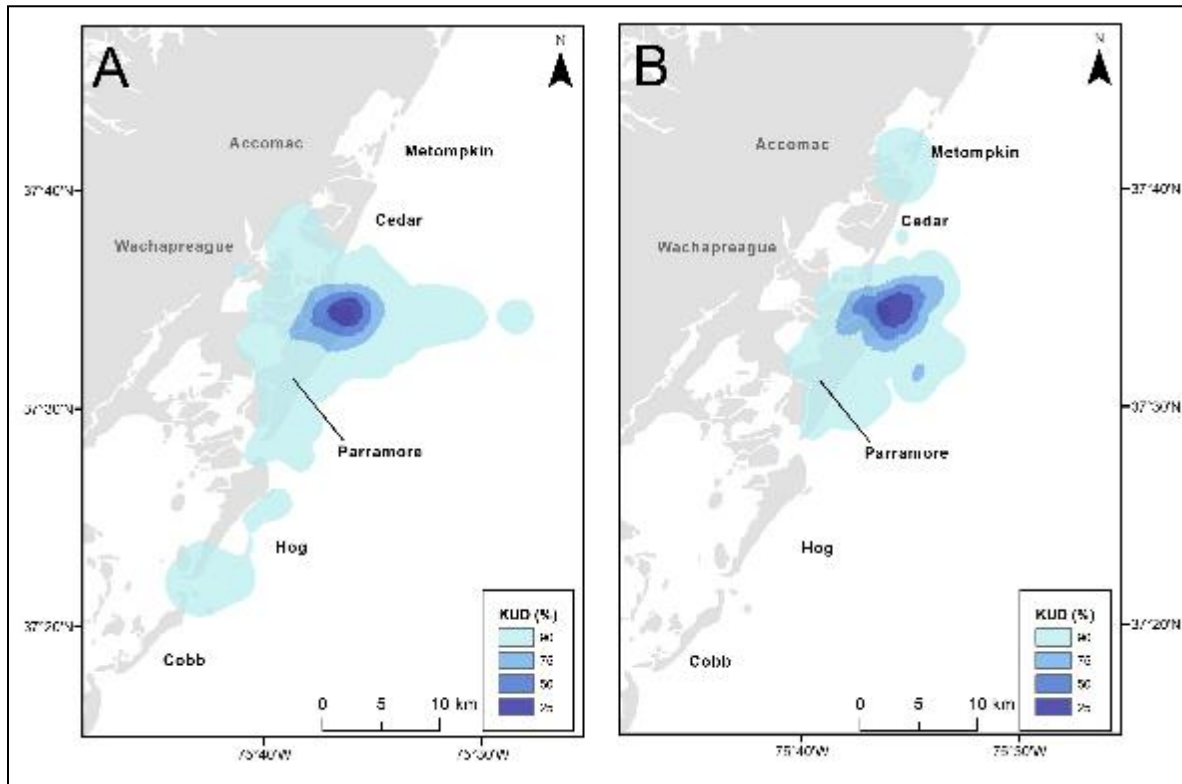

Fig. 14. (A) KUD analysis of diurnal flights and (B) KUD analysis of nocturnal flights

SUFFICIENT SAMPLE SIZE ANALYSIS

To determine if our sample size was sufficient for our analysis, we created KUDs iteratively adding individuals to determine if the home range size would asymptote (Fig. 15). The overall home range size reached an asymptote at approximately eight individuals. When evaluating KUDs on 'clear' days, the home range size reached an asymptote at approximately 12 individuals and approximately 10 individuals when evaluating KUDS on 'weather' days. The home range size reached an asymptote at approximately six individuals when evaluating KUDS of diurnal flights. The home range size may begin to reach an asymptote at approximately 12 individuals when evaluating KUDs of nocturnal flights but will need more data to determine the full nocturnal home range. This provides reason to assume that our sample size adequately represents the entire population during our study period.

RELATIONSHIP TO OFFSHORE WIND AREAS

We found no overlap with the movement analysis of our study population with the current Maryland and Virginia lease site areas. We found that the furthest an individual traveled was 13 km directly offshore. The Virginia lease area is approximately 43.5 km offshore[9] and the Maryland lease area is approximately 27 km offshore[10].

