Investigating spatial and temporal variability in Whooping Crane habitat selection preference in Kansas and implications for wind energy development.

by

Ifeoma Francesca Okonye

B.Tech., Federal University of Technology, Akure, 2018

A THESIS

submitted in partial fulfillment of the requirements for the degree

MASTER OF SCIENCE

Department of Geography and Geospatial Science
College of Arts and Sciences

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2025

Approved by:

Major Professor
Dr. J.M. Shawn Hutchinson

Copyright

Abstract

The Whooping Crane (Grus americana) is a federally endangered species that relies on strategically located stopover habitats to complete its long migration between breeding and wintering grounds. Therefore, we need to identify suitable stopover habitats to aid their survival and recovery. Despite conservation efforts, we still don't know how habitat preferences vary spatially and temporally, which hinders effective planning to balance species recovery with renewable energy development. To address this gap, we built upon recent research using machine learning algorithms to create species distribution models (SDM) for migratory avian species.

We created an enhanced habitat suitability model for whooping cranes along the Kansas flyway using Random Forest algorithms, incorporating spatial (latitude/longitude) and temporal (date) variables to capture dynamic habitat use. Telemetry data from 2010–2016 (n = 1,253) were combined with pseudo-absences (n = 2,000) and environmental predictors (e.g., wetland cover, urban proximity) to train the model, which was validated using AUC and out-of-bag error rates. Areas with high wind potential and low conflict with suitable habitats were identified and ranked, while conflict zones with existing turbines were mapped by overlaying high-suitability habitats with current turbine locations from the U.S. Wind Turbine Database, with a 5 km buffer to assess displacement risks.

Key results showed the improved model's robustness (AUC = 0.98), outperforming previous static approaches by showing fine-scale seasonal shifts and spatial variability. Wetland cover was the top predictor in Kansas, while distance from road networks was the driver of habitat selection in Nebraska, reflecting regional landscape differences. Time-series analysis (2010–2016) showed corridor narrowing during drought years and seasonal divergence, with

spring migrations using broader pathways than fall. The prediction map showed 75.07% of the study area was unsuitable and low conflict for energy development projects. 24.93% was mid-high conflict and should be designated as critical habitats. The wind-suitability overlay showed western Kansas's agricultural zones as the optimal low-conflict areas for energy development.

Table of Contents

List of Figures

List of Tables

Acknowledgements

Completing this thesis has been a challenging yet immensely rewarding journey, and I owe a great deal of gratitude to the many individuals and organizations who supported me along the way.

First and foremost, I want to express my deepest thanks to my advisor and major professor, Dr. J. M. Shawn Hutchinson, for his unwavering support, guidance and encouragement throughout my Master's program. His expertise was invaluable in shaping this research. Beyond his technical contributions, his patience, mentorship and willingness to have thoughtful conversations with me helped me grow not only as a researcher but as a critical thinker. I am so thankful for the time and effort he put into reviewing my work, giving me feedback and pushing me to refine my ideas.

I also want to thank my thesis committee members, Dr. Trevor Hefley and Dr. Douglas Goodin, for their thoughtful critiques and valuable suggestions. Dr. Trevor's expertise in ecological statistics provided the quantitative foundation for this study, helped me identify patterns and improve the reliability of the findings. Dr. Goodin brought a different perspective that really strengthened this thesis. Their encouragement and feedback during committee meetings and drafts were instrumental in improving this work.

This research wouldn't have been possible without the financial support of the U.S. Fish and Wildlife Service and the Kansas Department of Wildlife and Parks. Their funding and the datasets were critical to this project. I also want to thank the K-State Geographic Information Systems Spatial Analysis Laboratory (GISSAL) for the resources, software and technical support. I also want to thank the faculty of the Kansas State University Department of Geography and Geospatial Sciences and Department of Biology. The classes I took with each faculty member pushed me in ways I never thought possible and allowed me to develop new research skills that contributed to this thesis.

To my friends and colleagues in the Geography Department, thanks for the fun, good discussions and laughter that made graduate school less demanding. And finally, I want to thank my parents and siblings for their love, encouragement and believing in me. Their sacrifices and unwavering support have been the backbone of my academic journey. I can’t express how much their encouragement has meant to me.

To everyone who contributed to this journey in big and small ways—thank you.

Preface

One of the purposes of this project is to complete a master's degree in Geography from Kansas State University. To do this the project follows the "multiple publishable papers" structure instead of the traditional thesis monograph. So, the goal of "chapter" 4 and 5 in this project is to produce a standalone paper of sufficient quality and intellectual depth to be the core of a journal article. Each standalone chapter also contributes to the common research theme of better understanding spatio-temporal changes in whooping crane habitat selection.

Chapter 1 - Introduction

The whooping crane (*Grus americana*) is the rarest crane (family *Gruidae*) species and was listed in 1970 as endangered under the Endangered Species Preservation Act. This bird species is endemic to North America (French, Converse, & Austin, 2019) and faces critical challenges during its long migratory journey (Armbruster, 1990). At one time, the population of whooping cranes exceeded 10,000 individuals (Canadian Wildlife Service and U.S. Fish and Wildlife Service, 2007) but, by the late 1940s the species was close to extinction, with only about 15 individuals remaining in the wild. Through combined conservation efforts, including habitat restoration, captive breeding programs, and different protection measures, there has been a significant increase in the whooping crane population. Their numbers today have risen to approximately 600 individuals in the wild (Leaverton & Fellows, 2023; U.S. Fish & WIldlife Service, 2023) . Despite their increase in numbers, whooping cranes still face threats from land use changes, predation, and hunting pressures during migration (Pearse A. T., Metzger, Brandt, Shaffer, & Bidwell, 2021; U.S. Fish and Wildlife Service., 2009).

