

THE DELAWARE WATERFOWL TRACKER

by

Susannah Halligan

A thesis submitted to the Faculty of the University of Delaware in partial fulfillment of the requirements for the degree of Honors Bachelor of Science in Wildlife Ecology and Conservation with Distinction.

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Susannah Halligan

Approved: _____
Jeffrey Buler, Ph.D.
Professor in charge of thesis on behalf of the Advisory Committee

Approved: _____
Christopher Williams, Ph.D.
Committee member from the Department of Entomology and Wildlife
Ecology

Approved: _____
Mark Parcels, Ph.D.
Committee member from the Board of Senior Thesis Readers

Approved: _____
Earl Lee II, Ph.D.
Deputy Faculty Director, University Honors Program

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ABSTRACT

The state of Delaware is in the middle of the Atlantic Flyway of migratory waterfowl. This poses a problem for the poultry industry because waterfowl are the primary reservoir for avian influenza, which threatens the health of commercial poultry. When waterfowl migrate through and overwinter within Delaware, Delawarean poultry are at risk of exposure to the virus. Supplying industry stakeholders with locations of waterfowl can help improve their surveillance and biosecurity efforts. I created the Delaware Waterfowl Tracker as an interactive web application that provides maps of the distribution and density of overwintering migratory waterfowl in Delaware and the surrounding region. I developed the app using protocols that were used to develop the California Waterfowl Tracker, a similar web application developed to produce maps of waterfowl in California. I used weather surveillance radar data from the Dover (KDOX) radar to quantify waterfowl distributions by sampling them in the air as they take off for evening feeding flights during November through March of 2008-2016.. I built Boosted Regression Tree statistical models in R to predict radar-observed waterfowl distributions based on environmental and geographic variables (e.g. temperature, land cover, proximity to the Delaware coast) and produce maps of predicted waterfowl distributions throughout the MD and DE portions of the Delmarva Peninsula for each month and year combination, which are available to view on the web app.

Chapter 1

INTRODUCTION

Every year, over five hundred bird species migrate through the natural super-highway of the Atlantic Flyway. The Atlantic Flyway stretches from the Arctic to South America, sweeping across the entirety of the east coast of the United States. A flyway is any geographical region that indicates the corridor in which movement of an avian species occurs, and became a widely used concept in the twentieth century to better identify issues facing migratory birds and countries that can work to protect and manage those populations (Boere, 2006). Delaware is located in the middle of the flyway. This poses a problem for the poultry industry (Karesh et al., 2012; Newell et al., 2010), since waterfowl are the primary reservoir for avian influenza. Delawarean poultry could be at risk of exposure to the virus (Olsen et al., 2006).

This app has been based off of the methods and format used by the California Waterfowl Tracker. The California Waterfowl Tracker is a web-based application that allows poultry producers, risk managers, and backyard poultry enthusiasts alike to visualize waterfowl locations to assess any possible risk of the vectoring of avian influenza into the poultry stock of California's Central Valley. This app was developed by Dr. Jeff Buler's Aeroecology Program at the University of Delaware and Dr. Maurice Pitesky's lab at the UC Davis School of Veterinary Medicine-Cooperative extension.

The Delaware Waterfowl Tracker and the California Waterfowl Tracker use weather surveillance radars within the United States to measure reflectivity as an index to bird density in order to map bird distributions during their onset of nocturnal migratory flights (Buler et al. 2012). Weather radar data can be retrieved from the National Oceanic and Atmospheric National Climatic Data Center (NOAA-NCDC) radar archive and can be visually screened to filter out nights with precipitation or any such data that is not obviously migrating birds (Buler et al. 2012). These data can thus be processed through RStudio and ArcGIS to produce visual maps of migrating birds.

