Risk Assessment to Wildlife from Ohio On-Shore Wind Farm Development: A Landscape Model Approach

by

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To my parents (Jeff and Cindy), my fiancée (Brittany) and everyone who helped and supported me along my journey.

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List of Abbreviations

EIA	The U.S. Energy Information Administration
EPA	Environmental Protection Agency
DOE	Department of Energy
DOW	The Ohio Department of Natural Resources, Division of Wildlife
GIS	Geographic information system
GISci	Geographic information science
IUCN	The International Union for Conservation Nature
MRLC	Multi-Resolution Land Characteristics Consortium
MW	Mega-Watts
NIDCD	National Institute on Deafness and Other Communication Disorders
NLCD	National Landcover Database
ODNR	Ohio Department of Natural Resources
OPSB	The Ohio Power Siting Board
PADUS	Protected Areas Database of the United States
SA	Sensitivity Analysis
SGCN	Species of Greatest Conservation Need
SSI	Spatial Sciences Institute
USFWS	United States Fish and Wildlife Services
USC	University of Southern California
USGS	U.S. Geological Survey
WNS	White nose syndrome

Abstract

In Ohio, wind energy has been one of the fastest growing renewable energy sources. In 2003, Ohio's wind farms produced 3.6 Mega-Watts (MW). Today the wind farms are producing over 600MW with an additional 2,000MW planned or being built. With this rapid increase in wind energy, comes many environmental concerns: habitat loss and fragmentation, noise and light pollution, spread of invasive species, and most concerning direct mortality to birds and bats. The Ohio Power Siting Board (OPSB) has full regulatory power for wind energy production in Ohio. In 2009, the OPSB asked the Ohio Department of Natural Resources, Division of Wildlife (DOW) to create an environmental plan to help regulate the environmental concerns. The DOW created the On-Shore Bird and Bat Pre- and Post- Construction Monitoring Protocol for Commercial Wind Energy Facilities in Ohio. Within this protocol the DOW created a landscape model to predict areas that were likely to be less impacted by wind development. Under the authority of the OPSB, the DOW is able to recommend environmental surveys to wind energy companies based on the relative predicted impact to the environment. However, this model was created over 10 years ago and with limited data. The purpose of this study was to recreate this model with updated knowledge and additional layers. This updated model was created with the hypothesis that landcover is the main driver for avian and bat species mortalities in Ohio, and areas with higher predicted risk will experience higher mortality than areas with lower predicted risk. A total of 6 habitat layers were used to predict relative risk to birds and bats from wind energy production. Using sensitivity analysis to derive specific weights for each layer, a best fit model was created. Species richness during the breeding season, was used to validate the model. The model predicted more than 30% of Ohio to be classified within the two highest risk levels to wind energy development.

Chapter 1 Introduction

On-shore wind energy is proving to be a valuable source of renewable energy. More countries around the globe are installing wind turbines at increased rates each year. The advantages of wind are numerous, as are the disadvantages. Wind energy is capable of producing clean renewable energy for millions of humans, while at the same time destroying habitat and causing direct mortality to millions of wildlife species. Humans can and should continue to develop wind energy and other renewable energy sources to reduce climate change effects, but they should also be responsible for the wildlife and habitats they are affecting.

1.1. Renewable Energy

As climate change and global warming are global concerns throughout the world, there is an interest in reducing carbon dioxide (CO_2) emissions. The primary source of CO_2 emissions is the result of the burning of fossil fuels. In 2010, it was estimated that the global share of carbon emissions produced from energy production by the combustion of fossil fuels was 82% of all emissions (Heshmati et al. 2015). An additional concern is the increase in energy demand. As populations increase and cities develop, the need for electricity and transportation is also going to increase, consequently increasing the overall emissions. A method of reducing CO_2 emissions globally is to implement renewable energy sources such as hydropower, solar power, geothermal, biomass, and wind power. In 2017, the BP *Statistical Review of World Energy* (BP 2018) estimated that 8.4% of the global energy was produced by renewable energy. Of this percentage of renewables, wind and solar energy are predominantly utilized. Additional benefits of renewable energy include improvements to public health, increase in jobs and the economy, clean water, and save and restore ecosystems.

Renewable energy sources are on average cheaper to build, take less time to construct, and cost less to run when compared to alternatives like gas and coal. The least expensive power from gas costs about five cents per kilowatt-hour, from coal it costs near six cents, and from nuclear around ten cents (Nagy 2018). For renewables, the cost is near four cents per kilowatt-hour (Nagy 2018). These prices change over time and many debate over them; regardless, most agree that wind and solar will be the lowest-cost producers in the future, if not already (Toman et al 2008, Arnett & May 2016, Nagy 2018).

In addition to the relatively low cost of renewable energy sources, they are also creating more jobs than their fossil fuel competitors (NRDC 2017, Nagy 2018). In 2017, the Natural Resource Defense Council (NRDC) reported close to 1 million full-time employees working for renewable energy, which was five times more than non-renewable energy. When including part-time employees, such as construction workers, this total is 14 times higher than the non-renewable industry (NRDC 2017).

The world has invested billions of dollars into renewable energy sources. In 2016, estimates were close to $300 billion, making it the fastest growing energy source (EIA 2018). Currently, renewable sources generate a small portion of the global energy demand; generating only 17% of the global energy and 11% of The United States energy in 2017 (EIA 2018). Of the 11% in the U.S., biomass, hydroelectric, and wind energy made up 90% of the renewable energy sources. Wind energy has experienced more growth in the last 20 years than any other energy source, Figure 1. Wind energy is expected to continue to be one of the most widely used renewable energy sources in the world.

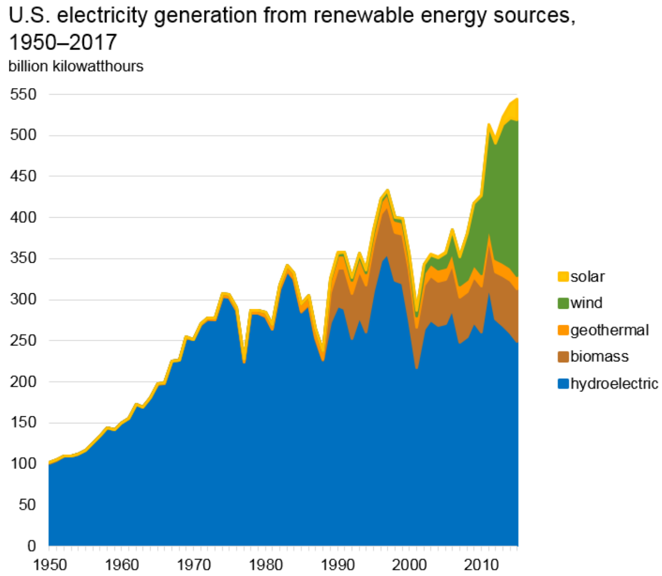

Figure 1: Total electricity generated by renewable energy sources in the United States, from 1950 to 2017. Graphic from EIA 2018.

1.2. Status of Wind Energy

1.2.1. Wind Energy Basics

Humans have been harnessing the wind for millennia. Wind was used to propel boats down the Nile as early in history as 5,000 B.C., and the Persians used it from 500-900B.C. to pump water and grind grain. In 1888, in Cleveland, Ohio Charles Brush created the first wind turbine used to generate electricity. However, it wasn't until the oil crisis in 1973 that wind turbines began to grow in popularity.

Capturing the wind to generate electricity is a simple concept illustrated by the U.S. Department of Energy (2019a), Figure 2. The wind usually moves over two or three blades causing them to rotate. The blades are attached to a rotor that is connected to the main shaft which rotates a generator to create the electricity. The rotation of the blades is not enough to generate electricity, usually causing the rotor to rotate at only 30-60rpm. Within the main shaft, there is a high-speed shaft, this high-speed shaft increases the rotational speeds from 60rpm to 1,000-1,800rpm, which is enough to generate electricity. Turbines have additional mechanics that allow them to rotate to face the wind direction, stop when wind speeds are too high, and many other advanced technologies to allow the turbine to communicate with other turbines in the area. All the mechanical systems sit in and on top of what is call the nacelle, which is attached to the tower. The energy generated in the generator moves down the tower through power cables which ultimately end at the substation to be shared to over 1,500 households per each 2.5-3MW turbine (EWEA 2019)

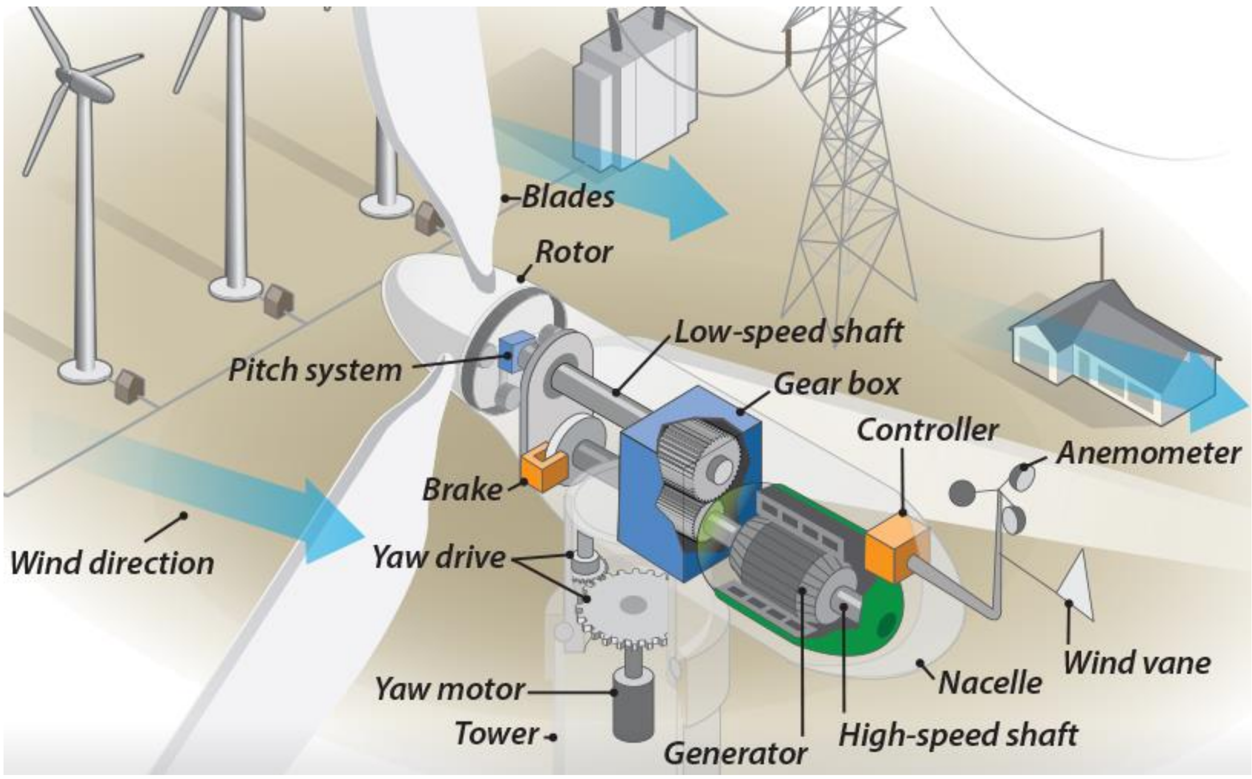

Figure 2: The inside mechanics of a wind turbine. Graphic from the U.S. Department of Energy "The Inside of a Wind Turbine" (2019b).

1.2.2. Capacity vs. Generation

One common energy question that is commonly misunderstood is, “what is the difference between the installed capacity and electricity generation of the energy source?” The answer to this question is important to understand in terms of energy statistics. Both are used to describe electricity outputs, but in different ways. According to the Department of Energy (DOE) and the

U.S. Energy Information Administration (EIA), energy capacity describes the maximum output of electricity that a generator can produce with ideal conditions (DOE, 2017), while generation describes the actual amount of electricity that is produced over a period of time.

For example, if a wind turbine has a capacity of 1.5MW and runs at maximum *capacity* for 2 hours then the turbine will *generate* 3MW-hours of energy (i.e. 1.5 MW X 2 hours). However, most turbines do not run under full maximum capacity due to low winds or other circumstances (i.e. curtailments), so this same turbine might only produce 1MW of power in the 2 hours resulting in a total energy *generation* of 2MW-hours (i.e. 1MW X 2 hours).

1.2.3. United States

In 2008, the DOE set a nationwide goal to have 20% of the nation's energy demand be generated from wind energy by 2030, and 35% by 2050. A total of over 4 billion megawatt-hours (MWh) of energy was generated by all sources in 2017, wind energy produced just over 6% of the total, or 254 million MWh, Table 1 (EIA 2019a). If energy demand stays the same for the next 10 years (4 billion MWh), the U.S. would have to increase wind energy generation on average by at least 1% or 50 million MWh a year to reach the goal by 2030. According to the EIA, The United States has increased their wind energy development each year over the last 10 years by 0.5% on average, Table 1. These results show that in order for the U.S. to reach the 2030 goal, there will be a significant increase in wind energy production in the next ten years.

Table 1: Net generation of electricity by all energy sources, in The United States (EIA 2019a)

Period	***Wind***	***Total Generation at Utility Scale Facilities***	***%Wind***	***% increase Wind from previous year***
2007	34,450	4,156,746	0.8%	
2008	55,363	4,119,387	1.3%	0.5%
2009	73,886	3,950,331	1.9%	0.5%
2010	94,652	4,125,059	2.3%	0.4%
2011	120,177	4,100,140	2.9%	0.6%
2012	140,822	4,047,766	3.5%	0.5%
2013	167,840	4,065,964	4.1%	0.6%
2014	181,655	4,093,605	4.4%	0.3%
2015	190,719	4,077,602	4.7%	0.2%
2016	226,993	4,076,675	5.6%	0.9%
2017	254,303	4,034,268	6.3%	0.7%

In 2018 there were over 50,000 wind turbines in 41 states, with a combined capacity over 96,000MW (AWEA 2019, Nagy 2018). The wind energy sector employs over 100,000 people and is worth more than $145 billion (AWEA 2019, Nagy 2018).

1.2.4. Ohio

Ohio ranks 4th in the nation for CO_2 emissions (EIA 2019b). To reduce these emissions, Ohio passed an Alternative Energy Portfolio in 2008, that says Ohio has to have 12.5% of electricity generation be supplied from renewable energy with an additional half percent coming directly from solar power, by 2027 (ORC 2008, sec. 4928.64). Renewable energy by Ohio law includes solar photovoltaic or solar thermal, wind energy, hydroelectricity, geothermal, solid waste, biomass, biologically derived methane gas, or energy from nontreated by-products from pulping. As of 2018, Ohio is only generating 2.7% of its electricity by renewable energy sources. This is 2% lower than the goal set for 2018 in order to reach the 12.5% by 2027. Of the 2.7% being generated today, 53% is produced by wind energy, followed by biomass, hydroelectric and solar, 21%, 17% and 9%, respectively. The energy produced from wind turbines powers more than 145,000 homes in Ohio. Just like the rest of the U.S., Ohio is going to experience a rapid increase in renewable energy construction, specifically with wind and solar energy, in the coming years. The current wind projects in Ohio have created over 3,000 jobs and is worth more than $1.2 billion (AWEA 2019).

In Ohio, the OPSB has full regulatory authority over all wind energy projects supplying more than 5MW to the public grid. Currently, there are 327 wind turbines on 6 wind farms that are regulated by OPSB. In the next few years this will increase to 786 turbines and 12 wind farms. The Ohio Department of Natural Resources Division of Wildlife (DOW) is part of the voting board for the OPSB, which allows the DOW to contribute recommendations in how to better manage and protect wildlife and habitats. In 2009, the DOW and the OPSB established guidelines for pre- and post- construction surveys to monitor wildlife during these phases. The protocol that these guidelines are listed in is now called the "On-Shore Bird and Bat Pre- and Post-Construction Monitoring Protocol for Commercial Wind Energy Facilities in Ohio." The standard set of procedures for each wind facility allow the DOW and the OPSB to compare each wind farm to each other and make management decisions for each existing facility and all future wind facilities.