Traditionally, many whooping crane conservation plans have emphasized protecting wintering and breeding habitats since these areas are essential for the species' reproductive success and survival during the non-migratory period (Moore, Gauthreaux, Kerlinger, & Simons, 1995). Although these initiatives have significantly helped the species' recovery, they are not enough to guarantee long-term population stability. For effective conservation, top priority should be given to the identification and protection of stopover habitats as they provide vital resources for rest and refueling during migration (Canadian Wildlife Service and U.S. Fish and Wildlife Service, 2007). In the past, extensive wetland losses and agricultural land conversion across North America drastically reduced the availability of suitable stopover sites (French, Converse, & Austin, 2019) and created geographic bottlenecks for migratory birds including the whooping crane (Myers, 1983). Wetlands, which are crucial to migratory birds for feeding and resting, have been especially impacted by urbanization, landuse change, and drainage for farming. This loss of habitat disproportionately affects species such as the whooping crane which is highly specific in its habitat requirements during migration (Webb, Smith, Vrtiska, & Lagrange, 2010). Kansas is acritical part of the whooping crane's central migratory corridor. Wetlands like Cheyenne Bottoms and Quivira National Wildlife Refuge are important stops during migration.

The field of Geography has played an essential role in the advancement of habitat modeling for endangered species in many ways through spatial modeling, GIS-based studies, and remote sensing. Through the study of human relationships to the environment and by applying landscape ecology principles, geographers have helped improve conservation efforts by identifying areas of high biodiversity and patterns of habitat fragmentation. One example is the equilibrium theory of island biogeography proposed by MacArthur and Wilson (MacArthur & Wilson, 1967) which helped researchers better appreciate the relationship between habitat-area and species-abundance (Zimmerman & Bierregaard, 1986). This understanding has since led to new strategies for conserving habitats. By looking at how geography interacts with the environment—landcover, topography, and climate – researchers have been able to pinpoint critical habitats (Turner, 1989; Liverman, 1999; Andrén, 1994; Niemuth, et al., 2018; Pearse A. T., et al., 2020). Spatial analysis techniques have also helped predict how habitats mightchange under different land uses and climate change scenarios. That information is exactly what conservationists need to make informed decisions about how to manage those habitats (Geary, Fielding, McGowan, & Marsden, 2015). Studies on habitat fragmentation have also been able to illustrate the effect of land use changes on bird migration and their survival rates during migration (Andrén, 1994), while studies on ecosystem services have emphasized how important protected habitats are to sustaining migrating bird populations (Runge, et al., 2015).

Despite extensive research on whooping crane stopover habitat selection, there is still a significant information gap, especially along the Kansas migratory corridor. Prior studies have primarily focused on broad-scale habitat preferences across the Central Flyway (Pearse, et al., 2018; Harrell & Bidwell, 2020), often overlooking finer spatial and temporal variations critical for targeted conservation efforts. Habitat suitability models have traditionally been built using GIS-based methods (Kaminski, Comer, Garner, Hung, & Calkins, 2013; Watershed Institute, Inc., 2013). But opportunities exist to combine high-resolution spatial data with the latest machine learning techniques for habitat analyses (Cutler, et al., 2007). Since Kansas is a critical part of the whooping crante migration route – and a potential geographic bottleneck for the species, a more detailed approach to refine conservation and habitat management strategies is warranted.

This study aims to improve understanding of whooping crane stopover ecology to inform conservation strategies along the Aransas-Wood Buffalo migratory flyway. One question that will be investigated is whether characteristics of preferred whooping crante stopover habitats vary spatially, and potentially, temporally (i.e., depending on where and when they are in the migratory corridor. This study will also assess whether key variables change within (from one migratory season to the next) and between years by identifying important environmental factors (e.g., wetland cover, access to food, urban development, proximity to roads, and other land cover types) influencing whooping crane habitat selection in Kansasusing telemetry data in a random forest model (Breiman, 2001)By comparing the relative importance of these key environmental variables in Kansas and Nebraska, potentially important intra- and interstate differences might be uncovered. This study builds on past research suggesting that whooping cranes select areas with a higher percentage of wetlands and access to food while avoiding regions with substantial urban development.

Given the high wind resource potential in Kansas, another question that will be explored is how these migration preferences affect wind energy exploration within the state. This work will highlight the importance of integrating habitat modeling with land-use planning to facilitate prioritization of habitat protection and restoration while addressing potential conflicts with urbanization and renewable energy development along the migratory corridor.