My objective was to create an interactive, public web application that provides maps of the distribution and density of migratory waterfowl in Delaware and the surrounding region. Those who use the app may be those who study overwintering migratory waterfowl in the Delmarva Peninsula or poultry production stakeholders from backyard enthusiasts to factory farmers. Wildlife biologists may find the Delaware Waterfowl Tracker useful as well in order to pinpoint stopover sights and habitat for overwintering migratory waterfowl. This would assist ecological efforts in providing sizable and useful habitat for migrating birds, as well as showing if the birds are using already designated habitats. If a sizable enough avian influenza pandemic were to break out in major poultry producing countries such as the United States, the global export price of chicken meat could increase by 9.63% (Djunaidi, 2007). Creating an app to help assess the locations of waterfowl in Delaware is both applicable and useful to poultry producers and risk managers, as waterfowl serve as a

primary reservoir of Avian Influenza. By supplying stakeholders with locations of waterfowl, we can help better their surveillance and biosecurity efforts.

Chapter 2

STUDY AREA

Delaware is divided into two distinct physiographic provinces, the Appalachian Piedmont Province making up the northernmost 5% and the 95% remaining Atlantic Coastal Plain Province (Hess 2000). One third of Delaware's wetlands are estuarine or coastal, and nearly all occur in the Coastal Plain. The average monthly temperature of the state ranges from 0-24.3°C and includes temperate continental humidity and an average precipitation of 114.3 cm (Ziemecki, 2018).

I created a study area encompassing all of Delaware and some parts of Maryland, which encompasses the counties within the Delmarva Peninsula that are close to the KDOX radar in Dover, DE (Figure 1). The KDOX radar is signified by the blue dot in Figure 1.

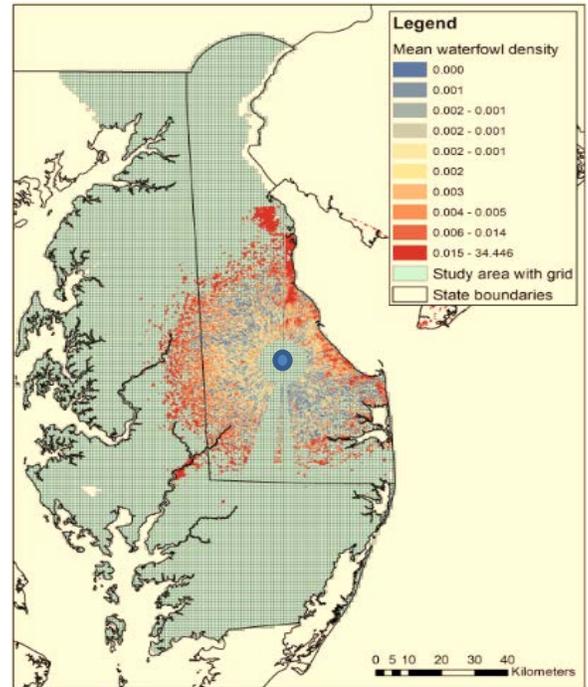


Figure 1: Map of study area (grey) within the Delmarva Peninsula, showing mean waterfowl density (reflectivity measured in cm²/ha from December 2015).

Chapter 3

METHODS

Bird distribution data:

Radar data are used to map wintering waterfowl distribution by sampling them as they take off from daytime roosting areas for evening feeding flights (Buler et al. 2012). I used data that was processed by a previous Summer Scholar Daniel Day, who quantified winter waterfowl densities in Delaware using the Dover (KDOX) Weather Surveillance Radar data from the winter months (November – March) of 2008-2016 downloaded from the National Oceanic and Atmospheric National Climatic Data Center (NOAA-NCDC) radar archive. He screened data for contaminations such as precipitation, clutter, or anomalous propagation within 100 km of the radar. For suitable days free of contamination by non-avian reflectivity, he determined the peak of evening takeoff time for waterfowl after sunset, also known as “peak exodus.” The data were interpolated to the peak exodus time and corrected for range bias following methods of Buler and Diehl (2009). I calculated mean bird density across sampling days by month and year and aggregated the radar data into a 1x1 km grid of the study area. Of all possible sampling nights during the winter seasons from 2008-09 through 2015-16, we identified 20% (240 of 1210 nights) as suitable for analysis. I excluded the remaining 80% due to contamination from precipitation (73%), missing data (4%), anomalous beam propagation (2%), and clutter (1%).