1.3. Motivation

Renewable energy and specifically wind energy can provide numerous benefits, as discussed in the previous sections; however, wind energy can have negative effects on human health, wildlife, and the environment. These harmful attributes of wind energy include noise and light pollution, habitat loss and fragmentation, spread of invasive species, and direct mortality of wildlife. There is limited research in many of these fields, as this is new research in a relatively new industry.

The basis of this research is strictly in reference to the direct mortalities to birds and bats from wind energy, namely how mitigation techniques can be used to assess and manage wildlife.

1.3.1. Ohio's Wind Farm Concerns

The biggest and most discussed cause for concern related to wind energy is the direct mortality to avian and bat species such as birds and bats. Every year millions of birds and bats are killed by coming in contact with the blades or tower of a wind turbine. This mortality can result in local population declines and potentially lead to wide spread declines in the species.

Another concern is the location of planned wind farms. Ohio has and is planning on building multiple wind farms throughout western Ohio. This is particularly concerning due to western Lake Erie being globally important for migratory bird species. Every year millions of birds use the shores of Lake Erie and the surrounding habitats as stopovers to rest and feed prior to navigating over or around the great lakes. The National Audubon Society has recognized this importance and has prioritized 70 Important Bird Areas (IBAs), 7 globally important and 63 state priority areas, totaling 3,687,883 acres prioritized as IBAs in Ohio.

Another reason for concern was brought to light in 2012 and 2018, the USFWS conducted avian and bat radar studies along the shores of Lake Erie. One finding of particular concern was the altitude bands at which species were moving across the landscape. The study found the highest densities between the 50-150m altitude bands. This is the same height most Ohio wind turbines are built to. If birds are navigating at the same altitude as wind turbine blades they are increasing their risk to mortality.

Wind farms have also been attributed with detrimental effects to terrestrial species, through high stress levels and trophic level changes (Thanker et al. 2018, Agnew et al. 2016, Lopucki et al. 2018, Ferrao da Costa et al. 2018). Not much research has been conducted regarding these species, but with the limited studies indicating turbines do have effects on ground-dwelling species comes a suite of additional considerations that wildlife managers must take into account when designing environmental protocols for wind energy siting.

The following sections will focus on the harmful effects wind turbines can have on wildlife and the environment. These are not to over shadow the beneficial effects of this renewable energy, instead the finding of this paper can be used to better manage the siting process of wind farms to both protect wildlife as well as generate the most energy possible. The model created here allows the OPSB and the DOW to site wind farms throughout Ohio with a better understanding of the possible threats that may occur. The goal of the study was to classify Ohio's landscape based on its relative risk to avian and bat species from on-shore wind energy development. By using a weighted overlay technique with key landscape feature layers, areas were able to be identified as lower or higher risk.

Chapter 2 Background and Literature Review

2.1. Risks From Wind Turbines

Risk from wind turbines are more than the direct mortality to avian and bat species. Many biologists and stakeholders have expressed concerns relating to: noise and light pollution, habitat loss and fragmentation, increase chance of invasive species dispersal, all in addition to the direct mortality. Noise and light pollution can cause harmful effects to humans and wildlife in similar ways. By adding new ambient noise and lighting to areas, the residents (wildlife and human) are having to change their lifestyle to address the new stressor. Habitat loss and fragmentation has been the largest threat to species facing extinction. Wind turbines have a larger footprint than related energy sources, causing concern for habitat protection throughout the world. From the habitat destruction and loss, the newly cleared area for pads, roads and service lines, increases the chance of the spread of invasive species. Lastly, the main discussion topic for this paper, direct mortality to birds and bats. Millions of birds and bats fall victim to turbine strikes each year, contributing to local population declines. In the following section I will discuss each one of these concerns in more detail.

2.1.1. Noise and Light Pollution

Noise and light pollution have been widely known to effect human and wildlife behavior. The health risks most commonly attributed to humans coincides with annoyance (Colby 2009, Muller 2012). With this annoyance many have reported loss of sleep, leading to other health issues (Onakpoya et al 2015, Songsore & Buzzelli 2016). The World Health Organization Europe has recognized these effects and has created guidelines and threshold levels for noise a wind turbine should make. Similarly, the OPSB has set a threshold for turbines to not exceed 45dBA near households (1,200ft setback). This matches what Kaliski (2009) found, where at a distance of 300ft from the blades, 45-50dBA was detected; at 2,000 ft**,** 40dBA; and at 1 mile, 30-35dBA. However, at the base of a turbine during high wind conditions, noise levels have reached as high as 78dBA within 15m of the turbine base (Jones et al. 2015). This is nearing the level of where the National Institute on Deafness and Other Communication Disorders (NIDCD) has identified prolonged exposure could cause deafness. Even though there are potentially harmful effects to humans from these noise levels, a study recently published by Firestone and Kirk (2019) discovered a preference for wind farms over other renewable energy sources, i.e. solar.

Research including wind turbines and noise and light pollution is relatively limited directly relating to wildlife. In the studies that have been published, noise and light pollution has been reported for multiple species. When discussing noise and light pollution in wildlife the most common reports entail avoidance and/or displacement. Avoidance is when species utilize the habitat but avoid certain areas within it, while displacement is when a species is displaced from one habitat and has to move to an entirely different area; Figure 3 shows a graphic representation of these effects. Shaffer and Buhl (2016) observed displacement in 7 of their 9 focal bird species. A study done by Winder et. al. (2014) found that female prairie-chickens express avoidance to wind turbines during their breeding season. This is concerning when discussing population level impacts, in that species are expressing breeding season responses to wind energy that may lead to decreases in population levels widespread or localized.

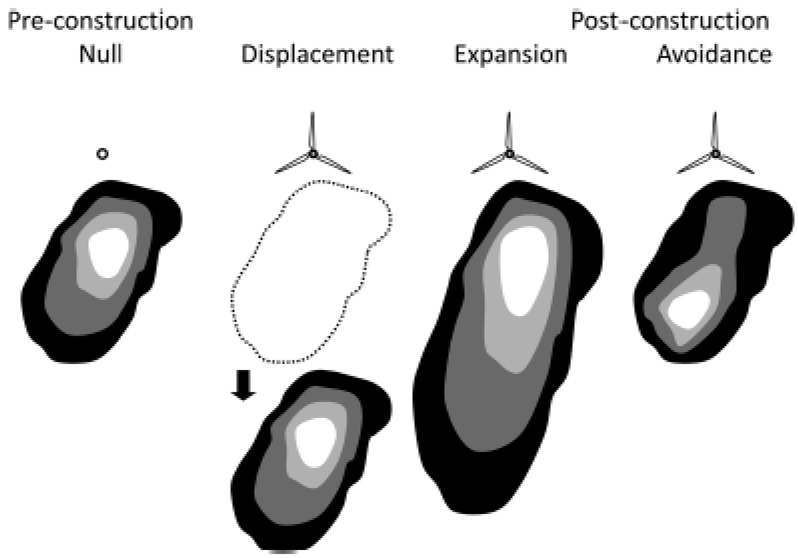

Figure 3: Threats from wind energy development may cause landscape use changes to certain wildlife. This figure identifies the four land use changes that could be exhibited by wildlife. With light colors representing high use compared to darker areas. Figure from Winder et. al. 2014.

Studies have looked at noise levels near roads and highways and how certain noise levels can affect wildlife. Using the findings from the research done in these studies, it could be an indicator for what is happening to wildlife in regard to wind turbine noise. Forman and Alexander (1998) found woodland birds and grassland birds begin to show population level declines when noise levels average 42dBA and 48dBA, respectively. These high noise levels could cause hearing loss, increase in stress levels, and interference with breeding calls (Forman and Alexander 1998, and Naugle 2011). Generalist species that utilize many habitats may benefit while intolerant species may see population level effects.

Another concern with wind turbines is the lights needed for each turbine. The FAA requires any structure over 199ft in height must have a light, they specifically recommend a flashing red light. However, these lights may be attracting insects resulting in birds and, more concerning, bats to forage around the turbines and increase their risk to direct mortality (NWCC

2010). Horn et al. (2008) found a direct correlation between insect activity and bat activity. If the lights are attracting birds and bats, there needs to be regulations that limit the lighting near and on wind turbines.

2.1.2. Habitat Loss and Fragmentation

Per unit energy, wind energy has a larger terrestrial footprint when compared to other energy production sources (Jones et al. 2015, Shaffer & Buhl 2015, Naugle 2011, Fargione et al. 2012). This is extremely concerning because habitat loss is one of the leading causes of species extinction in the world. For some researchers, they consider the habitat loss and fragmentation from wind turbines a bigger threat than the direct mortality (Gill et al. 1996). Currently, wind energy requires more land per MW (70 acres) than coal (12 acres), natural gas (12 acres), nuclear (13 acres), and solar (43 acres) (Stevens 2017, Obermeyer et al. 2011). Habitat fragmentation from the construction of service roads for each turbine can affect more land than the direct habitat loss from the wind turbine pad. The fragmentation caused by these roads can restrict movement of species, and can cause population level impacts and genetic effects by isolating populations (Obermeyer et al. 2011).

From the habitat loss and fragmentation, many species can be displaced (Arnett & May 2016). One study has found that wind development displaced a species of breeding shorebird (European Golden Plover, *Pluvialis apricaria*) by a quarter mile (Sansom et al. 2016). Similar to the noise and light pollution, not much research has been conducted with wind energy specifically, but direct similarities can be made from other land transformations such as roads and deforestation.

2.1.3. Spread of Invasive Species

Human development can greatly facilitate the movement of organisms to areas that they were not once present or were not naturally occurring (Naugle 2011). These organisms are referred to as nonnative or invasive species. These invaders usually have a competitive advantage over the native species, the invaders are able to out compete for resources. Not much research on the spread of invasive species directly from wind energy development, but some studies indicate that the disturbance from oil and gas development and roadsides, can act as conduit for invasive species (Jones et al. 2015, Naugle 2011, Obermeyer et al. 2011).

Naugle (2011) has provided an entire chapter toward invasive species and energy development. In the chapter he describes how the process of installing energy facilities will help facilitate invasive species. The process begins with the clearing of vegetation and the topsoil to install roads and powerlines. This "opens the door" for invasive species to move in. Then during construction many vehicles are driving along these roads and corridors, all while potentially transporting invasive seeds and depositing them along the way. Once the invasive species is present it can spread rapidly, and most treatments are slow to combat the species.

2.1.4. Terrestrial Species Effects

This area of study is lacking, as most of the research with wildlife and turbines is regarding avian and bat species. Within the limited research, high stress levels have been reported from some terrestrial species that occur near wind turbines. Agnew et al. (2016) found badgers living <1km from wind turbines had a 264% higher cortisol level when compared to badgers living >10km away from the turbines. Similarly, a study by Lopucki et al. (2018) found higher levels of corticosterone in common voles living closer to turbines. Another study found wolves expressed avoidance of wind turbines and lower reproductive success during the first year of operation (Ferrao da Costa et al. 2018). After three years the wolves went back to using the area but did still show a displacement effect on their den sites of more than 2,700m and some packs were displaced as far as 6,400m. These studies show that wind energy development can affect terrestrial species. Wildlife managers should think about investigating these effects in the future.

2.1.5. Direct Mortalities to Wildlife

In the United States it is estimated that millions of birds and bats are killed from wind turbines each year (Muller 2012, Loss et al. 2013, Smallwood 2007 & 2013). Wind turbine related mortality estimates may be lower than other anthropogenic causes of mortality. Yet, some species could experience localized population level impacts, resulting in cumulative mortality when combined with the other anthropogenic sources, resulting in wide-spread declines (Arnett & May 2016). Estimating the total number of birds and bats killed by wind turbines is extremely difficult and can have biased results. Most post-construction surveys are not public information and the data reported can be biased and vary depending on the methods used, region, and turbine (monopole or lattice tower). Because of these complications, estimates of bird and bat mortalities are widely debated and different estimates are made. A study by Smallwood (2007) showed that different estimators for searcher detection and scavenger removal could increase mortality estimates by as high as 10 times.

Current studies estimate the number of birds killed by wind turbines to be as high as 573,000 birds per year and as low as 20,000 birds per year (Loss et al. 2013). While bat estimates are much higher with the upper limit estimated at 1.3 million and the lower limit around 400,000 bats per year (Smallwood 2013). These estimates change depending on the region and time of year data was collected for the estimation; Northeast Deciduous Forest region had the highest fatality rates compared to other regions of the U.S., 6.1-10.5 bats/MW (Arnett et al. 2016). Many researchers and wind companies debate these estimates are still lower than other anthropogenic stressors, i.e. cars, buildings, cats, etc. However, as previously mentioned with bird species the effects of wind mortalities and other stressors can cumulatively threaten local and widespread populations. Bats are also long-lived and have low reproductive rates causing their populations to grow slowly; in result, any increase to population level declines to bats can drastically hinder the chances of population recovery (Arnett et al. 2016). The one important difference to consider between wind mortalities and mortalities from other causes, is that wildlife mortalities from wind energy can be regulated through curtailment and proper siting and mitigation strategies.

2.1.6. Mitigation Practices and Role

Mitigation is an important first step in regulating the impacts of wind energy development, and any human development. The main principles behind mitigation are avoid, reduce, and compensate for impacts from wind development. There are numerous mitigation techniques used today, but all usually follow a hierarchy approach including four main stages; planning and siting, construction, operation, and decommissioning, figure 4 (Arnett & May 2016, Gartman et al. 2016, USFWS 2012). The focus of this paper lies solely in the planning and siting phase of the hierarchy.

Proper siting of wind energy facilities is extremely important and should always be the first step in any wind energy project. The method of identifying the best suitable location is not an easy feat. The goal of siting is to find areas that are of low spatial resistance, avoid conservation or important wildlife areas, and reduce the impact of habitat changes, all while providing the best potential for wind energy (Gartman et al. 2016, USFWS 2012). Many times, the best areas for wind overlap with the best areas for wildlife (Pocewicz et al. 2013). Gartman et al. (2016) recommends the use of buffering these areas to provide a distance between wind facilities and important wildlife areas. Some areas that regularly appear in studies as important wildlife areas include conservation areas, reserves, national parks and forests, federally and state protected lands, river corridors, forests, wetlands, and lakes. GIS software can play an important role in identifying these areas.