Chapter 2 - Literature Review

Importance and Conservation of the Whooping Crane

Significance of the Species

The Whooping crane (*Grus americana*) represents hope and perseverance for conservation. Despite their low abundance, the whooping cranes are a keystone species with a relatively high influence on the ecological network through strong connections. They are ecological linchpins in wetland ecosystems, helping to maintain ecosystem structure and function (Goetzman, 2024; The International Crane Foundation, 2024). As omnivores, they help keep those environments in balance by eating a wide variety of plants, small fish and invertebrates. This foraging behavior helps regulate the population of these organisms, preventing overpopulation and boosting biodiversity (Allen, 1952). As an indicator species, the whooping crane's presence or absence also reflects the health of its ecosystem (Lees, et al., 2022). Wetlands that support whooping cranes are usually biodiverse and free of major pollutants (Goetzman, 2024; Stehn & Haralson-Strobel, 2014). In addition, their dual role as both predator and prey highlights their ecological importance, as they interact with a wide range of species — from insects to large mammals — creating ripple effects that help maintain ecosystem health (U.S. Fish and Wildlife Service, n.d.).

The habitats designated for whooping craneprotection provide a stable sanctuary, offering food, shelter, and breeding grounds for numerous other organisms that share similar ecological niches. This interconnectedness helps to maintain biodiversity and ensures the survival of various species, many of which may also be threatened. The conservation efforts aimed at endangered species leads to broader environmental benefits, such as the restoration of degraded habitats, the improvement of water quality, and the enhancement of soil health.

Historical Population Decline and Current Population Status

In the 19th century, there were likely thousands of whooping cranes (Canadian Wildlife Service and U.S. Fish and Wildlife Service, 2007). By 1941, only 15 individuals remained in the wild. Habitat loss, unregulated hunting and environmental changes—driven by agriculture and urban development—had taken their toll (Lewis, Kuyt, Schwindt, & Stehn, 1992; Pearse A. T., Metzger, Brandt, Shaffer, & Bidwell, 2021). Wetlands were drained, and hunting for feathers and meat pushed cranes to the brink of extinction. Thanks to joint conservation efforts in both Canada and the United States, the recovery of the species, although slow, has been steady. Some of the key milestones in their recovery include establishment of protected areas such as the Aransas Wildlife Refuge in Texas and the Wood-Buffalo National Park in Canada, used respectively as wintering and breeding grounds (Canadian Wildlife Service and U.S. Fish and Wildlife Service, 2007).

Today, there are about 800 whooping cranes. Of those, 540 belong to the Aransas-Wood Buffalo population which is the only remaining natural, self-sustaining population. The other 260 were bred in captivity with some reintroduced into the wild to form new population (U.S. Fish & Wildlife Service, 2023; Vartanian & Conkin, 2023; Bidwell & Conkin, 2023; U.S. Fish & Wildlife Service, 2024). The Eastern Migratory Population is an experimental flock that was re-introduced between 2001 to 2010 and has a current population of about 70 individuals (U.S. Fish & Wildlife Service, 2024; The International Crane Foundation, 2024). With the help of scientists and through different assisted migration techniques, this flock migrates from its breeding ground in Wisconsin to wintering grounds in Florida (Thompson, Gordon, Bolt, Lee, & Szyszkoski, 2022; U.S. Fish & Wildlife Service, 2024). The Central Florida population (restored between 1993 and 2005) and the White Lake Louisiana population (reintroduced in 2011) are two examples of non-migratory populations that have been restored or reintroduced. Despite these successes, several challenges continue to threaten the species' survival. To maintain a steady population increase and promote the species' ongoing survival, important legislative measures have also been implemented.

Legislation and Conservation Efforts

Several legal protections and international agreements have been enacted to make help facilitate the whooping crane’s recovery. In the United States, the Endangered Species Act (ESA) of 1973 has been instrumental in safeguarding the species and its habitats (U.S. Fish and Wildlife Service, 2003). The primary purpose of the ESA is to provide a legal framework for habitat protection and ecosystem conservation and to set up recovery programs that bring endangered and threatened species to the point where their protection under the Act is no longer required (Jones, 2005).

The Migratory Bird Treaty Act (MBTA) of 1918 has helped the US and Canada work together to preserve whooping cranes across their entire migratory range. The Species at Risk Act of 2003, passed in Canada, has helped in the recovery of extirpated, vulnerable, or endangered wildlife species resulting from human activity (Environment Canada, 2007). These legislative protections have stopped more declines and provided a foundation for recovery efforts. For instance, the MBTA has reduced threats from hunting and habitat loss while the designation of critical habitats under the ESA and SARA has helped save important breeding and wintering sites in both countries (Lewis, 1995). These laws together provide a safety net for the whooping crane, freeing conservationists to concentrate on population building and recovery.

Rebuilding the population has proved rather successful with captive breeding initiatives. These initiatives, like the one at the Patuxent Wildlife Research Center in Maryland, have bred and reintroduced cranes into the wild, greatly increasing population numbers (Urbanek, Zimorski, & Wellington, 2010) and led to the establishment of a new Eastern Migratory Population which lowers the risk of extinction by through creation of additional flocks. Whooping cranes rely on stopover habitats during their long journeys.

Habitat management efforts along migratory routes helps ensure whooping cranes have access to food and shelter (Stehn T. , 2011). Wetland restoration projects like the Cheyenne Bottoms Preserve and Quivera National Wildlife Refuge in Kansas have provided critical habitats for cranes migrating through the state (Kansas Department of Wildlife & Parks, 2023). Programs like the Kansas, Nebraska, Oklahoma Migratory Birds, Butterflies, and Pollinators SAFE (State Acres for Wildlife Management) initiative (Farm Service Agency, 2023) support migrating wetland species by restoring playa wetlands to their natural function. The eastern parts of Kansas, which have more agricultural land and fewer wetlands, are the focus of the SAFE initiative.