During early March of 2019, a team from Dr. Buler’s Aeroecology Lab and I ventured to Woodland Beach (a pinpointed hot spot in the app) to conduct twilight

ground surveys using thermal imaging and night vision cameras. Our goal was to attempt to identify species engaging in nighttime feeding flights to confirm waterfowl radar detection. We observed several flocks of Canada geese (*Branta canadensis*) and snow geese (*Chen caurulescens*), each flock containing an estimate of 100 individuals. We also noted the presence of mallards (*Anas platyrhynchos*).

Predictive Modeling:

I built Boosted Regression Tree (BRT) models from radar-observed monthly mean bird density to predict waterfowl distributions within 1x1 km grid cells across the entire study area based on a set of 18 predictor variables and created raster maps of predicted bird densities. The boosted regression tree is a combination of regression trees and boosted analysis that serves as an additive regression model to show the relationships between individual and multiple predictors as trees (Elith 2008). Because of probable spatial autocorrelation among neighboring grid cells, I partitioned the data into 25 subsets where data cells for each partition were 5 km apart. Thus, I fit 25 BRT models and averaged results across the models when producing predictive maps. I used the `gbm` step function to fit BRT models. This function builds the ensemble of trees with 50% of the data (i.e., training data) and performs cross validation with the remaining 50% of the data (i.e., test data) to optimize model fit by preventing overfitting of the training data. I set the model tree complexity to 10 to allow for complex interactions among predictors and tuned the learning rate to produce a final ensemble of about 1500 trees for each BRT model.

Predictor variables included measures of land cover, geographic position, weather, and time quantified within the 1 km grid cells for each month and year (Table 1). The predictor variables included: year, month, mean monthly temperature, monthly total precipitation, distance from radar, latitude, longitude, presence of corn, distance to bright light, distance to Atlantic coast, wetlands, elevation relative to radar antenna height in meters, fraction of open water, and measures of the proportion various land cover types within a 5 km radius landscape including emergent marsh,

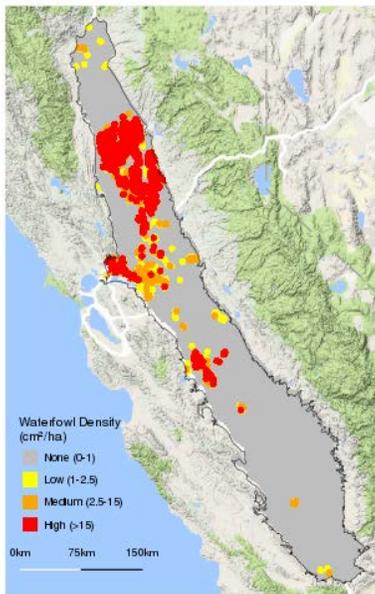


Figure 2: The California Waterfowl Tracker showing daily exposure risk of poultry farms from waterfowl.

agricultural land, coniferous forest, hardwood forest, and urban land. I had to change one of our main agriculture covariates from rice to corn and soy, as Delaware's primary agricultural output is corn and soy rather than rice. Waste grains, especially corn, have been an important source of autumnal foods for wildlife (Warner 1989). Migratory waterfowl in California rely on fallow rice fields as foraging habitat, which also may benefit farmers, as foraging behavior increases rice straw decomposition (Bird 2000). The NARR

data were sourced from the National Oceanic and Atmospheric Administration website. The land cover data were sourced from the National Land Cover Dataset, and the bright light data came from the Defense Meteorological Satellite, in which Falchi

et al. 2016 identified bright areas where artificial light (sky brightness) was 5 times the natural level (Falchi et al. 2016). I used those past data to build statistical models in RStudio to predict waterfowl distributions based on environmental and geographic variables to produce maps of waterfowl distributions that are posted in the web app.