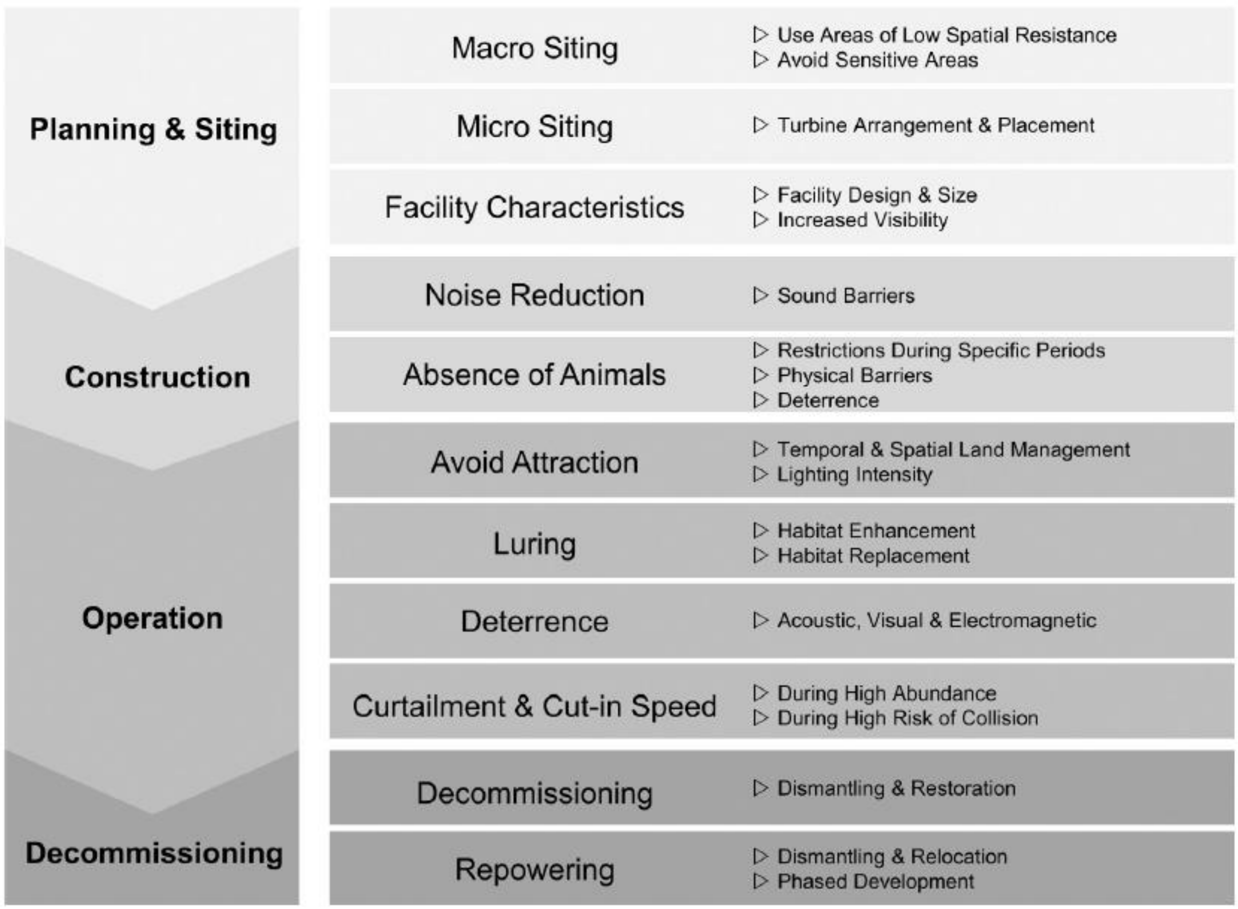

Figure 4: Hierachy approach for mitigation of wind energy development. Graphic from Gartman et al. 2016.

2.2. Literature Review

The concept of using ArcGIS modeling techniques for wildlife risks is a relatively new method in the field of environmental and natural resources. There are however, a few research teams that have explored this technique. Obermeyer et. al. (2011) designed a mitigation model for the state of Kansas. The goal of this project was to develop a model using a three-step elimination process: first identify areas to avoid, then find areas that can be developed but with offsets, lastly the remaining areas are areas that can be developed for wind energy with minimal impacts to wildlife. Avoidance areas were considered areas that were within one of the following: (1) 3.2km from a wetland with repeated whooping crane sightings, (2) 800m of "very high" quality playa lakes in the whooping crane corridor, or 400m of "very high" quality playa lakes outside the whooping crane corridor, (3) 16km from Cheyenne Bottoms Wildlife Area and Quivira National Wildlife Refuge wetlands, (4) 24km of a cluster of caves, (5) 1.6m optimal prairie-chicken habitat and (6) an area designated as having presence or habitats of threatened or endangered species. The study was successful in identifying areas that were potentially of higher risk of mortality to the species mentioned above, including a "green certification" incentive for wind energy companies that comply with avoiding these at risk areas. However, the study lacked in two ways; the first, it limits the habitat to avoid by only select wetlands, grasslands and playas. By limiting avoidance areas to only these habitats, one could relax the potential affects in other habitats. The second, there is not process in place to validate the model. By not having a validation method, the model is acting solely on speculation and expert opinion (Sargent 2011).

Fargione et. al. (2012) based their research on the goal of identifying the subset of land in the Northern Great Plains that is predicted to have low impacts to wildlife. They did so with the premise that the 20% by 2030 goal could be met by constructing wind energy on lands that were already disturbed. By identifying areas that were disturbed and not near wildlife priority areas, they found areas best suitable for wind farms. Six land cover types were selected as disturbed areas from the National Land Cover Database (NLCD): Cultivated Crops, Developed-high, -low, and -medium intensities, developed-open space, and hay/pasture. One aspect that was particularly concerning was the identification of hay/pasture. This habitat type is often considered important to grassland species of birds (USDA 2010). By identifying it as areas of disturbance in this model, wind companies may develop wind farms in areas that are bird hotspots, increasing the risk of mortality for these species.

Pocewicz et. al. (2013) created specific models to allow wildlife managers and wind company to assess risk based on specific functional groups. The four functional groups considered in this study were wetland birds, riparian birds, raptors, and sparse grassland birds. For each functional group a unique model was created, using an equation that gave each cell a migratory importance score. The variables used in each model were weighted depending on the importance of the variable to the group. Validation of the model was completed using two techniques, expert opinion surveys and observational data. Lastly, model sensitivity was completed for functional group model. One concern regarding this method is the output of four models. Wind energy groups may only consider the model that has the most available areas for them to develop wind farms; conversely, wildlife managers may use the model that has the most areas protected for wildlife. By having one model output these biases can be avoided.

Manes and Fuhr (2017) found low risk areas in the Central Great Plains using an elimination technique. The ideology was based on previous studies already discussed, Fargione et al (2012) and Obermeyer et al. (2011). In this study two layers, key wildlife areas and restricted lands, were created and merged together. The area that was outside of these merged layers was identified as potentially low risk areas for wind energy development. A key addition to this study when compared to others, was the creation of a web application. The application allows energy companies to navigate to their potential site and visually see if they are in an area of low or high risk. The disadvantage of this study was the limiting classification scale, only low risk areas. By only identifying areas classified as low risk based on an elimination technique, a wind farm can be established directly adjacent to a high priority habitat. By including multiple risk classification, i.e. lower risk and higher risk, a model can indicate the relative risk based on the proximity to key features to wildlife. Thomas et. al. (2018) utilized the idea of species richness as a measure of risk in Arizona. This study highlights the relationship that higher use of an area by multiple species can be correlated to direct mortality risk. However, if species sightings were used to create the richness model, as in the case of this study, validation methods are limited.

Most of the research completed in risk assessment from wind energy has been complete in the Western United States. With the creation of the model for the Ohio protocol, Ohio became one of the first states to develop a model for a state in the Eastern United States. Another benefit of the Ohio model, in comparison to previously mentioned models, is that Ohio is one of the few states that utilizes the model to recommend mitigation decisions. In other states, standard protocols are optional. In a survey completed by the USFWS in 2008, most of the field offices in region 5 indicated the wind industry in their state rarely followed the guidelines suggested by the USFWS (Sullivan 2008). The OPSB and the DOW have developed the model to recommend pre- and post-construct survey effort. The survey effort is related to the relative risk towards the wildlife in the area. However, the current model was created in 2009, prior to most research on this topic; because of that, the model was created using expert opinion and the best resources at the time for to what attributes on the landscape could cause risk to wildlife (Figure 5). Now, ten years later, more research has been conducted and Ohio has built six wind farms to collect data from. This creates ideal circumstances to recreate the risk model, allowing for better and more accurate management decisions by wind energy companies and wildlife agencies.

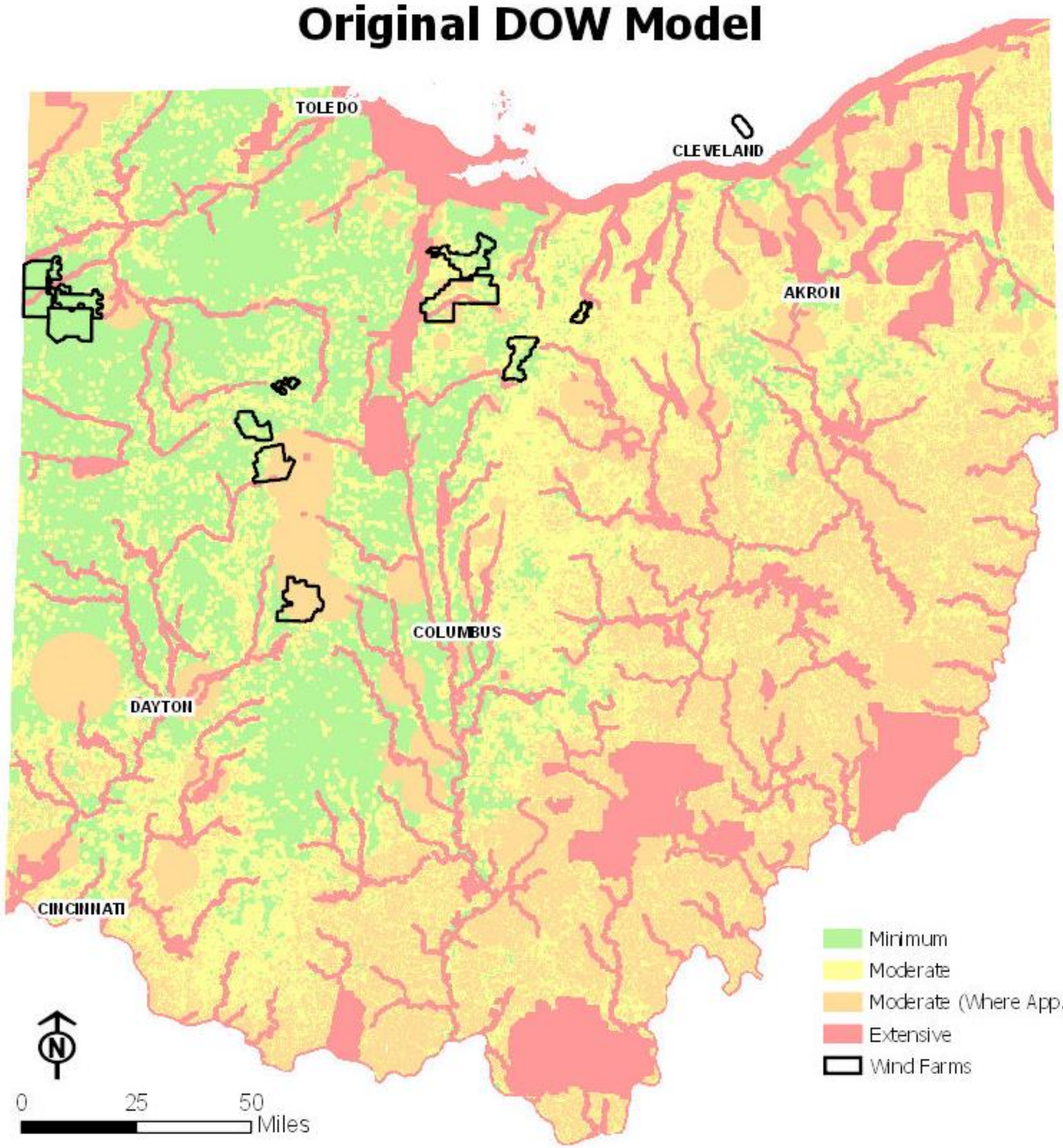

Figure 5: Original model created by DOW in 2009, for assessing risk to wildlife and assigning survey effort for wind energy projects. Model is from Ohio's On-Shore Bird and Bat Pre- and Post-Construction Monitoring Protocol for Commercial Wind Energy Facilities in Ohio.

The past studies have all proven a GIS can be used to predict relative risk to wildlife. However, as mentioned previously, some of the past research has limitations or drawbacks when using their methodology. The research presented in this paper aims to fill these limitations and find solutions for the drawbacks, all while continuing to add progress in the field of GIS modeling for wildlife. By providing a single output assessing risk to all avian and bat species, bias is eliminated, and by using a classification scale of 6 categories relative risk can be shown as you move away from predicted higher risk areas. Also, the methods here include sensitivity analysis to eliminate weight biases and includes validation strategies using sightings data. The methods presented in this paper can provide a common methodology that can be replicated and potentially be a standard for other risk assessment models.

2.3. Weighted Overlay

Weighted overlay techniques have been shown to have the ability to rate suitable locations based on multiple layers of data (Mitchell 2012, Bolstad 2016). By utilizing the same classification scale for each layer, values can be compared across layers and they can be mathematically overlaid with statistically sound results (Mitchell 2012, Bolstad 2016). The classification scale is usually designated by expert opinion, published research, or industry standards. The most common scales are usually comprised of three, five, seven, or nine levels (Mitchell 2012). By having more suitability levels, it allows for more flexibility when drawing conclusions (Mitchell 2012). In this research, a scale using seven values was used (0-6, lower risk-higher risk). To express the importance of certain layers in the model, weights can be assigned to each layer. The higher the weight, the higher the importance. All final weights must sum to equal 100%. Final weights can be assigned similar to the scale values, either by expert opinion, published records, industry standards, or through the use of a sensitivity analysis.

2.4. Sensitivity Analysis

Using expert opinion has been a popular means of generating rankings and final weights for layers. However, this method lacks mathematical foundation making results difficult to interpret and is usually the center of controversy amongst decision makers (Elsheikh et al. 2015). One method of overcoming these issues is the utilization of the Analytic Hierarchy Process, and its use of a ratio matrix. Within a GIS this process is referred to as sensitivity analysis (SA) (Elsheikh et al. 2015). Sensitivity Analysis can be defined as “the evaluation of the impact or effect of changes in input values on the model outputs” (Al-Mashreki et al 2011). SA is accomplished by assigning different weighting schemes to each layer used in the model (Elsheikh et al. 2015, Al-Mashreki et al 2011). For each layer, a schema group is created. This group consists of a set number of models that are ran for that layer. Each weighting scheme is ran through a weighted overlay process resulting in a model output. The model output is then summarized for each schema group based on the variance score. Variance scores are calculated by finding the difference of a single risk category between each model in the schema group. By comparing the variation scores of each schema group to the sum of all the variation scores, a percent variation is calculated for the layer. The final percentage is the overall importance of that layer in the final model (Elsheikh et al. 2015, Al-Mashreki et al 2011). This number can be rounded to the nearest whole number and used as the weight for the final overlay process.

2.5. Validation Technique

When using a model-based approach many decision makers are concerned with the accuracy or if the results are “correct”. Model validation answers these questions (Sargent 2011). The adopted definition for this paper of model validation is “substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model" (Sargent 2011). The specific use of the model developed in this project was to evaluate relative risk to avian and bat species in Ohio from wind energy development, using the assumption that land cover and certain habitats will result in higher mortalities of these species. To validate the model in the present study, species richness was used; where species richness can be defined as the number of species within a designated area. This validation method worked under the assumption that risk was correlated to species richness; thus, in areas of predicted higher relative risk the model will have higher species richness. Conversely, in areas predicted to have lower relative risk, species richness will be low. The identification of these "hot-spots" has been utilized in multiple studies to identify potential areas of protection and measure the value of unique habitats (Braun 2005).

2.6. Multicollinearity Test

Another important step in the modeling process is to assure decision makers that layers were unique and expressing their own phenomenon. By testing for multicollinearity, it can show relationships between predictor variables (Joshi 2012, Hair et al 1998). If variables show perfect relationships between one another, it is difficult to draw conclusions. This is due to the multicollinearity inflating parameters lead to a lack in statistical significance (Joshi 2012). Detection of these relationships can be completed using a correlation matrix. If the correlation matrix results in values exceeding 0.90 the two layers are expressing collinearity and need to be dealt with. If no values exceed 0.90 the model is not expressing any collinearity and can proceed with any further analysis (Hair et al. 1998).

Chapter 3 Data and Methods

Prior to any layers being created or used, a meeting was held between all Department of Wildlife (DOW) biologists to gain insight on what layers were believed to be important for a wind risk model. After the focus group meeting a short questionnaire was sent out to answer some specific questions regarding the model. From the meeting and additional questionnaire, six layers were derived for use in the model: NLCD, rivers, wetlands, lakes, and caves/hibernacula. All layers were obtained through the DOW.