---

[9] https://www.dominionenergy.com/about-us/making-energy/renewables/wind/coastal-virginia-offshore-wind
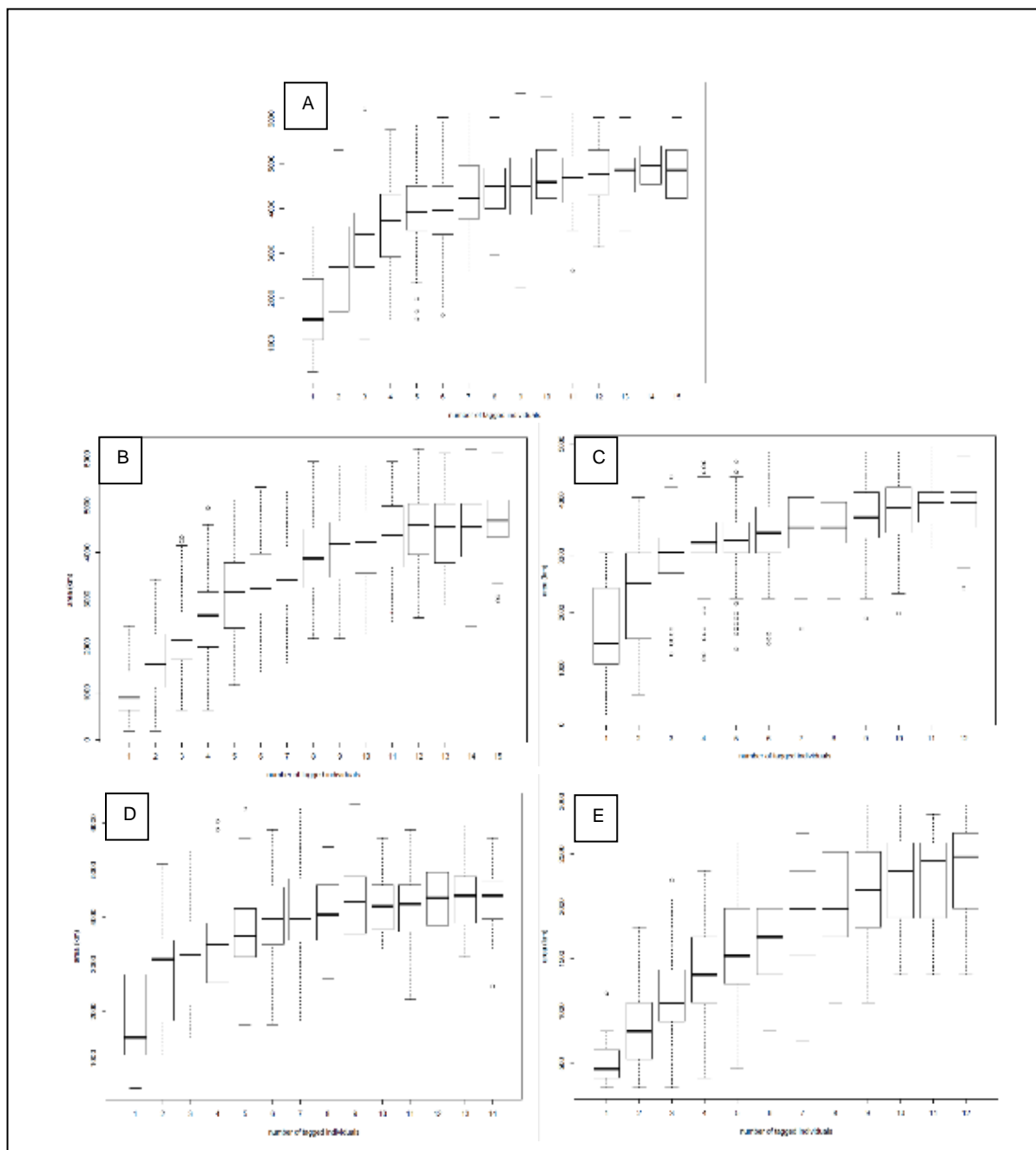[10] http://www.uswindinc.com/maryland-offshore-wind-project/

Fig. 15. Sample size analysis. (A) Asymptote analysis of total population 90% KUD, (B) asymptote analysis of 90% KUD on 'clear' days, (C) asymptote analysis of 90% KUD on 'weather' days (i.e. fog, rain, thunderstorms), (D) asymptote analysis of 90% KUD of diurnal flights, and (E) asymptote analysis of 90% KUD of nocturnal flights