Web mapping application:

I developed the app using the same protocols used to develop the California Waterfowl Tracker, a similar web application developed to produce maps of waterfowl in California (Fig. 2). Once the models were created, I wrote R software code and used the web-mapping service Leaflet to map our models, and ultimately use Shiny, a web framework for R, to publish the application onto Dr. Buler's University of Delaware faculty and research page. R is a statistical computing program language used by statisticians and researchers alike (R Core Team 2017). It allows researchers to perform linear and nonlinear modelling and other statistical tests. Leaflet is a simple JavaScript library that allows a user to create maps and web applications (Graul 2016). I then placed the raster maps put them into Leaflet in order to display them on a greater world map in a way that highlights the study area and displays the densities of waterfowl using the VIRDIS color palette. Finally, I used Shiny, a web framework for R, in order to provide a framework and interactive app that allows the user to display various raster files in an interactive web application according to the user's selection of month and year.

Chapter 4

RESULTS

The mean cross validation coefficient of BRT models was 0.735, which explains about 54% of the variation within our models. Year, emergent marsh within five kilometers, and temperature were the three most influential predictors of waterfowl density along Delmarva Peninsula, respectively (Table 2). The remaining predictor variables had diminishing/negligible influence with varying trends (Figure 3). The partial response plots depict both emergent marsh within 5 kilometers predictor variables and temperature have positive correlations with waterfowl density, while the winter plot appeared to generally increase until 2012, and suddenly decreasing down until 2015. Further analysis showed that the variables emmmarsh5km and ag5km exhibit a significant two-way interaction, in which waterfowl density increases with landscapes that have both agriculture and emergent marsh cover types (Figure 4). After creating subsequent Leaflet maps for each month and year combination and running the Shiny app in R, the app was launched and now displays waterfowl density for each model (Figure 5). The month with the highest waterfowl densities was January. One can visit the Delaware Waterfowl Tracker using the link below.

https://delawarewaterfowltracker.shinyapps.io/Delaware_Waterfowl_Tracker/

Table 1: Predictor variables used in the boosted regression tree models.

Variable Name	Description	Type
winter	Winter year	Temporal
month	Month	Temporal
ppt	Total monthly precipitation (cm?)	Weather
tmn	Mean monthly temperature (C)	Weather
LAT	Latitude	Geographic
LONG	Longitude	Geographic
dRdr	Distance from radar	Geographic
dAtl	Distance to Atlantic coast (kilometers)	Geographic
dBright	Distance to bright light (kilometers)	Geographic
relelev	Elevation versus radar (meters)	Geographic
emmarsh5km	Emergent marsh proportion within 5 kilometers	Landscape Composition
ag5km	Agricultural land proportion within 5 kilometers	Landscape Composition
crn	Presence of corn	Landscape Composition
wtl	Wetland proportion	Landscape Composition
hw5km	Hardwood forest proportion within 5 kilometers	Landscape Composition
cnf5km	Coniferous forest proportion within 5 kilometers	Landscape Composition
wat	Open water proportion	Landscape Composition
urb5km	Urban land proportion within 5 kilometers	Landscape Composition

Table 2: Mean relative influence of predictors/variables across 25 BRT models that predict waterfowl density in the study area.

Variable Name	Description	Relative influence (%)
winter	Winter year	15.10
emmarsh5km	Emergent marsh proportion within 5 kilometers	11.71
tmn	Mean monthly temperature (C)	10.86
month	Month	10.63
dRdr	Distance from radar	9.58
LAT	Latitude	7.05
ag5km	Agricultural land proportion within 5 kilometers	4.33
crn	Presence of corn	4.01
dBright	Distance to bright light (kilometers)	3.87
ppt	Total monthly precipitation (cm?)	3.55
LONG	Longitude	3.34
dAtl	Distance to Atlantic coast (kilometers)	2.84
wtl	Wetland proportion	2.51
relelev	Elevation versus radar (meters)	2.50
hw5km	Hardwood forest proportion within 5 kilometers	2.35
cnf5km	Coniferous forest proportion within 5 kilometers	2.27
wat	Open water proportion	2.05
urb5km	Urban land proportion within 5 kilometers	1.37