Non-governmental groups like the International Crane Foundation have also been instrumental in conservation efforts by working on captive breeding and public education initiatives, often in close collaboration with government agencies and local communities (International Crane Foundation, 2021). Citizen science programs that encourage the public to report whooping crane sightings have provided valuable data on crane movements and habitat use (compiled by the U.S. Fish & Wildlife Service, Nebraska Field Office). To ensure the species' survival, adaptive management will need to be put in place by integrating scientific research, community engagement, and policy advocacy.

Biology and Ecology of the Whooping Crane

Migration and Stopover Sites

Whooping cranes are known for their long seasonal migrations and transit thousands of miles between breeding and wintering grounds (Pearse A. T., et al., 2020; Hefley, Baasch, Tyre, & Blankenship, 2015). This journey takes 50 days in the fall and just 10-11 days in the spring (Kuyt, 1992). The whooping cranes' main route—the Aransas-Wood Buffalo Flyway—spans from Wood Buffalo National Park in northeastern Alberta, Canada to Aransas National Wildlife Refuge along the Gulf Coast in Texas. This route is vital for the species. It gives the cranes access to key stopover sites where they can rest and refuel (Johns, Stehn, & Windingstad, 2005). Stopover sites like the Platte River in Nebraska and Quivira National Wildlife Refuge in Kansas are vital for recharging energy reserves during the long journey. These habitats have abundant food resources like aquatic plants and invertebrates, and safe roosting areas (Pearse, et al., 2015). Understanding these migration pathways is crucial for identifying and protecting critical habitats that support the species' survival.

Migration events are the most limiting time of a migratory bird's annual life cycle (Carlisle, et al., 2009; Baasch D. M., Farrell, Pearse, Brandt, & Caven, Diurnal habitat selection of migrating Whooping Crane in the Great Plains, 2019). This phase is challenging for several reasons; however, the ecology of migrating birds at their stopover habitats is still not well understood (Webb, Smith, Vrtiska, & Lagrange, 2010; Arzel, Elmberg, & Guillemain, 2006; Faaborg, et al., 2010). During its migration, the whooping crane is exposed to several unpredictable challenges that affect its population, such as habitat loss and adverse weather conditions. Weather can affect the timing of migration and energy expended significantly. Favorable tailwinds save energy while headwinds can delay the migration and also increase mortality (Harrell & Bidwell, 2020). Climate change is making all of this even more complicated. Rising temperatures and altered precipitation patterns are affecting the availability, quality, and distribution of those critical stopover habitats. Drought, in particular, reduces the availability of wetlands and forces cranes to travel further to find suitable stopover sites (Pearse A. T., et al., 2020).

Habitat fragmentation and land use changes have reduced the quality and availability of those critical stopover sites where cranes can rest and refuel (Baasch D. M., Farrell, Pearse, Brandt, & Caven, Diurnal habitat selection of migrating Whooping Crane in the Great Plains, 2019). Research shows that, on average, 70% of fledged mortality occurs during migration (U.S. Fish and Wildlife Service., 2009). After hours of continuous flight, the birds' fat reserves become depleted, making stopover sites essential for successful migration (Myers, 1983). For migrating whooping cranes, survival and body conditions going into breeding season depend on the decisions they make regarding stopover habitats, where factors such as habitat quality play a crucial role (Whitham, 1980; Baasch D. , Farrell, Pearse, Brandt, & Caven, 2019; Myers, 1983; Moore, Gauthreaux, Kerlinger, & Simons, 1995). High-quality stopover habitats are what keep individuals in the population healthy, improving survival and successful reproduction (Rodewald, 2015).

Advances in tracking technology have given us a much clearer picture of whooping crane migration. With satellite GPS, radio telemetry, and geolocators, researchers can now map those migration routes, track movement patterns and pinpoint critical habitats with much greater precision (Kuyt, 1992; Stehn & Wassenich, Whooping Crane Collisions with Power Lines: an Issue Paper, 2008). For example, GPS tracking has shown that whooping cranes can travel over 400 km in a day (Pearse, et al., 2015; Hefley, Baasch, Tyre, & Blankenship, 2015). These tools have also given us insight into mortality risks such as collisions with power lines (Watershed Institute, Inc., 2013), wind turbines (Belaire A. J., Kreakie, Keitt, & Minor, Predicting and Mapping Potential Whooping Crane Stopover Habitat to Guide Site Selection for Wind Energy Projects, 2013), and predation during migration (Caven, Rabbe, & Malzahn, 2020). By combining tracking data with habitat modeling, we can identify high-risk areas and implement targeted mitigation.

Population Health and Trends

In the 1940s the whooping crane population was near extinction with limited genetic diversity, increased risk of inbreeding, and reduced adaptability to environmental change (Glenn, Stephan, & Braun, 1999). To address this, the Canadian Wildlife Service and U.S. Fish and Wildlife Service (2007) have been working to maintain genetic diversity and while studies show that these efforts have helped reduce inbreeding risks challenges remain in ensuring long-term genetic health (Canadian Wildlife Service and U.S. Fish and Wildlife Service, 2007; Hoban, et al., 2021). One of the strategies being explored to boost genetic diversity is gene flow (Fontsere, et al., 2024; Thompson, Caven, Hayes, & Lacy, 2021). That means introducing genetic material from captive populations into the wild. But that approach requires careful planning to avoid disrupting the population structures. Introducing new genetic material too quickly or in the wrong way could cause more problems than it solves.