3.1. Current Study

The study presented here builds off the earlier mentioned studies, while addressing the concerns regarding each. The goal of the study was to identify areas with a relative risk level to wildlife from wind energy development. By having one model to assess the potential risk, confusion and bias can be eliminated and discussions can proceed for best mitigation methods. Similar to the research conducted by Pocewicz et al. (2013) a pre-model survey was sent out to DOW biologists and in addition, an in-person meeting was held to discuss model construction. From the results of the survey and discussions, variables were defined for each potential layer. The use of six risk classification levels was utilized, allowing for sufficient flexibility and differentiation for each layer (Mitchell 2012). The risk levels are not necessarily saying there will be no mortality in lower risk areas. The risk levels are a relative estimate; thus, a lower risk area might experience direct mortality of multiple species, but it can be assumed the value will increase with each relative risk level higher. Previous studies indicated the importance of buffers around important wildlife habitat, this method was expanded upon and a multiple ring buffer technique was used to create each buffer. The multiple ring buffer was used to indicate that the risk level decreases as you move further away from the at-risk habitat. Once all the layers were created in ArcGIS, a weighted overlay method was used to create the final risk assessment model.

3.1.1. Study Area

The study area for this study was the entire state of Ohio, U.S. The state has a land area of approximately 105,830 km^2 and is home to close to 12,000,000 people, in 88 counties. There are many unique habitats throughout the state. For years, ecologists have utilized physiographic regions to framework research and conservation (Rodewald et al 2016). Ohio can be divided into five regions, Figure 6. Forests (deciduous and coniferous) account for 32% of the land area with 60% being in the south-east portion of Ohio, the Ohio Hills (Rodewald et al 2016). Agricultural land (cultivated crops, hay, and pasture) accounts for half of the land area in Ohio, with 70% in the Upper Great Lakes Plain and the Prairie Peninsula regions. Grasslands in Ohio are usually dominated by hay and pasture, however there are a few remnant prairies, while some have been established from reclaimed surface mining grasslands. During European settlement Ohio lost nearly 90% of its wetlands. Since then Ohio has restored some wetlands and has provided incentives to landowners to restore and create wetlands on their properties. Ohio also has 262 miles of shoreline on Lake Erie and over 124,000 miles of streams with varying riparian habitats (USGS 2014). Ohio’s four largest cities, Cleveland, Columbus, Cincinnati, and Toledo help to make up the 7% of land area that is now developed. Over half of the development in Ohio can be found within the Prairie Peninsula and Allegheny Plateau regions.

Ohio’s diverse habitats help support an abundance of terrestrial and aquatic species. Ohio’s vast wildlife populations includes: over 150 species of fish (Rice and Zimmerman 2019), more than 430 speces of birds with half of the species breeding in Ohio (Ohio Ornithological

Society 2018, Rodewald et al 2016), 57 mammal species ten of which are bats, 44 reptilian species, and 39 amphibians, and many insects, spiders and butterflys (DOW 2015).

Figure 6: Ohio's physiographic regions, based on geological profiles and distinct plant and animal communities.

3.1.2. Model Layers

A total of six layers were used to create a final model using a weighted overlay process: the 2011 NLCD, wetlands, lakes, rivers, protected lands, and caves and hibernacula. Many studies have used the National Land Cover Database (NLCD) for researching spatial scenarios relating to land cover (Bonter et al. 2008, Obermeyer et al. 2011, Fargione et al. 2012, Gorsevski et al. 2012). The NLCD was used here to value the land cover types according to their importance and relative risk level to birds and bats.

One habitat that plays a dynamic role for many wildlife species are wetlands. The USFWS estimated that nearly 43% of all federally threatened and endangered species require wetland habitats during at least one stage of their annual life cycle (Mitsch and Gosselink 2007, Braun 2005). Wetlands are of particular importance to many bird species, particularly waterbirds but also songbirds, for foraging, stopovers, and breeding (Braun 2005). Mitsch and Gosselink (2007) estimated eighty percent of America's breeding bird population rely on wetlands during their life cycle. In Ohio many species utilize this habitat, with some being state-endangered, i.e. American Bittern, King Rail, Sandhill Crane, among other listed species. Not only does alterations to the wetland itself affect avian and bat richness and abundance but changing the surrounding habitat has also shown signs of affecting bird species (Braun 2005). Many species forage in wetlands and then utilize the surrounding habitat (forest, scrub-shrub, vernal pools, etc.) for nesting, cover and additional food resources. Wetlands additionally, play an important role for many mammal species. Specifically, for this paper's purpose, wetlands are important for many bat species. Bats are well known to forage over aquatic habitats with some studies indicating a bats using wetlands to forage (Lookingbill et al. 2010). Many other mammal species utilize wetlands as well, such as, otter, mink, beaver, muskrats, and many vole and mouse species (NRCS 2001).

Based on the above knowledge of wetlands importance, a layer with all wetlands greater than five acres was used for further analysis. Changes to wetland density or size have been shown to influence species richness and abundance, and a reduction in breeding success. Additionally, changes to the surrounding habitat can cause detrimental effects to wildlife as well (Braun 2005). The protection of these habitats will benefit humans as well as many wildlife species.

The recognition of the importance of birds and other aquatic systems, lakes and rivers, has gained significant interest since the 1980s (Hoyer 2013). Many species of waterbird utilize lakes for part or all life stages (Smith et al. 1989). Numerous species use shoreline habitat for breeding, feeding, or cover habitat. However, for some species of waterbirds lakes play a more significant role. For species such as loons and grebes, the ability to walk on land is difficult and the behavior is rare. The location of the legs on these species are far back on their bodies making them efficient swimmers/divers, however, walking is extremely difficult such that most of their life they spend in large bodies of waters. For these species large bodies of water provide the needed habitat. Most feeding sites used by diving ducks are between six and fifteen feet of water depth (Ewert 2006). This is important to consider when other large waterbodies, i.e. wetlands, are most commonly filled so most habitat is ideal for dabbling species who prefer depths between 0.5 and 2 feet of water (Ewert 2006). For bats, a study completed by Downs and Racey (2006) found more bat activity in larger expanses of water than in smaller ones. This could be associated to the insect densities over larger bodies of water. This is supported by additional studies that have also expressed the importance of larger bodies of water to bats (Arnett et al. 2016)

In Ohio, there is estimated to be over 52,000 ponds, lakes, and reservoirs, 988 of them are of five acres are larger, which leads to over 156,000 acres of water (USGS 2014). Lakes of five acres or larger were used since biodiversity increases with size of lakes, these lakes would be able to support more species of birds than the smaller lakes.

Rivers and their corresponding riparian corridors have been widely known to be used by birds for migration, feeding, and mating (Peak and Thompson 2006, Rushton et al. 1994, Hoyer et al. 2006, Rodewald et al. 2016, Braun 2005). More recently however, is the role different habitat play along the corridor. Recent studies have found greater species richness of birds when specific habitat adjacent to the stream is wider than 90m and waters depth is not more than 2m (Peak and Thompson 2006, Hoyer et al. 2006). Waterbirds also use these river corridors to navigate during migration (Pocewicz et al. 2013)Multiple studies have found that bat activity also increases when the habitat adjacent to the river is of preference. Downs and Racey (2006) observed an increase in bat activity when adjacent habitat was wooded areas and within 20m of the bank. Similarly, Seidman and Zabel (2001) found bats utilize riparian corridors along streams of variable widths, but with increased activity as width increases, possibly because larger streams have more standing water for drinking. Additionally, these riparian areas may provide roosts locations for several species (Seidman and Zabel 2001)

Braun (2005) expressed the limited availability there is of these dynamic habitats; in the U.S. riparian habitat makes up 1% of the landscape, and more than 70% of the original corridors have been lost. Rodewald et al (2016) estimated 65% of Ohio streams being classified as intermittent or ephemeral streams, with a high percentage being within intensively farmed or developed areas. Since areas surrounding rivers that are of high use to avian and bat species is limited, these areas are of high significance to avian and bat species and their protection and management is imperative.

Bats can be split into two main categories based on their roosting behaviors. Cave dwelling bats hibernate in caves while migratory tree bats typically do not. Migratory tree bats account for more than 90% of the direct mortalities from wind turbines in Ohio. While cave dwelling bats only account for 10% of the mortalities, the numbers are still concerning to biologists due to the compounding effects of white nose syndrome. White nose syndrome (WNS) is a disease that causes irritation to the skin during hibernation and wakes the bat causing them to burn their energy storage faster, resulting in death during the winter months when they should be hibernating. At some sites the death totals have been as high as 90% and 100% (USFWS 2018). From the effects of WNS and high mortalities the USWFS recommend buffering current or historical hibernacula with more than 10,000 bats by 20 miles, buffering current or historical hibernacula with between 1,000-9,999 bats by 10 miles, and buffering current or historical hibernacula with less than 999 bats by 5 miles. For migratory tree bats, the protection of roost site habitat is recommended, with Baerwald and Barclay (2009) finding higher activity of migratory species within these areas.

Various methods to protect these key habitats mentioned prior and many additional ones as well, have been imposed globally. More than 155,584 terrestrial areas have been legally classified as national protected areas, covering 12.5% of earth's surface (Watson et al 2014). The International Union for Conservation Nature (IUCN) defines protected lands as: "an area of land and/or sea especially dedicated to the protection and maintenance of biological diversity, and of natural and associated cultural resources, and managed through legal or other effective means" (Chape et al 2005) In Ohio there are nearly 3,000 areas that constitute as green space or a protected area. These include ODNR own lands, IBAs, city metroparks, and National Parks and Forests. Protected areas do much more than conserve landscapes and provide habitat for wildlife, they also support local and national economies through tourism, as well as, contribute to livelihoods in the surrounding area (Watson 2014). More than 80% of the world's threatened birds, amphibians, and mammals use the resources within a protected area during their life cycle (Watson et al 2014). Ohio has more than 150 species listed under the DOW action plan as endangered, threatened, species of concern, or species of interest. Most, if not all, can be found within one of Ohio's protected areas during the species life cycle (DOW 2015). Since these protected areas are of state and national importance, they should be protected for wildlife management and conservation.

3.2. Pre-Model Questionnaire

Prior to construction of any layers or any models, a brief questionnaire was sent to a select group of experts within the DOW. These experts included the bird and bat biologists, wind energy expert, and the endangered species expert from the Department of Natural Resources, DOW. By surveying these experts, I was able to gain the knowledge they each have within their specific fields and use this information to guide the decisions made to create a model that would better predict risk from wind energy development in Ohio. The questionnaire was sent out to the 12 experts using Survey 123. The experts were asked a total of 11 questions, ranging from do you think we need this model to what is a good measure for mortality? The full questionnaire can be seen in appendix A. The most central questions for this research were the questions within the survey that allowed each expert to give a buffer size that they would use to better protect habitats from wind energy development. This allowed me to make decisions on final buffer sized based on the average answer for each layer. The response rate for the survey was 62% and average answers were used for each question were able to be used to create the final layers.

3.3. Layer Creation

A total of six layers were used for the risk model, table 2. Each layers final raster was created using ArcGIS 10.3, and involved a two or three step process (Figure 7); first create multi-ringed buffer, second create raster from feature, and third reclassify raster into risk categories. A multi-ringed buffer was used to give more importance to areas closer to a feature and decrease the importance as one moves further away from the feature. Once the buffer was created the feature to raster tool was used to generate a raster from the buffer. This raster was then reclassified into one of the 7 classification rankings; 0, 1, 2, 3, 4, 5, 6; with 0 being less risk and 8 being the highest risk. The only layer that did not follow these three steps was the NLCD, this layer only had to be reclassified since it was already a raster.

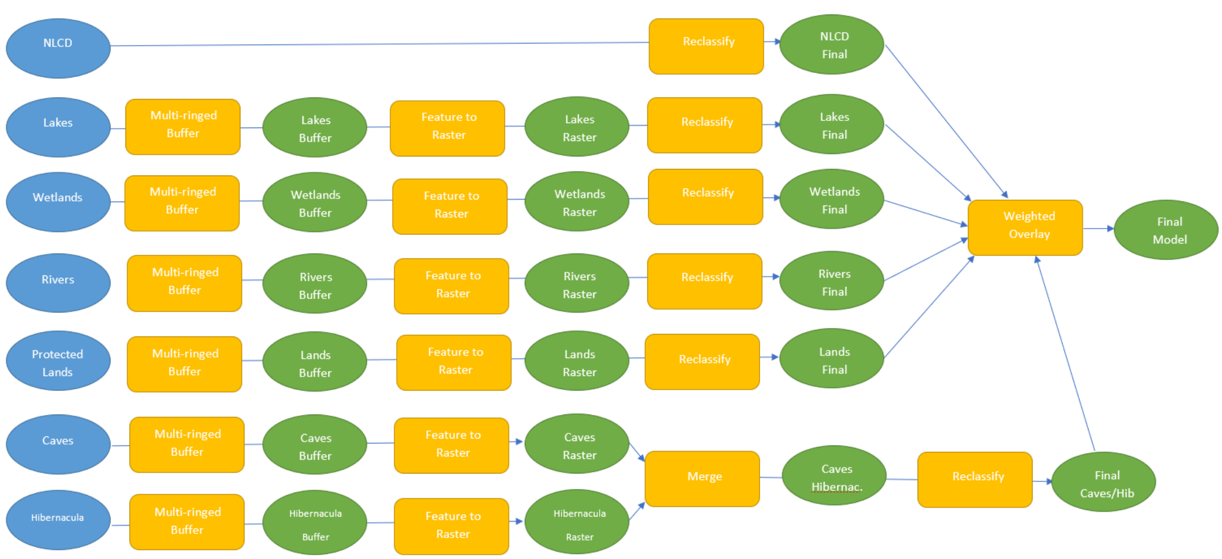

Figure 7: Steps taken to create a wind energy risk assessment model, to assess the risks to avian and bat species in Ohio.

Table 2: List of layers that were used in the creation of a landscape model to predict wind energy risk to birds and bats in Ohio.

Layer	*Source*	*Purpose*	*Raster/Vector*	*Coordinate System*	*Attributes*
NLCD	USGS	Provided landcover classifications throughout Ohio	Raster	NAD 1983 State Plane Ohio South FIPS 3402 feet	**Grid Code**: landcover classification
Wetlands	Division of Wildlife - National Hydrology Dataset	Provided wetland habitats that were 5 acres are larger	Vector - Polygon	NAD 1983 State Plane Ohio South FIPS 3402 feet	**ID**: unique ID for each wetland **Area**: in acres
Lakes	Division of Wildlife - National Hydrology Dataset	Provided lake habitats that were 5 acres are larger	Vector – Polygon	NAD 1983 State Plane Ohio South FIPS 3402 feet	**ID**: unique ID for each lake **Area**: in acres
Rivers	Division of Wildlife - National Hydrology Dataset	Provided river segments of all orders throughout Ohio	Vector – Line	NAD 1983 State Plane Ohio South FIPS 3402 feet	**ID**: unique ID for each river **Length**: in miles
Protected Lands	Division of Wildlife, PADUS	Provided protected lands within Ohio	Vector – Polygon	NAD 1983 State Plane Ohio South FIPS 3402 feet	**ID**: unique ID for each area **Name**: name of each area **Area**: in acres
Caves and Hibernacula	Division of Wildlife	Provided locations of caves and hibernacula in Ohio	Vector - Point	NAD 1983 State Plane Ohio South FIPS 3402 feet	**ID**: unique ID for each **Type**: cave or hibernacula

3.3.1. NLCD

The National Land Cover Database (NLCD) was created by the U.S. Geological Survey (USGS) and Multi-Resolution Land Characteristics (MRLC) Consortium, in 2011. This Landsat-based dataset is a land cover database, with 30-meter resolution, for The United States. The NLCD uniquely identifies land cover types as one of the following sixteen: Open Water, Perennial Ice/Snow (not in Ohio), Developed Open Space, Developed Low Intensity, Developed Medium Intensity, Developed High Intensity, Barren Land, Deciduous Forest, Evergreen Forest, Mixed Forest, Shrub/Scrub, Grassland/Herbaceous, Hay/Pasture, Cultivated Crops, Woody Wetlands, and Herbaceous Wetlands.