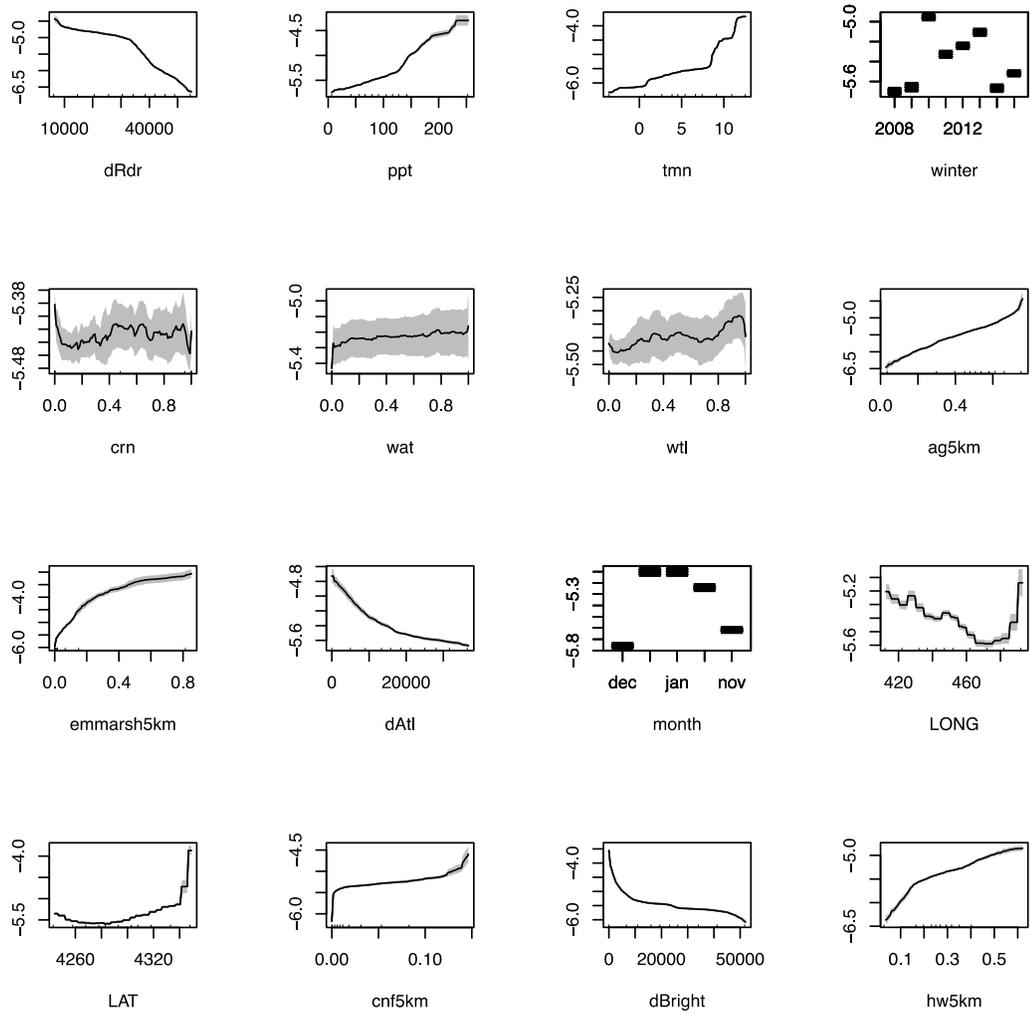


Figure 3: Mean partial regression plots of all Covariates/Predictors of the 25 BRT models.