DISCUSSION

This study was the first of its kind to describe the movements and behaviors of breeding common terns in coastal Virginia using GPS technology. We determined that while foraging, common terns tend to rely on areas close to their nests. If they have high residence in areas over 5 km from their nests, it is to northern or southern neighboring barrier islands. Even when traveling off the nest for short periods of time (low residence time), the common terns traveled less than 15 km in any direction from their nest site. The common terns utilized areas over 1 km from the nesting sites differently during various environmental conditions. Terns stayed closer to their nesting site and traveled to southern islands during 'weather' days while on 'clear' days they utilized all the common foraging areas such as Metompkin, Cedar, Parramore and Hog islands. Time of day also influenced their habitat distribution. Diurnally, common terns utilized a larger area and traveled up to 13 km offshore and utilized southern barrier islands such as Parramore, Hog, and northern Cobb islands. Nocturnally, they had a slightly smaller distribution and utilized Parramore and northern islands such as Cedar and Metompkin island. Furthermore, we found no overlap with this population of coastal Virginian common terns with both the current Maryland and Virginia offshore wind energy lease areas.

ANIMAL MOVEMENT AND BEHAVIOR

Our residence time analysis suggests that common terns stay close to their nesting site while foraging during their nesting season. Most locations (79.5%) occurred within a 5 km radius of the tag deployment site. The furthest high residence points from the nesting site occurred along the barrier island coastline. As higher residence indicates probable foraging areas (Torres et al. 2011) we suggest that even if common terns forage far from their nesting site, they may not forage that distance offshore. This information is used to analyze potential overlap and impacts of offshore wind energy sites on seabirds by applying 'uncommon' and 'common' foraging ranges while breeding. Applying 'common' foraging ranges resulted in less overlap than when the original foraging ranges from the literature is applied as the common terns' tended to commonly forage in northern and southern gradients along the coast instead of traveling directly offshore.

Our residence time analysis also found that the low residence locations occurred further away from the colony than the high residence locations. Low residence possibly indicates transiting behaviors, suggesting that the areas that were further from the nesting site were visited for only a short period of time and were simply traveling through. Though they spend short periods of time at areas further from the nest, again these more distant areas occurred along the coastline and not directly offshore. These areas may be used for foraging, but they did not remain in the area for a long period of time; thus, decreasing their potential for overlap with wind energy areas. There were some locations of high residence time that were over 5 km from the nest but, all except one of these locations were either north, south, or inshore from the nesting location (Fig. 11). This could indicate that the locations with high probable overlap with offshore wind energy still have a lower probability of impact as the time spent at these locations are short.

HOME RANGE AND ANIMAL DISTRIBUTION

The home range analysis further suggests that common terns stay close to the colony while foraging. Common terns foraged along the coastline of the barrier islands neighboring their nesting island as well as the inland marshes and wetlands. The results of these analyses are congruent with an observational study conducted on common tern populations in coastal Virginia that found that they were equally distributed in open bays, inlets and beaches, tidal creeks, and marsh and tidal pools (Erwin 1977). Some of the individuals in our study foraged offshore but only about 10 km, roughly half the literature suggested foraging range of 20 km (Erwin 1977).

ENVIRONMENTAL IMPACTS ON HOME RANGE

The results of the weather analysis found differences in common tern distribution on 'weather' days versus 'clear' days. Though the heavily utilized area (25% KUD) was 2.5% larger on 'weather' days, the overall distribution was 35% greater on 'clear' days. Our results agree with a previous study that found that common tern body mass development measures were affected by extremely bad weather events that could be a result of fewer, less effective foraging trips (Robinson et al. 2002). However, the core used areas (25% KUD) were very similar on 'clear' days and 'weather' days. The results of the diurnal versus nocturnal analysis found slight differences in common tern distribution on 'weather' days versus the 'clear' days. Though the heavily utilized area (25% KUD) was about 19% larger during nocturnal flights, the overall distribution was 39% greater during diurnal flights. However, the home range size did not

asymptote with the sample size used when assessing the KUDs of nocturnal flights, so more data at a larger sample size may change these results.