For the wind risk model there were fifteen of the sixteen land cover types in Ohio, Ohio did not have Perennial Ice/Snow. The fifteen land cover types were reclassified into one of the 7 risk categories based of expert survey results, table 2. The final raster can be seen in figure 8. Reclassification values were designated based off the results from the expert survey and meetings.

Table 3: Ohio land cover types originally derived from the 2011 NLCD, reclassified for a wind energy risk model to birds and bats.

<table>
<tr><th>Land Cover Type</th><th>Original Classification</th><th>Survey Results</th><th>Reclassification</th></tr>
<tr><td>Developed High Intensity</td><td>24</td><td>0.38</td><td rowspan="2">0</td></tr>
<tr><td>Developed Medium Intensity</td><td>23</td><td>0.38</td></tr>
<tr><td>Developed Low Intensity</td><td>22</td><td>0.38</td><td>1</td></tr>
<tr><td>Developed Open Space</td><td>21</td><td>0.38</td><td rowspan="2">2</td></tr>
<tr><td>Barren Land</td><td>31</td><td>1.63</td></tr>
<tr><td>Cultivated Crops</td><td>82</td><td>3.63</td><td>3</td></tr>
<tr><td>Pasture/Hay</td><td>81</td><td>3.63</td><td rowspan="2">4</td></tr>
<tr><td>Open Water</td><td>11</td><td>6.3</td></tr>
<tr><td>Grassland/Herbaceous</td><td>71</td><td>6.3</td><td rowspan="2">5</td></tr>
<tr><td>Shrub/Scrub</td><td>52</td><td>6.3</td></tr>
<tr><td>Woody Wetlands</td><td>90</td><td>7.13</td><td rowspan="5">6</td></tr>
<tr><td>Emergent Herbaceous Wetlands</td><td>95</td><td>7.13</td></tr>
<tr><td>Deciduous Forest</td><td>41</td><td>7.25</td></tr>
<tr><td>Evergreen Forest</td><td>42</td><td>7.25</td></tr>
<tr><td>Mixed Forest</td><td>43</td><td>7.25</td></tr>
</table>

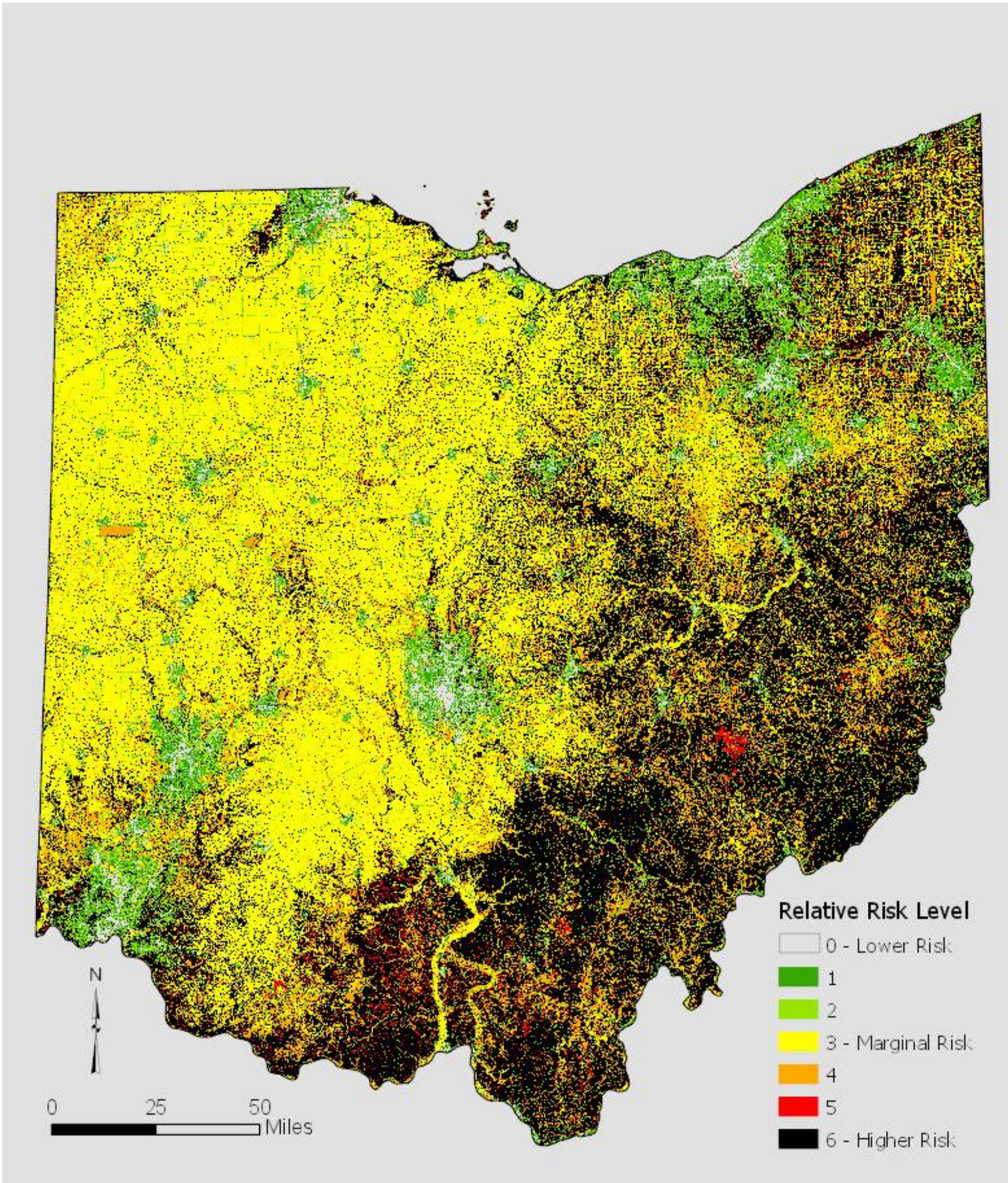

Figure 8: NLCD reclassified for relative risk level for birds and bats to wind farm development in Ohio.

3.3.2. Wetlands and Lakes

Wetlands and lakes were delineated by the DOW, prior to the study. For this study, all wetlands and lakes of 5 acres are larger were considered. A multi-ringed buffer was created for each unique wetland and each lake. The biologists surveyed showed a preference for a 2km buffer. So buffers were set at 0.33km, 0.66km, 1km, 1.33km, 1.66km, and 2km. The resultant layers were converted to a raster and reclassified to the corresponding risk level: 6, 5, 4, 3, 2, 1,

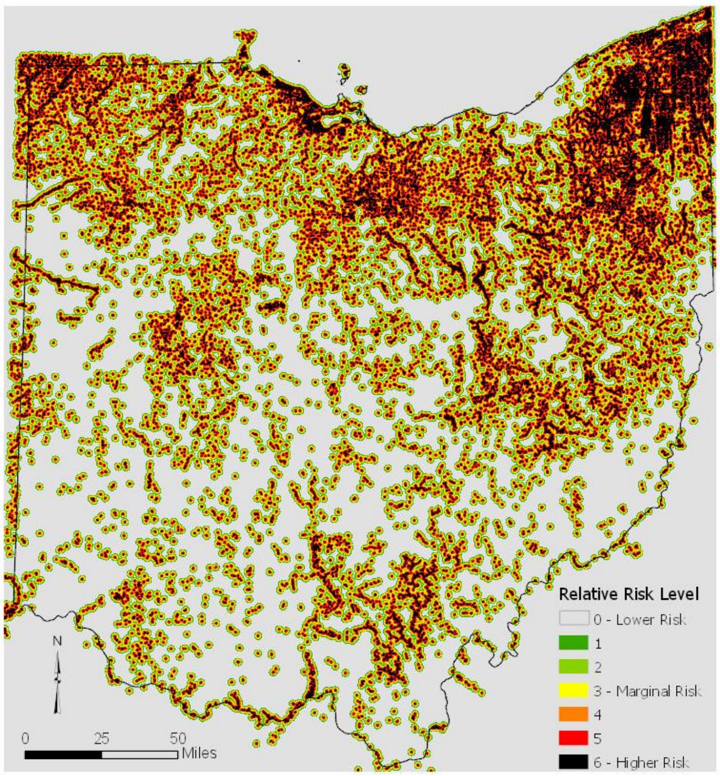

Figure 9: Wetlands raster reclassified for relative risk levels to wind energy development on Ohio's birds and bats.

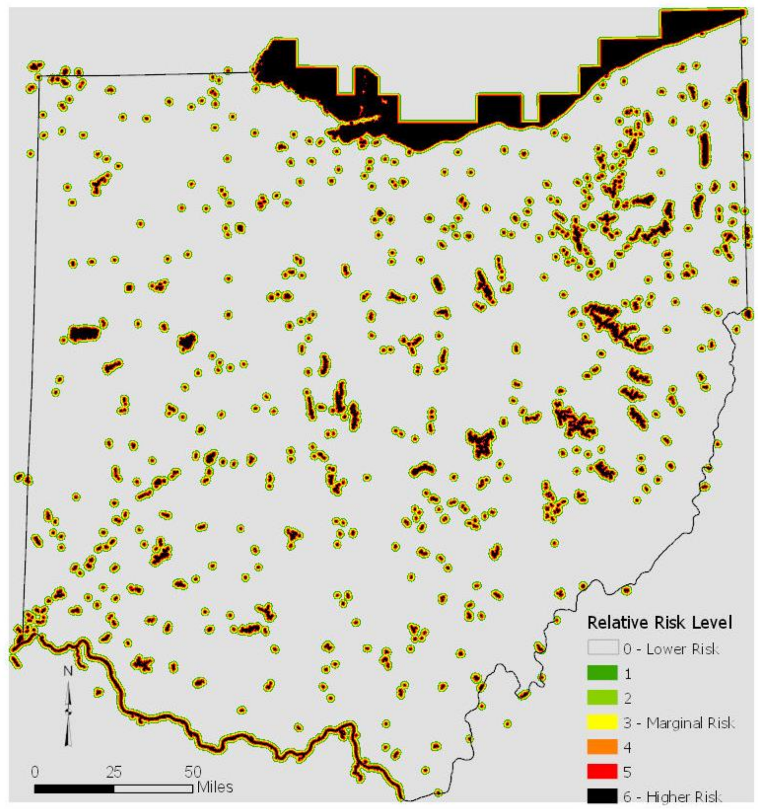

Figure 10: Lakes raster reclassified for relative risk levels to wind energy development on Ohio's birds and bats.

respectively. Areas that were greater than 2km were reclassified to 0. The final rasters can be seen in figures 9 and 10.

3.3.3. Rivers

Studies have shown that rivers with certain habitats surrounding the stream reach are more frequently utilized than reaches with less favorable habitats (Seidman and Zabel 2001, Downs and Racey 2006). To support these papers the biologists at DOW also suggested using stream reaches with specific habitats around them. For this reason, stream reaches with favorable habitat of 25 acres are larger on at least one side of the stream were used. Favorable habitat was considered to be: forested, herbaceous, or scrubland. These habitat types (41, 42, 43, 71, and 52) were selected from the NLCD and the appropriate reaches were selected for further analysis.

Once all rivers were delineated, a multi-ringed buffer was created for each reach. A 1km buffer was preferred by DOW biologists. The resulting multi-ring buffers were created at 0.16km, 0.33km, 0.5km, 0.66km, 0.83km, and 1km. This process was accomplished using ArcGIS modelbuilder since the number of rivers were to many for the tool to run at one time.

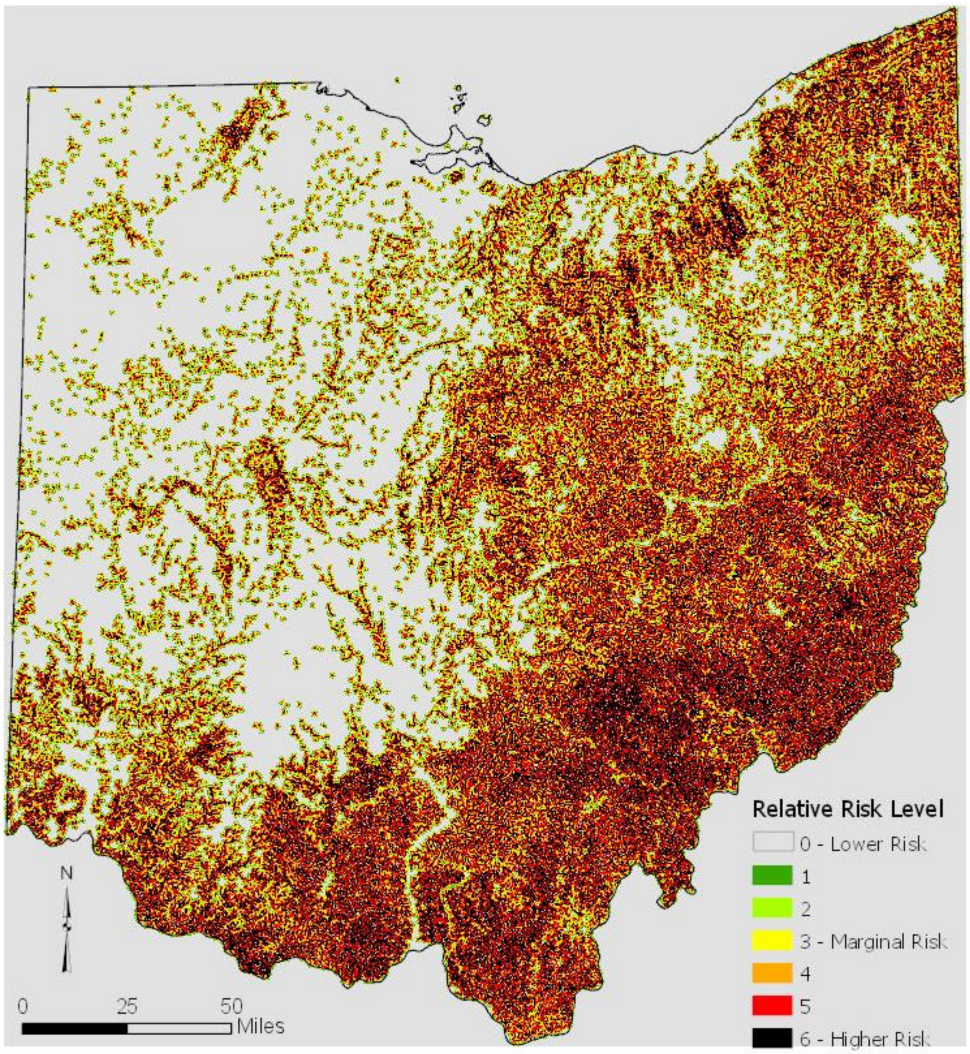

Figure 11: River raster reclassified for relative risk levels to wind energy development on Ohio's birds and bats.

Modelbuilder allowed me to select rivers by county and run the tool, the merge all river buffers upon completion of all counties. The resultant layer was converted to a raster and reclassified to the corresponding risk level: 6, 5, 4, 3, 2, 1, respectively. Areas that were greater than 1km were reclassified to 0. The final raster can be seen in figure 11.

3.3.4. Protected Lands

Within Ohio there are many landscapes that are managed through what this study refers to as protected lands. These lands consist of all ODNR owned properties, National Forests, National Parks, important bird areas (IBAs), and any remaining lands not listed prior that are listed In the Protected Areas Database of the United States (PADUS). The ODNR properties and National Forests and Parks were digitized by the DOW, prior to the study. IBAs were downloaded from National Audubon Society. The PADUS had many of the same properties but also had additional areas including metroparks (natural areas managed by city or metro area).