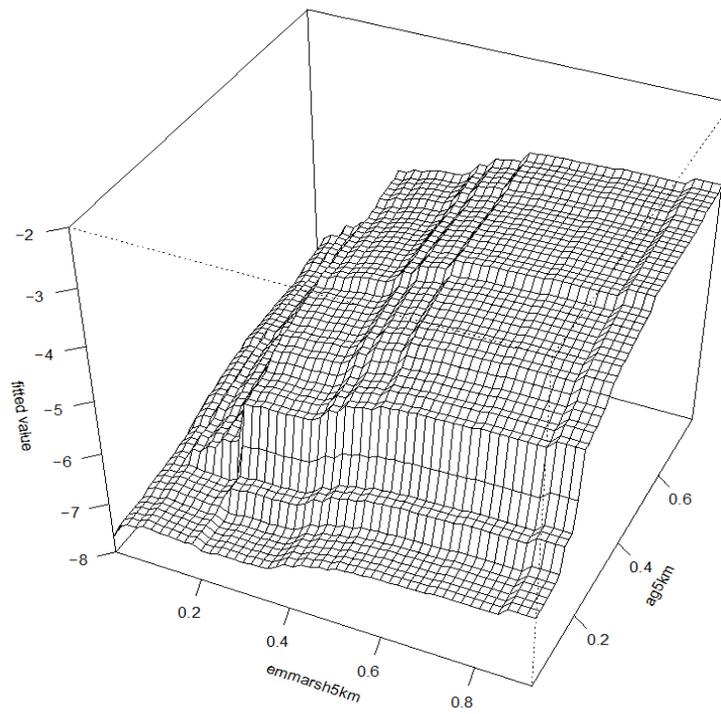


Figure 4: Perspective plot of two-way interaction between emmarsh5km and ag5km.

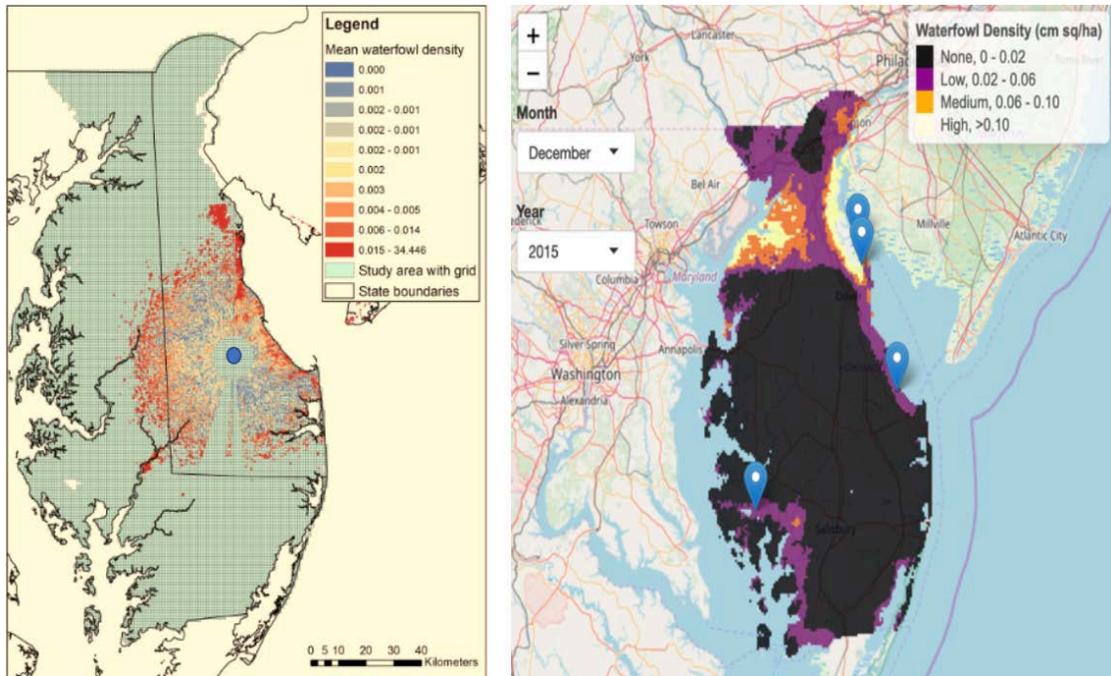


Figure 5: Waterfowl Density in the Delmarva Peninsula in December 2015 as displayed in the web app versus the predicted waterfowl density/reflectivity for December 2015.