IMPLICATIONS FOR OFFSHORE WIND ENERGY DEVELOPMENT

These analyses determined that this population of common terns stay close to their nesting site during the breeding season. Outside of Dawson Shoals, the common terns traveled to and highly utilized both Parramore and Cedar island. Because of this, the study population had no overlap with current Virginia and Maryland offshore wind lease or planning areas. Despite no interaction between our study population and offshore wind, our results can be applied to other common tern populations nesting closer to the leased wind energy areas. We found that common terns tend to travel off their nesting site in a northern and southern gradient and relied on nearby barrier islands or inshore areas for foraging. This suggests that the wind energy areas will have minimal overlap with common tern populations nesting closer to the wind sites as the heavily utilized areas did not occur as far offshore as the wind sites will be located. Our environmental impact analysis also suggests that weather and nocturnal visibility will have minimal impacts on common tern populations. During 'weather' days, the common terns utilized a smaller overall area and did not travel far offshore (up to 10 km). The population also stayed closer to the nests at night, therefore visibility would be greater at the times when they are flying further offshore (during diurnal flights) and could have a greater chance of avoiding wind energy structures. Our results are a promising suggestion that the impacts of offshore wind energy on common tern nesting populations are lesser than previously thought when satellite telemetry technology is used to analyze movement and behavior.

CONCLUSIONS

This study focused on the spatial analysis of a colonial common tern location data taken during their breeding season in June 2017. These spatial analyses provide a better understanding of common tern movement and ecology in coastal Virginia, which has not been previously studied using satellite telemetry methods. This project provides a better understanding of coastal Virginia common tern populations and their habitat usage during their critical and energetically-costing breeding life history stage. Further work could be expanded to include subsequent years of location data on common tern populations as well as other coastal Virginia breeding species such as black skimmers and gull-billed terns. Furthermore, including wind speed and wind direction in the weather analysis could provide more insightful results on the effect of weather events on flight patterns and foraging trips.

LITERATURE CITED

Bailey H, Brookes KL, Thompson PM (2014) Assessing environmental impacts of offshore wind farms: lessons learned and recommendations for the future. Aquat Biosyst 10:1-13.

Barraquand F, Benhamou S (2008) Animal movements in heterogeneous landscapes: identifying profitable places and homogeneous movement bouts. Ecology 89:3336-3348.

Bastos R, Pinhanços A, Santos M, Fernandes RF and others (2015) Evaluating the regional cumulative impact of wind farms on birds: how can spatially explicit dynamic modelling improve impact assessments and monitoring? J Appl Ecol 53:1330-1340

Boehlert GW, Gill AB (2010) Environmental and ecological effects of ocean renewable energy development: a current synthesis. Oceanography 23:68-81.

Breton SP, Moe G (2009) Status, plans and technologies for offshore wind turbines in Europe and North America. Renew Energy 34:646-654.

Briggs KT, Lewis DB, Tyler WB, Hunt GL (1981) Brown pelicans in southern California: habitat use and environmental fluctuations. Condor 83:1-15.

Burger AE, Shaffer SA (2008) Perspectives in ornithology application of tracking and data-logging technology in research and conservation of seabirds. Auk 125:253-264.

Busch M, Kannen A, Garthe S, Jessopp M (2013) Consequences of a cumulative perspective on marine environmental impacts: Offshore wind farming and seabirds at North Sea scale in context of the EU Marine Strategy Framework Directive. Ocean Coast Manag 71:213-224.

Camphuysen K, Fox T, Leopold M, Petersen IK (2004) Towards standardised seabirds at sea census techniques in connection with environmental impact assessments for offshore wind farms in the U.K. Accessed at: http://jncc.defra.gov.uk/pdf/Camphuysenetal2004_COWRIEmethods.PDF

Curtice C, Cleary J, Shumchenia E, Halpin PN (2016) Marine-life Data Analysis Team (MDAT) technical report on the methods and development of marine-life data to support regional ocean planning and management. Marine-life Data Analysis Team (MDAT). Accessed at: http://seamap.env.duke.edu/models/MDAT/MDAT-Technical-Report-v1_1.pdf

Dincer I (2000) Renewable energy and sustainable development: a crucial review. Renew Sust Energ Rev 4:157-175.

Drewitt AL, Langston RH (2006) Assessing the impacts of wind farms on birds. Ibis 148:29-42.

Erwin MR (1977) Foraging and breeding adaptations to different food regimes in three seabirds: the common tern, *Sterna hirundo*, royal tern, *Sterna maxima*, and black skimmer, *Rynchops niger*. Ecology 58:389-397.