These areas that were not included in one of the other groups were selected and added to the final dataset. All areas were then merged into a final dataset named protected lands. The protect lands layer was then used to create a multi-ringed buffer around each area. The preferred buffer distance from the survey was 1km. Buffers were created at 0.16km, 0.33km, 0.5km, 0.66km, 0.83km, and 1km. The resultant layers were converted to a raster and reclassified to the corresponding risk level: 6, 5, 4, 3, 2, 1, respectively. Areas that were greater than 1km were reclassified to 0. The final raster can be seen in figure 12.

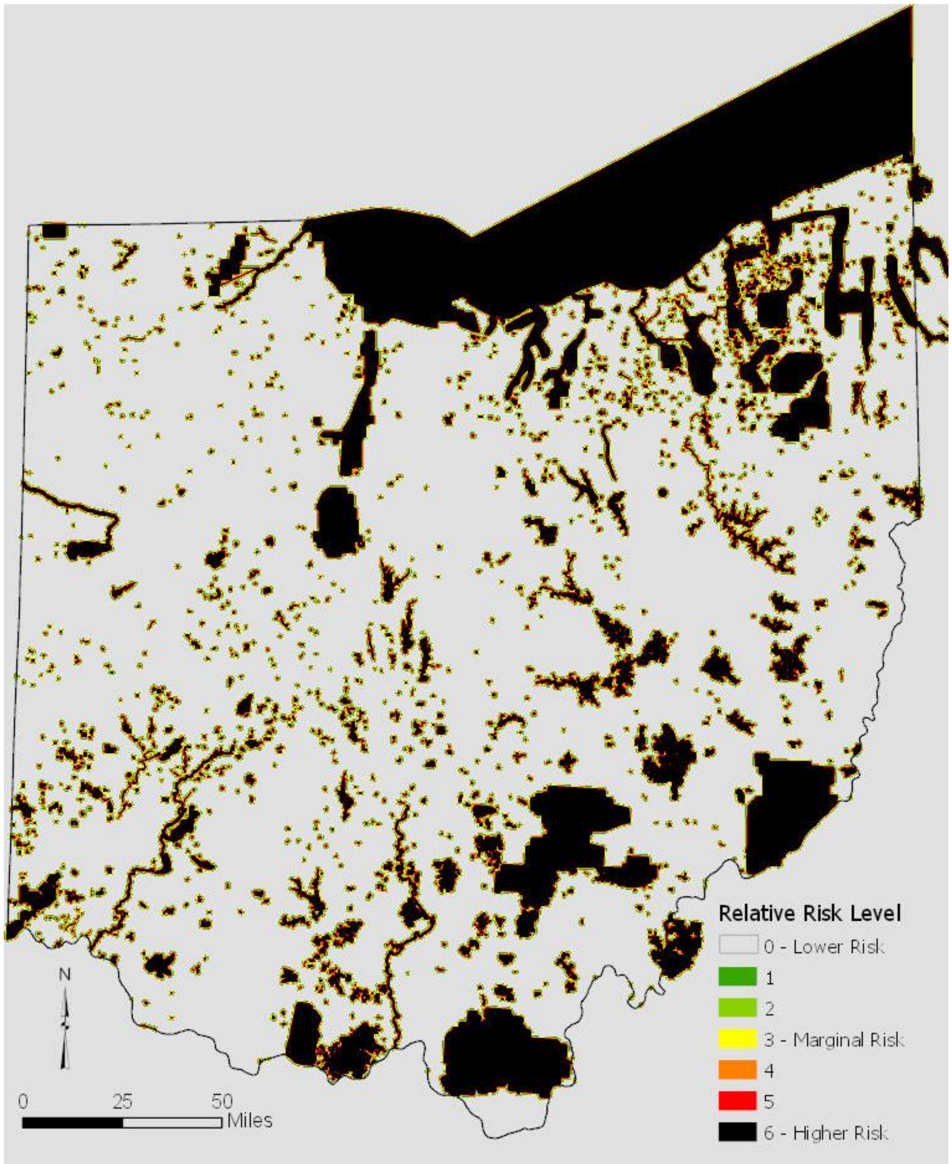

Figure 12: Protected lands raster reclassified for relative risk levels to wind energy development on Ohio's birds and bats.

3.3.5. Caves and Hibernacula

The final layer made for the model consisted of two landscape features that are extremely important for several bat species. Caves and hibernacula serve as habitats where bats can roost and hibernate. The USFWS suggest protecting each habitat, but at different spatial scales. For caves, the USFWS recommends using a 5-mile setback from any known cave with a bat population, whereas, for hibernacula the USFWS recommends a 20-mile setback. With these suggested setbacks multi-ringed buffers were created around all known caves and hibernacula in Ohio. For caves the buffers were 0.83 miles, 1.66 miles, 2.5 miles, 3.33 miles, 4.16 miles, and 5 miles. The hibernacula buffers were 3.33 miles, 6.66 miles, 10 miles, 13.33 miles, 16.66 miles, and 20 miles. Both layers were rasterized and reclassified to 6, 5, 4, 3, 2, 1, and areas farther than 5 miles and 20 miles equaled 0, respectively. Since the buffers of caves and hibernacula could potentially overlap these layers were merged using the raster calculator and the summed score was considered the final risk classification. For example, if a risk category 4 overlapped with a risk category 5, the resulting score was 9. The scores were later reclassified to maintain the 0-6 classification. This reclassification reclassed values larger than 6 into the highest risk category and kept the summed values as their responding risk category (Figure 13).

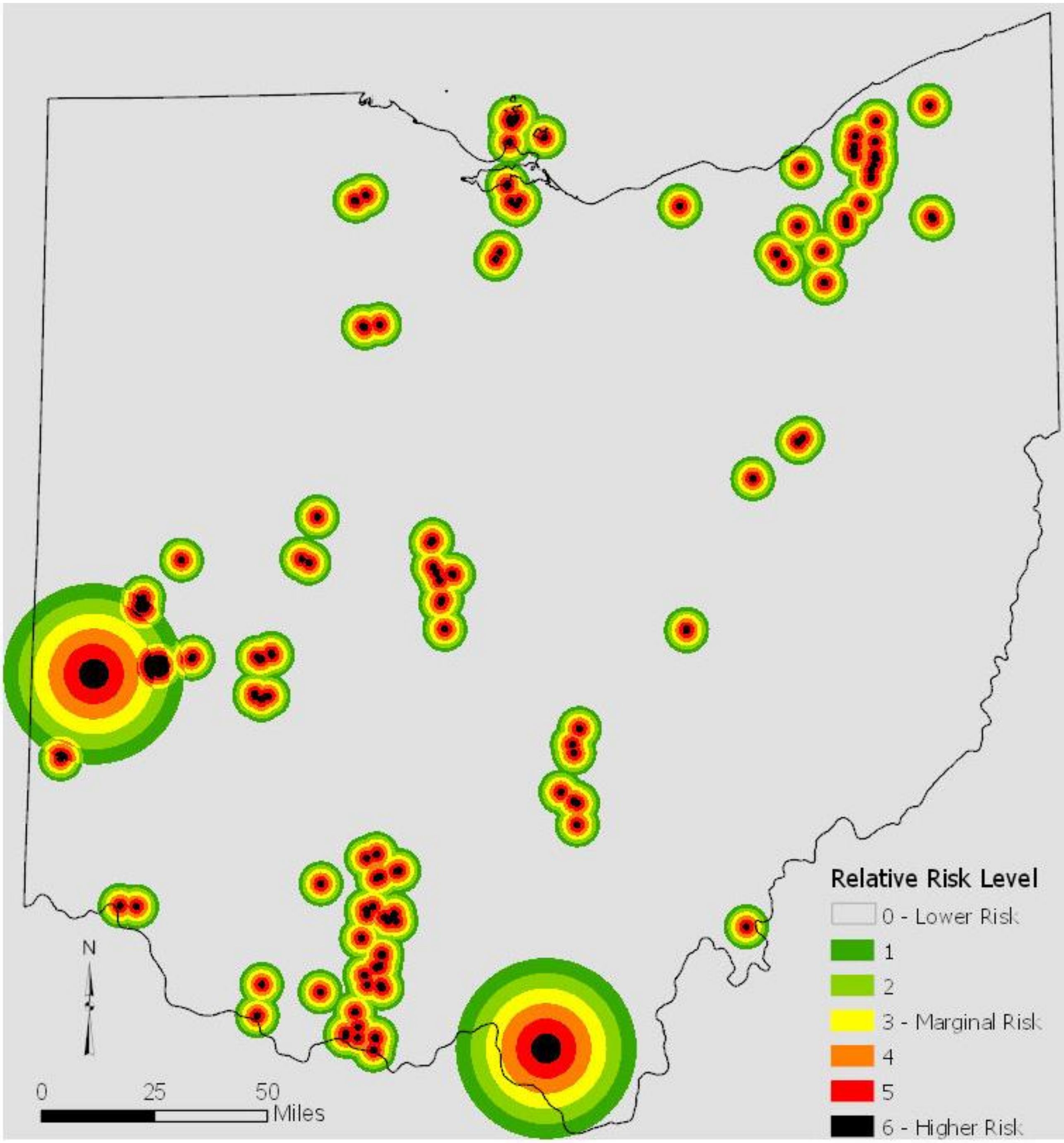

Figure 13: Caves and Hibernacula raster reclassified for relative risk levels to wind energy development on Ohio's bats.

3.4. Weighted Overlay

The weighted overlay process was used to determine areas of relatively higher and lower risk throughout the landscape of Ohio. By using the weighted overlay method, relative importance could be assigned to specific layers. To avoid biasing the model with user defined weights, sensitivity analysis was completed to reduce subjectivity of the weights. Sensitivity analysis distinguishes the most sensitive or most important layers as having large variance scores. By finding the percent of the variance score over all scores, the final weights for the model were identified.

3.4.1. Sensitivity Analysis

To determine the influence of each layer within the model and better predict risk from wind farms to birds and bats, sensitivity analysis was conducted. By applying different weighting schemes for each layer, identification of sensitive layers was possible. The layers that are found to be most sensitive are the most important in a model and should be weighted appropriately (Elsheikh et al. 2015, Al-Mashreki et al 2011). A total of twenty-five scenarios were used and implemented through a weighted overlay in ArcGIS, with all overlays using an evaluation scale of 0 to 6 by 1 (Table 3). The first scenario created had a schema with all criterion with equal weights. Each layer (wetlands, rivers, lakes, protected lands, caves, and NLCD) was grouped into schema groups. Each schema group consisted of four models. One model set the weight of the layer to 5% with all remaining layers set to 19% to sum to 100%. The second model weighted the layer at 25% and set the other layers to 15%. The last two models followed the same process with the layer being set to 50% and all others set to 10% and the layer set to 75% and all other set to 5%, for the third and fourth models, respectively.

Table 4: Weighting schemes for the 25 scenarios ran through a weighted overlay analysis, to test model sensitivity. Results used in model assessing relative risk to avian and bat species from Ohio's wind energy development.

SCENARIO	MODEL#	WETLANDS	RIVERS	LAKES	LANDS	CAVES	NLCD	TOTAL
EQUAL	1	17	17	17	17	16	16	100
WETLANDS 1	2	5	19	19	19	19	19	100
WETLANDS 2	3	25	15	15	15	15	15	100
WETLANDS 3	4	50	10	10	10	10	10	100
WETLANDS 4	5	75	5	5	5	5	5	100
EQUAL	1	17	17	17	17	16	16	100
RIVERS 1	6	19	5	19	19	19	19	100
RIVERS 2	7	15	25	15	15	15	15	100
RIVERS 3	8	10	50	10	10	10	10	100
RIVERS 4	9	5	75	5	5	5	5	100
EQUAL	1	17	17	17	17	16	16	100
LAKES 1	10	19	19	5	19	19	19	100
LAKES 2	11	15	15	25	15	15	15	100
LAKES 3	12	10	10	50	10	10	10	100
LAKES 4	13	5	5	75	5	5	5	100
EQUAL	1	17	17	17	17	16	16	100
LANDS 1	14	19	19	19	5	19	19	100
LANDS 2	15	15	15	15	25	15	15	100
LANDS 3	16	10	10	10	50	10	10	100
LANDS 4	17	5	5	5	75	5	5	100
EQUAL	1	17	17	17	17	16	16	100
CAVES 1	18	19	19	19	19	5	19	100
CAVES 2	19	15	15	15	15	25	15	100
CAVES 3	20	10	10	10	10	50	10	100
CAVES 4	21	5	5	5	5	75	5	100
EQUAL	1	17	17	17	17	16	16	100
NLCD 1	22	19	19	19	19	19	5	100
NLCD 2	23	15	15	15	15	15	25	100
NLCD 3	24	10	10	10	10	10	50	100
NLCD 4	25	5	5	5	5	5	75	100

After all twenty-five models were run, varience for each schema group was calculated using the following equation:

$$\boldsymbol{V} = \sum |\, f(xi + 1) - f(xi)|$$

Where V = variation of function and xi = model outputs. Since the aim of the project was to determine areas that were of highest risk to birds and bats, only the results from the highest risk level (classification = 6) were considered during the variation testing. The variation scores of each layer group were then summed to find a model variation score.

3.4.2. Final Weighted Overlay

Based on the results from the sensitivity analysis, final weights were identified for all six layers (Table 5). Final weights were calculated following equation:

$$\%V = \frac{x}{y}$$

Where %V is the perecent variation, x is the layers variance score, and y is the summed model variation score. This resulted in the percent importance of each layer. The percent importance was then rounded to the nearest whole number and used as the final weight for that layer. By using ArcGIS Desktop's weighted overlay tool, with an evaluation scale of 0 to 6 by 1, the final weights were used to create the "best fit" model for wind farm risks to birds and bats in Ohio.

3.4.3. Multicollinearity Testing

Multicollinearity is when two or more layers have a perfect or exact relationship between the predictor variables. This will result in incorrect conclusions for the overall outcome of a model. Detection of multicollinearity was completed by examining a correlation matrix between all six variables. If multicollinearity was identified further analysis (OLS and possibly layer removal) would have to be done.

3.4.4. Validation

To assure the model was accurate and predicting risk levels relative to the area, validation methods were used. Species richness during the summer was used to validate the model. For the purpose of this paper summer consisted of the months of May through August. This validation technique acted under the assumption that areas predicted with relatively higher risk will demonstrate higher species richness than areas with lower risk. To test this, the final raster was transformed into polygons for each risk level, without simplifying edges and dissolving based on risk level score. Next, species sightings were counted within each risk level score. Species sightings consisted of only bird and bat species listed by DOW as species of greatest conservation need (SGCN) from the Ohio Wildlife Action Plan (DOW 2015). Sightings data came from two sources; the first was from the Ohio Breeding Bird Database and the second was from DOW field surveys. To normalize the data, species sights were corrected by dividing by the acres of each risk level.

Chapter 4 Results

The weighted overlay technique was able to identify areas based on the relative risk to avian and bat species during the summer breeding season (Figures 14). To make summarization and visualization easier, a simplified model was made by merging risk classification levels together, creating 3 risk levels: lower risk, marginal risk, and higher risk (Figure 15). Lower risk categories were originally 0 and 1, marginal risk were originally categories 2, 3 and 4, and higher risk were categories 5 and 6. The model predicted 34% of Ohio's landscape to be within the lower risk levels, 63% within the marginal risk levels, and 3% within the higher risk levels, Table 5.

Table 5: Model results for the area of each risk level to avian and bat species from wind development in Ohio.