Reproductive success is key to whooping crane recovery. Nesting success, fledging rates and juvenile survival are influenced by many factors including wetland conditions, predation and parental care (Canadian Wildlife Service and U.S. Fish and Wildlife Service, 2007; Thompson, Glass, Wellington, Boardman, & Olsen, 2022). Wetlands with abundant food resources and minimal human disturbance are critical for successful nesting and chick-rearing (Kačergytė, et al., 2021; Vest, et al., 2023). Predation, particularly by bobcats, wolves, and eagles, poses a significant threat to eggs and young chicks, while parental care plays a crucial role in ensuring chick survival (Stehn T. , 2011). Long-term monitoring has shown that reproductive success varies significantly between years, with environmental conditions playing a significant role. For example, drought years often result in lower nesting success due to reduced food availability (Riggio, et al., 2023).

Threats and Challenges to Survival

Habitat loss is the single biggest threat to whooping cranes. Agricultural expansion, urbanization and wetland drainage have reduced the availability of suitable habitats (Austin, Morrison, & Harris, 2018; Pearse, et al., 2018). The whooping cranes' migration corridor spans through areas of high land use change, including rapid wind energy development. Wetlands which are critical for nesting, foraging and stopover sites have been affected. Protected areas like national wildlife refuges have helped with habitat loss but more needs to be done to restore and conserve wetlands along the migration route (Meretsky, Atwell, & Hyman, 2011). Wetland restoration projects in Kansas and Nebraska have shown promise in providing habitat for migrating cranes.

Whooping cranes face a multitude of dangers from human activities—power lines, wind energy projects, and the people enjoying the great outdoors. (Heisman, 2019; Stehn & Wassenich, 2008; Canadian Wildlife Service and U.S. Fish and Wildlife Service, 2007; Sime, et al., 2024) Wind farms are recognized for their potential to reduce greenhouse gas emissions and meet renewable energy goals. But development of these facilities in critical migratory pathways introduces new challenges to wildlife conservation (American Bird Conservancy, 2021; Hands, 2024; Belaire J. A., Kreakie, Keitt, & Minor, 2014). For whooping cranes the risks are multiple:

collision with wind turbines and associated infrastructure like power lines which are already a leading cause of mortality during migration (Belaire A. J., Kreakie, Keitt, & Minor, 2013; Lewis, Kuyt, Schwindt, & Stehn, 1992). Wind farms can also disrupt flight paths and cause cranes to avoid nearby suitable stopover habitats forcing them to expend extra energy searching for alternative sites (Ellis, et al., 2022). All these impacts make clear the need to carefully consider where wind farms are sited so that the need for green energy development is balanced with conservation of critical migratory habitats.

Environmental Variables in Habitat Modeling

Key Variables and Their Relevance

Whooping cranes are very selective about their stopover habitats and actively seek areas that meet their specific needs for food, water and shelter. Individuals make decisions about where to stop and what resources to use after stopover (Baasch D. M., et al., 2019). According to Watershed Institute, Inc. (2013) factors that affect habitat suitability include wetland size, water depth, water regime, visibility and obstructions, proximity to disturbances and proximity to food. Wetlands are the most important habitat type, providing abundant food resources and safe roosting sites (Johns B. W., 1992; Pearse, et al., 2018; Allen, 1952). Agricultural fields, especially corn and wheat, can be a supplemental food source depending on the farming practices employed and proximity to wetlands (Austin & Richert, Patterns of Habitat Use by Whooping Cranes During Migration: Summary form 1977-1999 Site Evaluation Data., 2005; Urbanek & Lewis; Niemuth, et al., 2018). Habitat use varies by season, time of day, and individual behavior so habitat selection is complex. For example, cranes use agricultural fields during the day and wetlands at night because they need food and safety (Lehnen, Sesnie, Butler, Pearse, & Metzger, 2024; Harrell & Bidwell, 2019).

Hydrological and Wetland Characteristics

Wetlands provide the resources for resting and refueling during migration (Webb, Smith, Vrtiska, & Lagrange, 2010; Baasch D. M., et al., 2019). The connectivity of surface water, water depth and seasonal flooding patterns are important factors that affect the probability of use of a particular wetland (Austin & Richert, Patterns of Habitat Use by Whooping Cranes During Migration: Summary form 1977-1999 Site Evaluation Data., 2005; Johns, Woodsworth, & Driver, 1997). Cranes are usually found in palustrine wetlands (e.g. marshes and swamps) which have seasonal to semi-permanent regimes (Austin & Richert, 2001; Hefley, Baasch, Tyre, & Blankenship, 2015). Shallow wetlands with abundant aquatic vegetation are ideal foraging grounds for cranes to feed on plants, invertebrates, and small fish (Tacha, Bishop, & Brei, 2010; Johns B. W., 1992; Baasch D. M., et al., 2019), while deeper waters are more suitable for roosting (Austin & Richert, 2001). Hydrological regimes create dynamic habitats that support diverse food sources and reduce predation risks (Austin & Richert, 2001) with wetlands that are semi-permanently or artificially flooded being more favorable because they are more consistently available (Armbruster, 1990; Watershed Institute, Inc., 2013; Niemuth, et al., 2018).