Ezard THG, Becker PH, Coulson T (2007) Correlations between age, phenotype, and individual contribution to population growth in common terns. Ecology 88:2496-2504.

Fasola M, Bogliani G (1990) Foraging ranges of an assemblage of Mediterranean seabirds. Colon Waterbird 13:72-74.

Fritts TH, Irvine AB, Jennings RD, Collum LA and others (1983) Turtles, birds, and mammals in the northern Gulf of Mexico and nearby Atlantic waters. US Fish and Wildlife Services: Biological Services Program. Accessed at: https://www.osti.gov/biblio/5443083.

Furness RW, Wade HM, Masden EA (2013) Assessing vulnerability of marine bird populations to offshore wind farms. J Environ Manage 119:56-66.

Gill AB (2005) Offshore renewable energy: ecological implications of generating electricity in the coastal zone. J Appl Ecol 42:605-615.

Gilman R, Maurer B, Feinberg L, Duerr A, and others (2016) National offshore wind strategy: facilitating the development of the offshore wind industry in the US. Dept of the Interior, Department of Energy. Accessed at: https://www.osti.gov/biblio/1325403-national-offshore-wind-strategy-facilitating-development-offshore-wind-industry-united-states.

González-Solís J, Wendeln H, Becker PH (1999) Within and between season nest-site and mate fidelity in common terns (*Sterna hirundo*). J Ornithol 140:491-498.

Hazen EL, Maxwell SM, Bailey H, Bograd SJ and others (2012) Ontogeny in marine tagging and tracking science: technologies and data gaps. Mar Ecol Prog Ser 457:221-240.

International B (2016) *Sterna hirundo*: the IUCN red list of threatened species 2016. IUCN Red List International.

Jinjin C (2011) Development of offshore wind power in China. Renew Sust Energ Rev 15:5013-5020.

Kernohan BJ, Gtizen RA, Millspaugh JJ (2001) Analysis of animal space use and movements. Pages 125-166 in J. J. Millspaugh and J. M. Marzluff, editors. Radio tracking and animal populations. Academic Press, Inc., San Diego, California.

Kinlan BP, Winship AJ, White TP, Christensen J (2016) Modeling at-sea occurrence and

abundance of marine birds to support Atlantic marine renewable energy planning: Phase I report. US Dep Commer, NOAA, NOS, NCCOS.

Maxwell SM, Breed GA, Nickel BA, Makanga-Bahouna J and others (2011) Using satellite tracking to optimize protection of long-lived marine species: Olive Ridley sea turtle conservation in Central Africa. PloS One 6:e19905.

Maxwell SM, Conners MG, Sisson NB, Dawson TM (2016) Potential benefits and shortcomings of marine protected areas for small seabirds revealed using miniature tags. Front Mar Sci 3:264.

Montevecchi W, Hedd A, Tranquilla LM, Fifield D and others (2012) Tracking seabirds to identify ecologically important and high risk marine areas in the western North Atlantic. Biol Cons 156:62-71.

Morris RD, Black JE (1980) Radiotelemetry and herring gull foraging patterns. J Field Ornithol 51:110-118.

Palestis BG (2014) The role of behavior in tern conservation. Curr Zool 60:500-514.

Panwar N, Kaushik S, Kothari S (2011) Role of renewable energy sources in environmental protection: a review. Renew Sust Energ Rev 15:1513-1524.

Punt MJ, Groeneveld RA, Van Ierland EC, Stel JH (2009) Spatial planning of offshore wind farms: A windfall to marine environmental protection? Ecol Econ 69:93-103.

Robinson JA, Hamer KC, Chivers LS (2002) Developmental plasticity in arctic terns (*Sterna paradisaea*) and common terns (*Sterna hirundo*) in response to a period of extremely bad weather. Ibis 144:344-346.

Rome MS, Ellis JC (2004) Foraging ecology and interactions between herring gulls and great black-backed gulls in New England. Waterbirds 27:200-210.

Safina C, Burger J (1985) Common tern foraging: seasonal trends in prey fish densities and competition with bluefish. Ecology 66:1457-1463.

Shahabuddin M, Ahmed S, Mohan A (2016) Environment protection through renewable energy sources. Int J Adv Res 2:97-99.