Risk Level	*Area (Acres)*	*% of Ohio*
0	477,593	1.81%
1	8,505,739	32.20%
2	9,109,458	34.49%
3	4,738,866	17.94%
4	2,751,400	10.42%
5	819,976	3.10%
6	12,587	0.05%
Total	**26,415,619.42**	**100%**

4.1. Sensitivity Analysis Results

Sensitivity analysis was able to be completed using the 25 different weighted scenarios. Variation within schema groups was able to rank the level of importance of each layer. For an example, the Lakes variation score (0.54) was calculated by the following equation:

$$\boldsymbol{V} = |0.0003 - 0.0007| + |0.0007 - 0.0002| + |0.0002 - 0.0005| + |0.0005 - 0.0047|$$

$$\boldsymbol{V} = 0.0004 + 0.0005 + 0.0003 + 0.0042$$

$$\boldsymbol{V} = 0.0054 = 0.54\%$$

Results from the variation scores, found that protected lands and the NLCD layers were most sensitive or the most important to the model's final output and the least sensitive layer was the caves and hibernacula layer (Table 5).

From the variation scores the final weights for each layer were calcualted. By calucalating the final summed model variation score (4.53%) the percent varation of each layer could be calculated. Each schema group's variation score was divided by the model variation score to find the percent varation of that layer; for example, wetlands percent varatiation was found using the following equation:

$$\%V = \frac{0.64}{4.53} = 14.20\%$$

The percent varation was then rounded to the nearest whole number to obtain the weight to be uesd in the final model (figure 14).

Table 6: Sensitivity analysis results from 25 models to assign final weights to be used in a landscape model assessing relative risk from Ohio's wind energy development to birds and bats

Criteria	*Variance*	*Percent Variation*	*Final Weights*
Wetlands	0.64%	14.20%	**14**
Rivers	0.63%	13.82%	**14**
Lakes	0.54%	11.87%	**12**
Lands	1.17%	25.78%	**26**
Caves	0.41%	9.10%	**9**
NLCD	1.14%	25.23%	**25**
Total	4.53%		

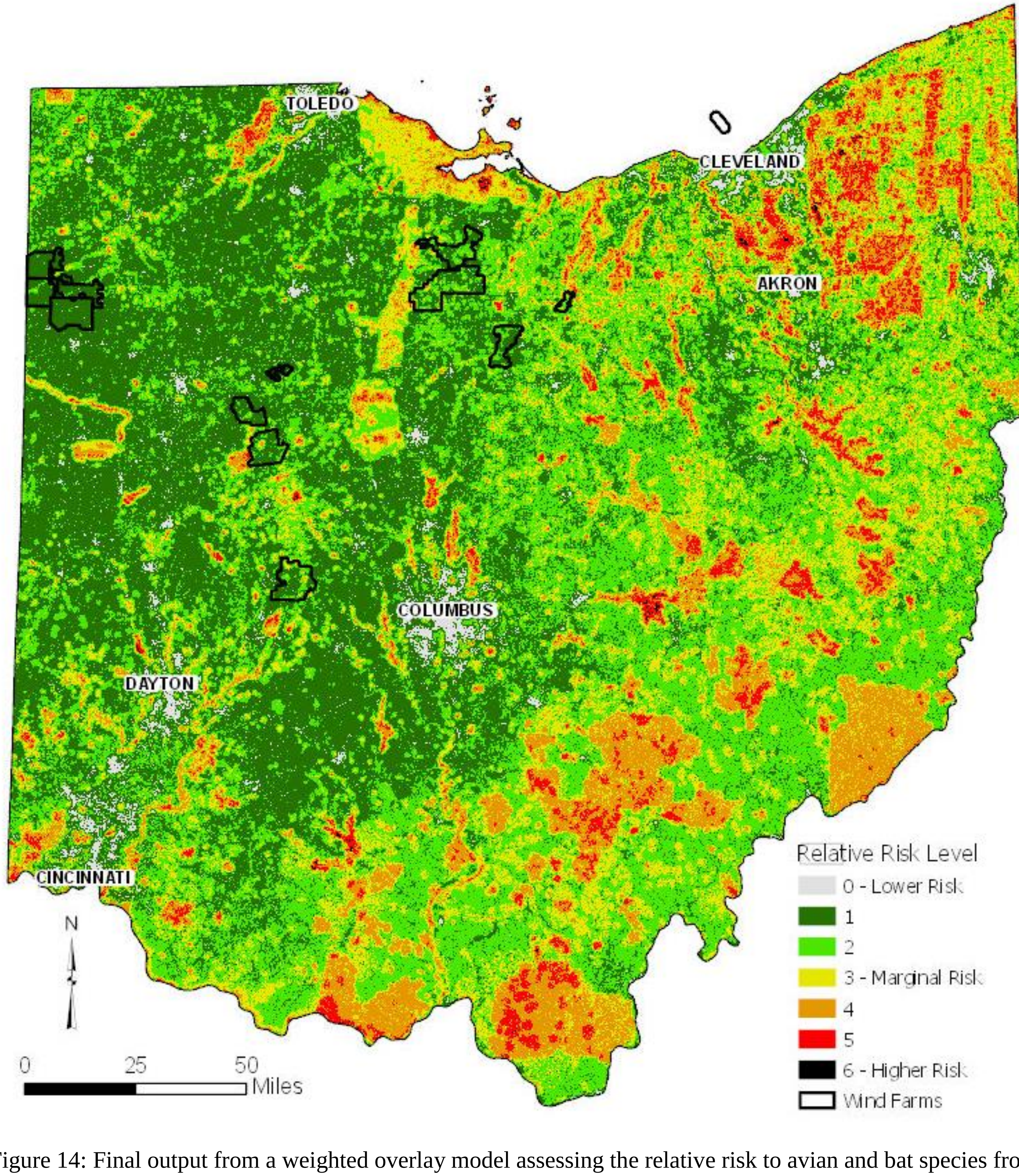

Figure 14: Final output from a weighted overlay model assessing the relative risk to avian and bat species from Ohio's wind energy development, during the summer breeding season.

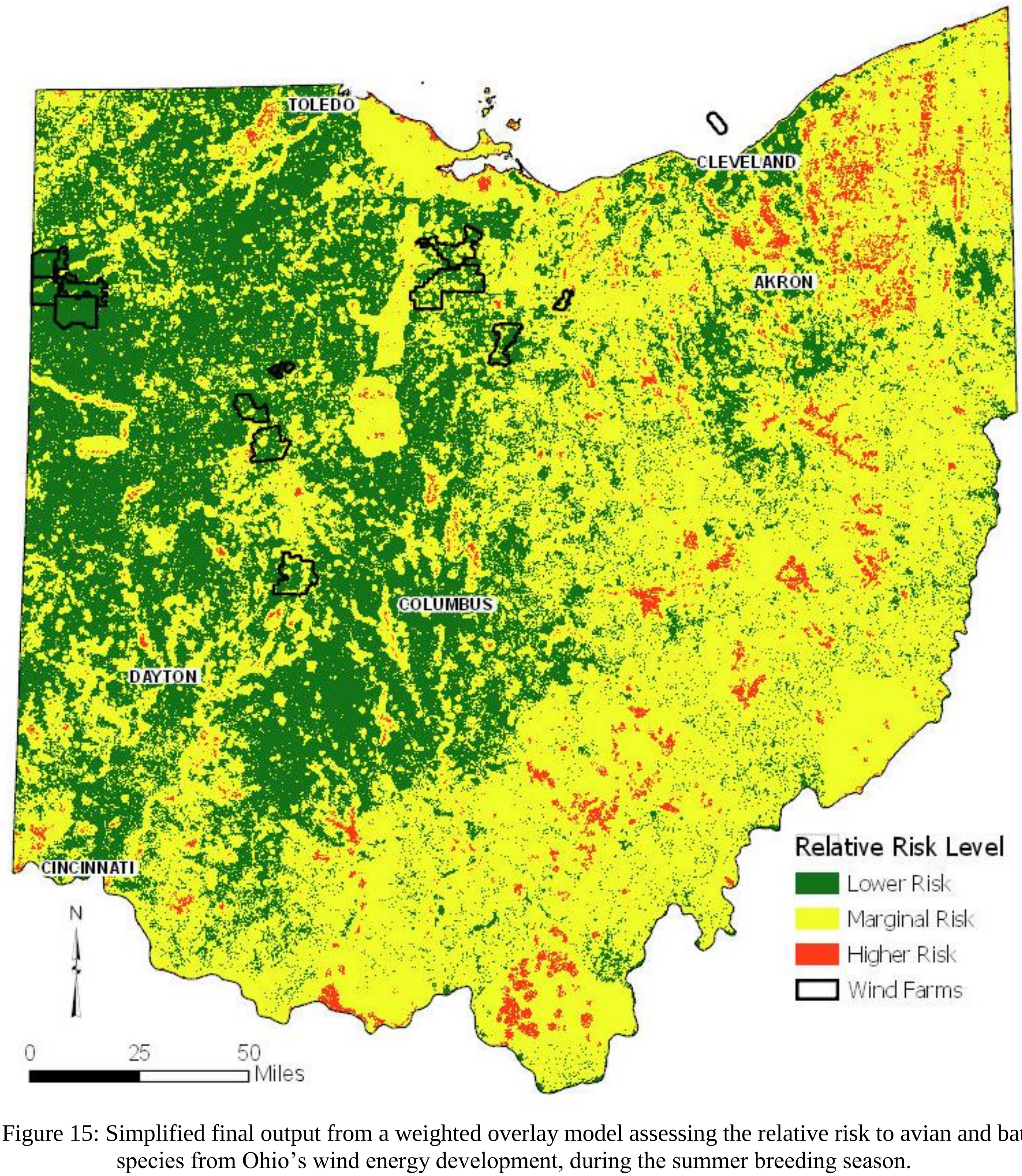

Figure 15: Simplified final output from a weighted overlay model assessing the relative risk to avian and bat species from Ohio's wind energy development, during the summer breeding season.

4.2. Multicollinearity Test Results

Band collection statistics within ArcGIS was able to calculate a correlation matrix (table 6). The matrix the showed the highest relationship was between rivers and NLCD, at 0.73. However, for full collinearity to exist between two layers, relationship values need to higher than 0.90. These results show that the layers used in the model are unique and do not express multi-collinearity and further analysis can be conducted.

Table 7: Correlation matrix results to test for multicollinearity between layers used in landscape model to assess avian and bat species risk from Ohio's wind energy development.

LAYER	RIVERS	LANDS	LAKES	CAVES/HIBER.	NLCD	WETLANDS
RIVERS	1	0.22	0.00	0.12	0.73	0.25
LANDS	0.22	1	0.37	0.16	0.28	0.19
LAKES	0.00	0.37	1	0.06	0.07	0.11
CAVES/HIBER.	0.12	0.16	0.06	1	0.18	-0.01
NLCD	0.73	0.28	0.07	0.18	1	0.45
WETLANDS	0.25	0.19	0.11	-0.01	0.45	1

4.3. Validation Results

Originally validation was to be completed using mortality data collected by wind farms in Ohio. However, this data was limited and was not evenly distributed across all risk levels. Alternatively, species sightings were used to complete validation tests. To avoid biasing the validation results with generalist species, only species that were listed as "species of greatest conservation need" (SGCN) in the Ohio State Wildlife Action Plan were used for validation, appendix B. Species sightings were counted per risk level. The model was validated using species richness and having more sightings as you increase in risk levels, figure 16. A total of 68 unique species were seen throughout the study area, for a total of 75,299 sightings. Only two species listed as SGCN were not seen, Eastern Small-footed Bat and Rafinesque's Bat. One concern from the validation results was the sightings in risk level 0. The results for risk level 0 can be attributed to the fact that many of the SGCN are species that have adapted to city landscapes, i.e. urban adapters, and more than 75% of risk level 0 is within city limits throughout Ohio. From conversations during an in-person meeting; Matthew Shumar, Ohio's Program coordinator for Lights Out Ohio and co-author of Ohio's second Breeding Bird Atlas, concluded that it is a common occurrence and others have found similar results to this study (Matthew Shumar, March 4th, 2019, in-person conversation). Also discussed in the conversations with Matthew Shumar were how the complex matrix of habitats within cities allow multiple species to live within these developed areas (Matthew Shumar, March 4th, 2019, in-person conversation). From the conversations with Matthew Shumar and other experts, along with the validation test, the model was considered validated.

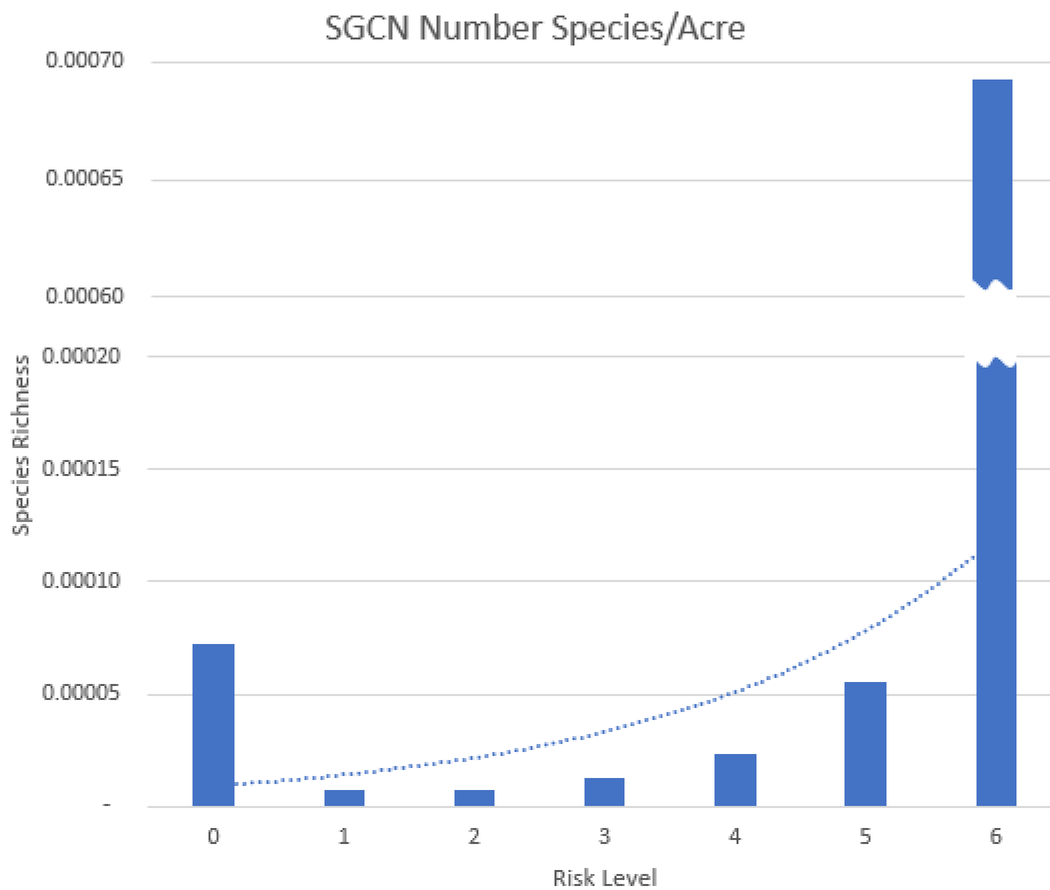

Figure 16: Species richness by predicted relative risk level to birds and bats from Ohio wind turbines, during summer breeding season.

Chapter 5 Discussion and Conclusion

The goal of the study was to create a model that would be able to identify areas of relatively higher risk from wind energy development to bird and bat species throughout Ohio. The results show the model was able to predict these areas with high validation success for summer/breeding season. For Ohio to achieve their goal of 12.5% electricity from renewable energy, Ohio would have to have 15,000,000 MW be generated by wind turbines. With an average turbine generating 3,285 MW at 25% capacity (Lee 2018), Ohio will need an additional 4,130 turbines to meet this energy requirement. These additional turbines mean Ohio will need to convert approximately 290,000 acres of land (70 acres/MW), or 41,000 acres per year to meet the 12.5% by 2026. Given the results from this study this is possible within the 9 million acres of lower risk lands (risk levels 0 and 1). Currently, Ohio's wind farms are built or are being built in areas of predicted lower risk, with 68% of the area within all farms classified as risk level 1 and 26% as risk level 2 (Figure 17). With more than 30% of Ohio within the lowest risk levels there is ample opportunity for wind energy companies to develop in areas with lower risk to summer resident avian and bat and bat species. However, the model did indicate some areas that are being developed that could pose a higher threat than other areas (Figure 18). These areas should be monitored by biologists to assess the effects on the wildlife in the area. Proper location of a wind farm is just the first step in a multiple step process. Mitigation, advances in detection technology and curtailment regimes can lower risk to wildlife, potentially allowing wind farms to be built in higher risk areas. With that said, risks still need to be evaluated for other times of the year and threshold levels for mortality still need to be determined, and how these risk levels relate to the permitting and surveying process.