Land Cover and Vegetation

Land cover types play an important role in determining habitat suitability for whooping cranes. Grasslands, agricultural fields, and open water are the most important land cover types, providing food, shelter and nesting sites (Baasch D. M., et al., 2019; Belaire J. A., Kreakie, Keitt, & Minor, 2014). Vegetation height and density are also important, and cranes prefer areas with short vegetation for foraging and tall vegetation for roosting and nesting (Watershed Institute, Inc., 2013).

Anthropogenic Disturbance and Infrastructure

Human activities and infrastructure pose some of the biggest challenges to where whooping cranes can safely stop during migration. Proximity to roads, power lines, cities, and wind farms can disrupt migration patterns and increase the risk of death (Pearse A. T., Metzger, Brandt, Shaffer, & Bidwell, 2021). For example, power lines are a major cause of death for cranes in flight (Stehn & Wassenich, Whooping Crane Collisions with Power Lines: an Issue Paper, 2008). Urban expansion and agriculture intensification both fragment suitable habitats and reduce their availability (Austin, Morrison, & Harris, 2018). Wind energy projects, an important source of renewable energy, can also create barriers to migration and alter crane behavior. Mitigating these impacts requires careful planning and the implementation of conservation measures, such as marking power lines and establishing buffer zones around critical habitats (Watershed Institute, Inc., 2013).

Temporal Changes in Variable Importance

Over the past 100 years, whooping crane habitats have changed dramatically due to land use changes, wetland degradation, and urbanization. Historical satellite imagery and land cover change models show that many wetlands along the migration route have been drained for agriculture or urban development. (Stehn & Haralson-Strobel, 2014; Austin, Morrison, & Harris, 2018). The Platte River Basin was once a haven for cranes, but has lost over 70% of its wetlands due to water diversion and land conversion (Canadian Wildlife Service and U.S. Fish and Wildlife Service, 2007; U.S. Fish & Wildlife Service, 2024). These changes have forced cranes to adapt by using alternative habitats, such as agricultural fields and managed wetlands.

Climate change is also reshaping the whooping crane's landscape. Rising temperatures, more frequent droughts, and altered precipitation patterns are making it harder for cranes to find the wetlands they need. According to some models, climate change will cause wetlands to become less extensive in some areas while becoming more abundant in others, posing new and uncertain difficulties for crane migration (Londe, 2023; Wauchope, et al., 2016; The International Crane Foundation, n.d.). For instance, the Great Plains' extended droughts have decreased the number of shallow wetlands, requiring cranes to travel farther in search of appropriate habitats (International Crane Foundation and Muraviovka Park for Sustainable Land Use, 2010).

Habitat use varies by season, time of day and individual behavior making habitat selection a complex process. Environmental variables important for habitat suitability can differ greatly between seasons and years. Water is key during dry seasons and vegetation is more important during breeding season. Interannual variations in hydrology, land cover, and food availability further complicate habitat selection and require cranes to adapt their behavior and migration timing (Pearse, et al., 2024).

Habitat Suitability and Spatial Modeling

Techniques and Approaches in Existing Studies

Spatial Modeling

Using Geographic Information Systems (GIS), spatial modeling combines and analyzes spatial data including land cover, elevation and climate factors, therefore enabling the analysis and prediction of species distribution across landscapes. While methods like overlay analysis and spatial interpolation have been used to find areas that meet particular habitat needs, kriging is also a popular predictive technique for forecasting environmental variables over vast areas (Li & Heap, 2011; Zhu, Jia, Lü, & Yan, 2012; Walker, et al., 2008; Hengla, Sierdsema, Radovic, & Dilo, 2009). Geostatistical models like kriging and variogram analysis are particularly good for modeling spatial autocorrelation and predicting species distribution in heterogeneous landscapes

(Cressie , 1990; Walker, et al., 2008; Sadoti, Pollock, Vierling, Albright, & Strand, 2014; Mielke, et al., 2020).

Advanced spatial modeling techniques like geographically weighted regression (GWR) and environmental niche-based approaches address the complexity of species-environment relationships by accounting for spatial heterogeneity and dynamic processes. Perfect for modeling species distribution in fragmented environments, GWR lets relationships between variables change across space (Mellin, Mengersen, Bradshaw, & Caley, 2014). Environmental niche-based approaches such as the Maximum Entropy (MaxEnt) model predict habitat suitability utilizing niche theory adapted to human managed landscapes linking species (or crop) presence data with environmental variables (Amici, Eggers, Geri, & Battisti, 2013; Heumann, Walsh, Verdery, McDaniel, & Rindfuss, 2012). Combining remote sensing with these methods has even increased the accuracy and scalability of spatial models, therefore allowing large-scale habitat suitability mapping and conservation planning (Hopkins, Hallman, Kilbride, Robinson, & Hutchinson, 2022; Guo, et al., 2018).