Shiming Z, Bo J, Huifen X, Shouhong L and others (2010) Exploration and application of ocean wind energy resources in coastal sea of China. Ocean Technol 29:117-121.

Soanes LM, Arnould JP, Dodd SG, Sumner MD and others (2013) How many seabirds do we need to track to define home-range area? J Appl Ecol 50:671-679.

Sun X, Huang D, Wu G (2012) The current state of offshore wind energy technology development. Energy 4:298–312.

Tetra Tech, Inc. (2014) Annual avian survey report (April 2013 – April 2014): Virginia offshore wind technology advancement project (VOWTAP). Page 36. Dominion Resources, Inc., VOWTAP Avian Survey Report.

Torres LG, Thompson DR, Bearhop S, Votier S and others (2011) White-capped albatrosses alter fine-scale foraging behavior patterns when associated with fishing vessels. Mar Ecol Prog Ser 428:289-301.

Watts BD, Paxton BJ (2014) Status and distribution of colonial waterbirds in coastal Virginia: 2013 breeding season. CCBTR-14-03. Center for Conservation Biology, College of William and Mary/Virginia Commonwealth University, Williamsburg, VA 1:1-23. Accessed at: http://www.ccbbirds.org/wp-content/uploads/2014/04/ccbtr-14-03_Watts-Status-and-Distribution-of-Colonial-Waterbirds-in-Coastal-Virginia-2013-Breeding-Season.pdf.

Williams KA, Stenhouse IJ, Johnson SM, Connelly EE (2015) Wildlife densities and habitat use across temporal and spatial scales on the mid-Atlantic outer continental shelf: final report.in D. o. E. E. W. a. W. P. T. Office, editor.

Willmott J, Forcey G, Kent A (2013) The relative vulnerability of migratory bird species to offshore wind energy projects on the Atlantic outer continental shelf: an assessment method and database. Pages 1-275 in U. D. o. t. Interior, editor. Bureau of Ocean Energy Management, Herndon, VA.

VITA

Jeri Lynn Wisman
Department of Biological Sciences, Old Dominion University, Norfolk, VA 23529

EDUCATION

Master of Science: Biology   Anticipated: August 2018
Old Dominion University, Norfolk, VA   GPA: 3.96
Advisor: Dr. Sara Maxwell; Committee: Dr. Helen Bailey (UMCES), Dr. Kent Carpenter

Bachelor of Science: Marine biology concentration   May 2015
Old Dominion University, Norfolk, VA   GPA: 3.56
Minors: Psychology; Honors college graduate

PUBLICATIONS

Wisman JL and SM Maxwell. (In review). Sea turtle bycatch in the US mid-Atlantic sea scallop
    (Placopecten magellanicus) dredge fishery: causes and solutions.

Maxwell, SM, TM Dawson, **JL Wisman**. (2015) Key oceanographic variables for common
    pelagic bycatch species in the California current in Highly Migratory Species Team Report on
    Swordfish Management and Monitoring Plan Hardcaps. June 2015 Briefing Book for the Pacific
    Fishery Management Council, 10 pp.

PRESENTATIONS

Virginia Coast Avian Partnership Annual Meeting: Oral Presentation   Mar 2018
Melfa, VA
Pacific Seabird Group Meeting: Oral Presentation   Feb 2018
La Paz, Mexico
Animal Nutrition: Guest Lecture   Nov 2017
Old Dominion University, Norfolk VA
Marine Vertebrate Ecology, Management & Conservation: Guest Lecture   Feb 2017
Old Dominion University, Norfolk VA
NASA DEVELOP Program Symposium: Oral Presentation   Nov 2015
Stennis Space Center, Stennis, MS

PROFESSIONAL EXPERIENCE

Marine Biologist Pathways Intern   Apr 2017 - Present
Bureau of Ocean Energy Management, New Orleans, LA
Graduate Teaching Assistant   2016 - 2018
Old Dominion University, Norfolk, VA
Disney Aquatic Research Intern   Spring 2016
Walt Disney World, Orlando, FL
NASA DEVELOP Program Intern   Fall 2015
Stennis Space Center, Stennis, MS

GRANTS

Rudd Mayer Fellowship   2018
ODU Biology Graduate Student Travel Award   2018
Sustainable Energy Fund Fellowship   2017
ODU Biology Graduate Student Research Award   2017