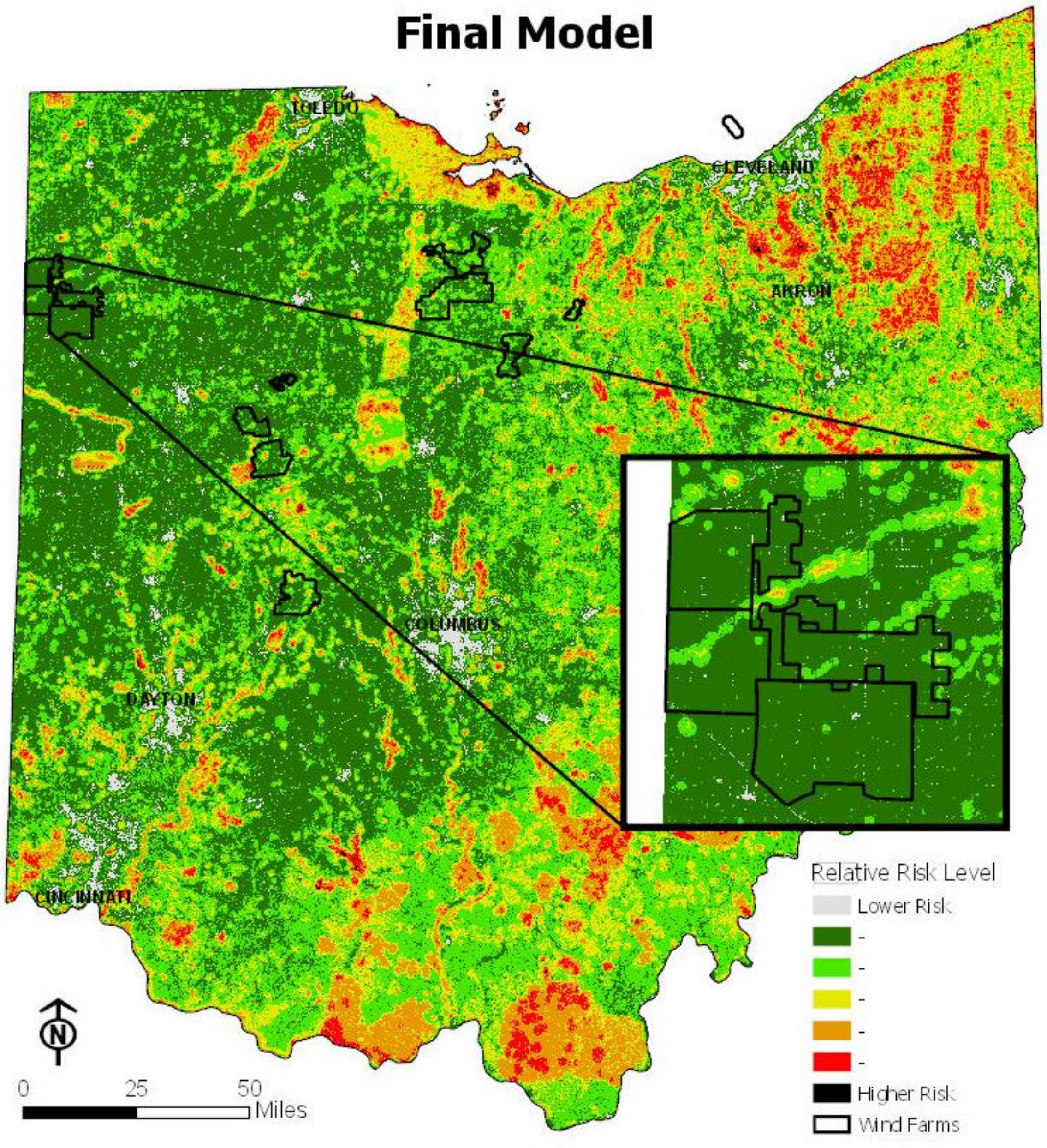

Figure 17: Final results from the weighted overlay model for risk to wildlife from wind energy development in Ohio. Inset map of wind farm with lower predicted risk areas.

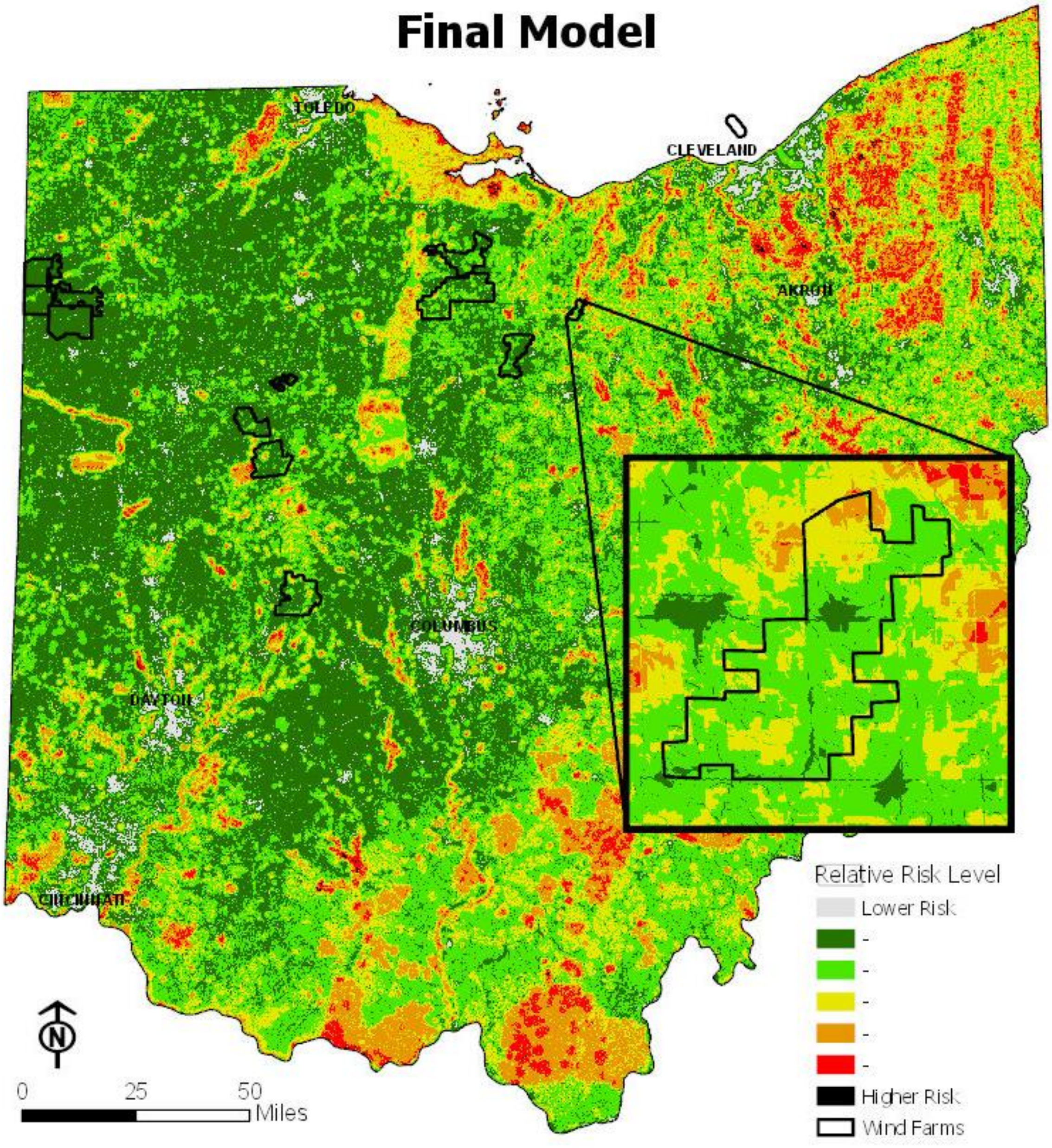

Figure 18: Final results from the weighted overlay model for risk to wildlife from wind energy development in Ohio. Inset map of wind farm with higher predicted risk areas.

The results from this study allows a manager to estimate mortality in areas where wind farms have not yet been built. By using mortality data collected in lower risk areas, managers can estimate mortality in areas not yet developed and increase the estimated deaths with risk level. The model was validated using species richness rather than number of individuals. Many studies have used species richness to be an indicator for habitat values and importance to wildlife species, due to the simplicity to create and comprehend (Braun 2005). For that reason, a manager will be able to predict the number of species effected rather than number of direct individuals. From the results of this model, the lower risk areas had a total mortality of 95 species, taking the assumption of increased risk levels, this number is likely to increase as wind energy develops in higher risk areas. It is imperative for managers to properly site wind farms for the protection of wildlife and the ecosystem. By using this model, managers within Ohio can be better informed on where higher-risk areas are and properly site wind farms. The model also can be used for other states to follow and provide consistency in methodology for siting practices.

Further research can be done in many areas to improve upon the results from this model and deal with its limitations. One limiting aspect of this study is the use of only summer data to validate the model. By limiting it to only summer, the model is only valid for a brief period, yet an important period. For this reason, it would be beneficial to validate the model with data from other seasons. A model using each season (fall, spring, winter) could be created to inform wind companies and wildlife managers what to expect during each season and use proper mitigation techniques (i.e. curtailment) for each season and throughout the year. Another area that could be further developed is the use of different buffer sizes. The use of different buffers can be used to emphasize the importance of certain habitats or key areas. By changing the buffer size of these areas, managers can extend the range of importance for these areas within the model. An additional aspect that was a limitation that can be further developed is the use of more up to date data. This model was created using the 2011 NLCD, by using the 2016 NLCD land cover data will be more accurate. Additional further research could include a method to better assess the displacement/avoidance hypothesis estimates from pre-construction surveys can be compared to post-construction surveys to determine if birds/bats are expressing these negative effects. Data from Ohio’s first and second Breeding Bird Atlases could also be used to test this hypothesis. Lastly, a migration model using bird migration paths might be as successful or more successful at predicting risk to bird species. By looking at wind speeds, directions and flight paths of multiple species of birds and bats a migration model could be created. This model would allow managers to predict where the birds and bats will be and when, to better site wind turbines.

The use of this model, or like models, in the GIS and wildlife community is imperative. This model has the potential to be utilized within the DOW as a new method to assess risk to avian and bat species throughout Ohio from wind energy development. This is possible by replacing the model currently in use for Ohio's On-Shore Bird and Bat Pre- and Post-Construction Monitoring Protocol for Commercial Wind Energy Facilities in Ohio. Additionally, this model provides a standard protocol for future wind energy risk models for further comparative studies.

Wind energy is rapidly growing with the global demand for renewable energy sources. Wind energy provides multiple benefits from economic growth to sustainability. However, wind energy can cause negative effects on the landscape. Millions of birds and bats are effected from direct mortality from wind turbines each year. For this reason, proper siting of wind farms is vital for protecting species richness across the landscape. The GIS model presented here provides an example of how landcover can be used to aid in the siting process for wind farms on a state level.

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Appendix A - Pre-Model Survey

Do you see a need for a wind energy risk assessment model?

1. No
2. Neutral
3. Yes

For each of the following potential layers, which layers would you consider in a wind energy risk model for wildlife?

1. Would never be included
2. Might Include
3. Could not be without

Potential Layers Asked:

Land Cover
Habitat Patch Size
Wetlands
Rivers
Bird Sightings
Bat Sightings
Terrestrial Species Sightings
Protected Lands
Important Bird Areas (IBAs)
Wind Speed
Wind Direction
Aspect/Slope

Do you think land cover type is important to wildlife and should be considered in a wind risk assessment model?

1. Yes
2. No

If yes, please indicate which rank you would give to each land cover type for its importance to wildlife and level of protection from wind farms?

1. 0
2. 1
3. 2
4. 3
5. 4
6. 5
7. 6

8. 7
9. 8

Land Cover Types

Water - Lakes/Ponds
Developed
Barren – Rock/Sand/Clay
Forest
Scrubland
Herbaceous
Planted/Cultivated – pasture/hay and cultivated crops
Wetlands

What is more important to birds and bats?

1. Stream size/order
2. Surrounding habitat around the stream
3. Both

Is wetland size important to birds/bats?

1. Yes
2. No

Is lake/reservoir size important to birds/bats?

1. Yes
2. No

For each potential layer, what size buffer should be used to protect each habitat?

1. No Buffer
2. 0.5 km
3. 1 km
4. 2 km
5. >2 km

Potential Layers/Habitats

Rivers/Streams
Wetlands
Protected Areas
Bat Sightings
Focal bird species sightings

For a species diversity indicator what is the best measure for a wind risk assessment model?

1. All species – use every species distribution model
2. Only avian species – use only bird/bat distribution models
3. Avian species weighted – use all species distributions but weight the avian species models higher
4. Focal species only – use only focal species, avian and terrestrial

For each of the following questions, please indicate in the box provided a number of deaths per turbine per year (#deaths/turbine/year)

1. What level/number of mortality do you feels is LOW bird/bat mortality?
2. What level/number of mortality do you feels is MODERATE bird/bat mortality?
3. What level/number of mortality do you feels is HIGH bird/bat mortality?

What is the best method to use to validate the model?

1. Mortality
2. Band Recover
3. eBird
4. Other, please list.

Do you have any overall comments/concerns regarding model? Please type in them in the text box provided.

Appendix B – Species of Greatest Conservation Need

1. Acadian Flycatcher
2. American Bittern
3. American Black Duck
4. American Redstart
5. American Woodcock
6. Barn Owl
7. Bell's Vireo
8. Big Brown Bat
9. Black Tern
10. Black-and-White Warbler
11. Black-Billed Cuckoo
12. Black-Crowned Night-Heron
13. Blue-Gray Gnatcatcher
14. Blue-Winged Teal
15. Blue-Winged Warbler
16. Bobolink
17. Cattle Egret
18. Cerulean Warbler
19. Chimney Swift
20. Common Gallinule
21. Common Tern
22. Dickcissel
23. Eastern Meadowlark
24. Eastern Small-Footed Bat
25. Eastern Whip-Poor-Will
26. Evening Bat
27. Field Sparrow
28. Grasshopper Sparrow
29. Great Blue Heron
30. Great Crested Flycatcher
31. Great Egret
32. Henslow's Sparrow
33. Hoary Bat
34. Hooded Warbler
35. Indiana Myotis
36. Kentucky Warbler
37. King Rail
38. Lark Sparrow
39. Least Bittern
40. Little Brown Bat
41. Loggerhead Shrike
42. Louisiana Waterthrush
43. Marsh Wren
44. Northern Bobwhite

45. Northern Harrier

46. Northern Long-Eared Bat

47. Peregrine Falcon

48. Pine Warbler

49. Phothonotary Warbler

50. Rafinesque’s Bat

51. Red Bat

52. Red-Bellied Woodpecker

53. Sandhill Crane

54. Sedge Wren

55. Sharp-Shinned Hawk

56. Short-Eared Owl

57. Silver-Haired Bat

58. Sora

59. Tri-Colored Bat

60. Trumpeter Swan

61. Upland Sandpiper

62. Veery

63. Virginia Rail

64. Wilson’s Phalarope

65. Wood Duck

66. Wood Thrush

67. Worm Eating Warbler

68. Yellow-Billed Cuckoo

69. Yellow-Breasted Chat

70. Yellow-Throated Vireo