Habitat Suitability Modeling

Habitat suitability modeling (HSM) is where conservation and management come together. By using statistics and computational methods, scientists can predict where species are likely to be found based on the environment around them. This is where traditional approaches like niche models and regression-based models come in. Niche models like BIOCLIM and DOMAIN use climate variables to define what a species needs to survive. Regression-based models, like logistic regression and generalized linear models, look at the relationships between a species' presence and the environmental factors that influence it (Booth, 1985; Guisan & Zimmermann, 2000; Hijmans & Graham, 2006). By incorporating spatial data layers—like land cover and topography— using GIS assessments, detailed maps of habitat suitability can be achieved (Tirpak, et al., 2010). Those models have been used extensively to inform conservation planning and prioritize habitat restoration efforts (Guisan & Zimmermann, 2000).

In whooping crane habitat studies, researchers have used a variety of techniques to predict where cranes are likely to be found. One of the most common is logistic regression, which looks at the probability of crane presence based on factors like wetland availability and land cover (Pearce & Ferrier, 2000; Niemuth, et al., 2018). Maximum entropy (MaxEnt) models, which are particularly effective for presence-only data, have been applied to identify key habitat features for cranes during migration (Phillips, Anderson, & Schapire, Maximum entropy modeling of species geographic distributions, 2006). Machine learning techniques, such as generalized additive models (GAMs) and decision trees, have also been used to capture complex, nonlinear relationships between crane habitat use and environmental predictors (Liu, Newell, & White, 2015; Becker, et al., 2020). These methods have provided valuable insights into the factors driving habitat selection and the spatial distribution of suitable habitats for whooping cranes.

Limitations and Advancements in Habitat Modeling

Traditional habitat models have important limitations. One of the biggest problems with regression-based models, including logistic regression and generalized linear models, is that they are unable to effectively handle collinearity among predictors. This weakness can lead to unstable parameter estimates and reduced model performance (Phillips, Anderson, & Schapire, Maximum entropy modeling of species geographic distributions, 2006). They also tend to overlook complex interactions between variables, such as nonlinear relationships and threshold effects, that are common in ecological systems. That means low predictive accuracy when models are applied to new areas or under changing environmental conditions (Elith et al., 2011). Furthermore, traditional models usually need presence and absence data. That can be difficult to obtain for many species, especially rare or elusive ones. In contrast, presence-only data (species occurrence records) are more readily available. But presence-only data pose their own set of challenges with regards to modeling habitat suitability.

One of the biggest difficulties when working with presence-only data is the lack of information about where a species isn't found. The lack of true absence data makes it challenging to know where a species is absent and where it simply is unobserved. This ambiguity can lead to biased predictions. Models may overestimate how suitable an area is for a species if it is under sampled or inaccessible (Lee-Yaw, McCune, Pironon, & Sheth, 2021). To address this problem, researchers often use pseudo-absence data—background points that are generated as a stand-in for true absences. However, how these pseudo-absence locateds are selected can affect the outcome of the model. Improper selection can risk introducing bias or reducing the model's accuracy (Iturbide, et al., 2015; Hefley, Baasch, Tyre, & Blankenship, 2015). For example, if pseudo-absences are sampled from areas that are ecologically unsuitable for the species, the model may underestimate habitat suitability. Conversely, if pseudo-absences are sampled from areas that are suitable but unoccupied, the model may overestimate suitability.

Recent breakthroughs in machine learning and remote sensing have helped overcome many of the limitations that previously hindered progress in these fields. Algorithms such as Random Forest and Maximum Entropy (MaxEnt) are especially effective at handling high-dimensional data and capturing the complex relationships between species and their environments (Cutler, et al., 2007; Coxen, Frey, Carleton, & Collins, 2017). These algorithms can incorporate interaction terms and threshold effects, which increasesthe accuracy of their habitat suitability predictions. One example is MaxEnt. It was originally designed to work with presence-only data, but its ability to handle complex species-environment relationships has made it a popular tool in ecological modeling (Phillips, Anderson, & Schapire, 2006). Remote sensing satellites and sensors including Landsat and MODIS have given habitat modeling a boost by providing a time series of multispectral data of varying spatial resolutions to assess land cover, vegetation health and other environmental factors. Integrating this data with habitat models yields more accurate and scalable predictions. Geospatial analysis and GIS have also advanced to the point where researchers can now incorporate fine-scale environmental variables like topography and hydrology into their models, which often improves results and increases their ecological relevance.

Despite these advancements, challenges remain in modeling habitat suitability using presence-only data. Spatial bias in species occurrence records (e.g., uneven sampling effort or accessibility) can lead to biased predictions if not properly accounted for (Phillips, et al., 2009; Kramer-Schadt, et al., 2013). Techniques like spatial filtering and bias correction have been developed to address this but their effectiveness depends on the quality and representativeness of the data. That transferability of habitat models to new regions or time periods can be limited by differences in environmental conditions or how species interact with their environment. Telemetry data provides high-resolution, continuous tracking of individual birds, offering insights into their movement patterns, habitat use, and behavioral responses to environmental changes. By offering a more thorough and representative sample of species occurrences across the terrain, this information can help to offset spatial bias (McDuie, et al., 2019). By recording fine scale habitat preferences and temporal dynamics difficult to detect with presence-only data alone, telemetry data can also enhance habitat models. Combining telemetry data with remote sensing and environmental variables will help to create stronger and transferable habitat models that more accurately represent the ecological requirements of the species (Hebblewhite & Haydon, 2010).