Chapter 5

DISCUSSION

Migratory waterfowl are most densely concentrated in several areas along the Delaware Bay and Chesapeake Bay coasts, including Blackwater National Wildlife Refuge in Maryland as well as Bombay Hook National Wildlife Refuge in Delaware. Less densely concentrated areas occur further inland or on islands such as Deal Island. Areas with the lowest density occur mostly inland, as can be seen in Northern Delaware. During this time, waterfowl are more densely distributed in areas with a higher proportion of emergent marsh, as the mean monthly temperature increases, and in areas with a higher proportion of agricultural lands. This is explained by the tendency for most duck species to depend on shallow-water habitats (Perry 1996). This may explain why waterfowl density decreases further inland and increases with proximity to coastal habitats and emergent marsh habitat exhibiting shallow water. Waterfowl distribution and abundance in the Chesapeake Bay Watershed is also affected by human population increases and the encroachment on shallow-water habitat, possibly decreasing densities with later years (Perry 1996). Bombay Hook almost always exhibits high waterfowl density in December and November, while further inland exhibits little waterfowl density. This is most likely due to the higher number of national wildlife refuges scattered along the coasts of the Delmarva Peninsula, which are pinpointed in Figure 5. Bombay Hook especially exhibits some fallow corn and soy fields, which are crucial foraging habitat for waterfowl and many other forms of wildlife (Warner 1989). It also exhibits shallow tidal marshes, a land

cover type within the refuge itself that many waterfowl species depend on (Perry 1996). We can attribute both of these facts to the observation of higher densities of waterfowl in areas with both emergent marsh and agriculture. However, Prime Hook only exhibits low density, showing that it is not nearly as popular a stopover or wintering site as Bombay Hook. This may be due a possibility of increased recreational use of the refuge, as recreational use of shallow-water habitats such as fishing and hunting have been shown to reduce waterfowl use (Perry 1996). One noticeable and surprising difference between the California and Delaware models is that soil moisture was not as important for Delaware as it was for California due to the two states having vastly different ecosystems.

Waterfowl densities tend to be lowest at Blackwater during the months of November and December, which may indicate it used more as an overwintering or spring stopover site rather than a fall stopover site. Throughout the entire peninsula, January and February show little waterfowl density or stopover on the web application but show the greatest relative densities according to the BRT results, perhaps due to it being the end of the migration season. December 2015 sees a lot of medium-high waterfowl density in upper inland Delaware and in the Elk River, Sassafrass River, Earleville Wildlife Management Area, and Sassafrass Natural Resource Management Area, but stays low anywhere between 2008 and 2014. Novembers 2009, 2011, and 2015 we see high levels of density in this area, but in every other year it is either low or nonexistent waterfowl density. Northern Delaware also sees low waterfowl density

in all years but November 2012, December 2014, December 2010 and all of January and February.

Due to privacy concerns, locations of waterfowl density relation to poultry farms are obtainable at the user's own discretion through the Avian Biosciences Center, coded by the producer. While the Delaware Waterfowl Tracker does not provide real-time predictions, it is useful for reviewing past waterfowl distributions. It still allows users to assess risk of exposure to waterfowl for poultry farmers by way of extrapolation and providing past data to give risk management teams an idea of yearly waterfowl density in the Delmarva Peninsula. The current state of the Delaware Waterfowl Tracker is much more of a reflection of a "proof of concept" case study. As it stands, the app only provides data from 2008 to 2015. However, because the Delaware Waterfowl Tracker plays a "proof of concept" effort, it lays the groundwork for developing near-time analysis that will be of greater use to farmers in the future. A future goal is to analyze radar data in near-real time so that distribution models can be made to predict distributions in near-real time as well. By doing this, we could provide poultry stakeholders with near-live updates of waterfowl densities, and thus biosecurity efforts to prevent avian influenza are much more proactive and are not merely modeled off of data from years past.

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