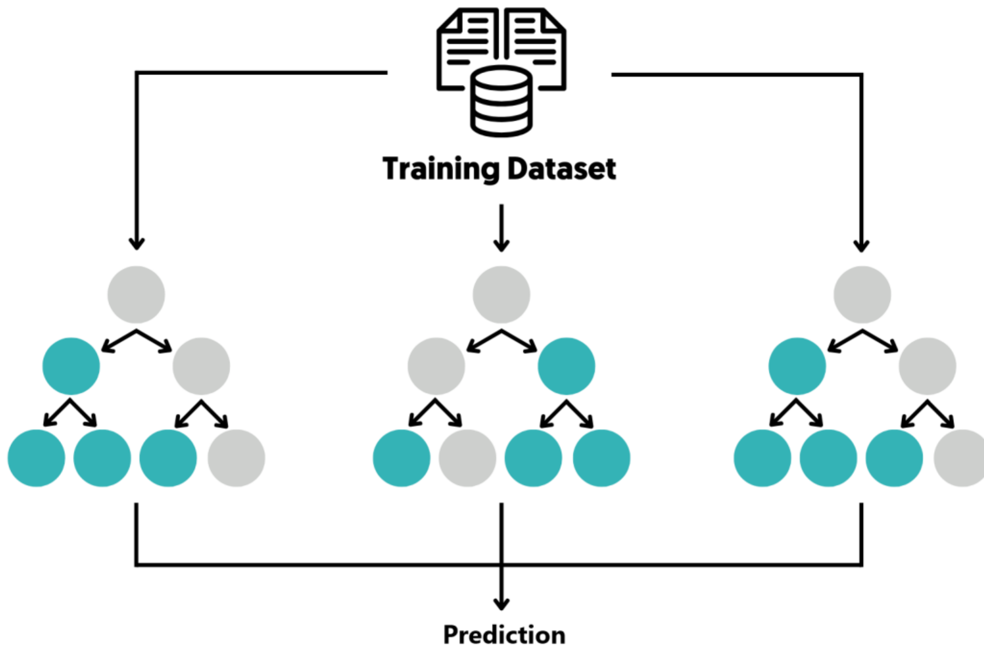
Application of Random Forest in Suitability Modeling

Random Forest (RF) is a well-known and popular choice ecological modeling because it can handle complex, non-linear relationships and high-dimensional data with ease. According to (Breiman, 2001), it consists of tree-structured classifiers

$$\{h(x, \Theta_k), k = 1, \dots\}$$

where the $\{\Theta_k\}$ are independent identically distributed random numbers. Each tree casts a unit vote for the most popular class at input x. (Breiman, 2001) further describes how it classifies data by building multiple decision trees during training and then determines the most common prediction from each one (Figure 2.1). Use of the Strong Law of Large Numbers (Chuprunov & Fazekas, 2009) shows that they always converge, which helps prevent overfitting and boosts prediction accuracy. Key benefits of RF are its ability to provide measures of variable importance and similarity of data points. This allows researchers to identify which environmental factors are more strongly associated with species presence or habitat suitability and makes RF a very powerful tool for ecological modeling and conservation planning (Cutler, et al., 2007).

Figure 2.1 The random forest visual model has several decision trees that make predictions. Original image from dida.do https://dida.do/what-is-random-forest



RF has been widely used in avian ecology to model habitat suitability and predict species distributions. For example, (Oppel, et al., 2012) used RF to predict the distribution of migratory birds in Europe. In whooping crane studies, RF has been used to model wetland and grassland habitat suitability, and to identify key environmental predictors like water availability and vegetation cover (Belaire J. A., Kreakie, Keitt, & Minor, 2014; Caven, et al., 2022; Drew, Wiersma, & Huettmann, 2010). These applications highlight the versatility of RF in addressing diverse ecological questions and its potential to inform conservation strategies for migratory birds.

RF has some advantages over other machine learning algorithms. Unlike MaxEnt, which is limited to presence-only data, RF can handle both presence-absence and presence-only data. That makes it more flexible for different study designs (Cutler, et al., 2007; Prasad , Iverson , &

Liaw , 2006). RF is also less sensitive to parameter tuning and provides more interpretable outputs like variable importance rankings (Huang & Boutros, 2016). While deep learning models can achieve high predictive accuracy, they require large datasets and computational resources, making RF a more practical choice for many ecological studies.

One of the reasons RF is so popular for habitat suitability modeling in conservation biology is its easy integration with remote sensing data and GIS layers. You can use RF to produce large-scale habitat suitability maps. For example, (Belgiu & Drăguţ, 2016) combined RF with high-resolution remote sensing data to map land cover and habitat suitability in complex landscapes, highlighting the scalability of RF. By combining RF with GIS and remote sensing, it is possible to produce detailed, spatially explicit models that support conservation planning.

Despite its advantages in handling ecological datasets, there are disadvantages to using RF models for ecological modeling. Some of these disadvantages include difficulty interpreting ecological relationships (i.e., the relationship between predictors and responses, high sensitivity to sampling bias, and the overestimation of variable importance due to a bias towards variables with more categories or greater range in values). Another limitation of RF is that the variables used during classification at different nodes are not defined. Finally, RF models are highly dependent on the quality and representativeness of input data, which is a major limitation, especially with presence-only data.

Chapter 3 - Study Area

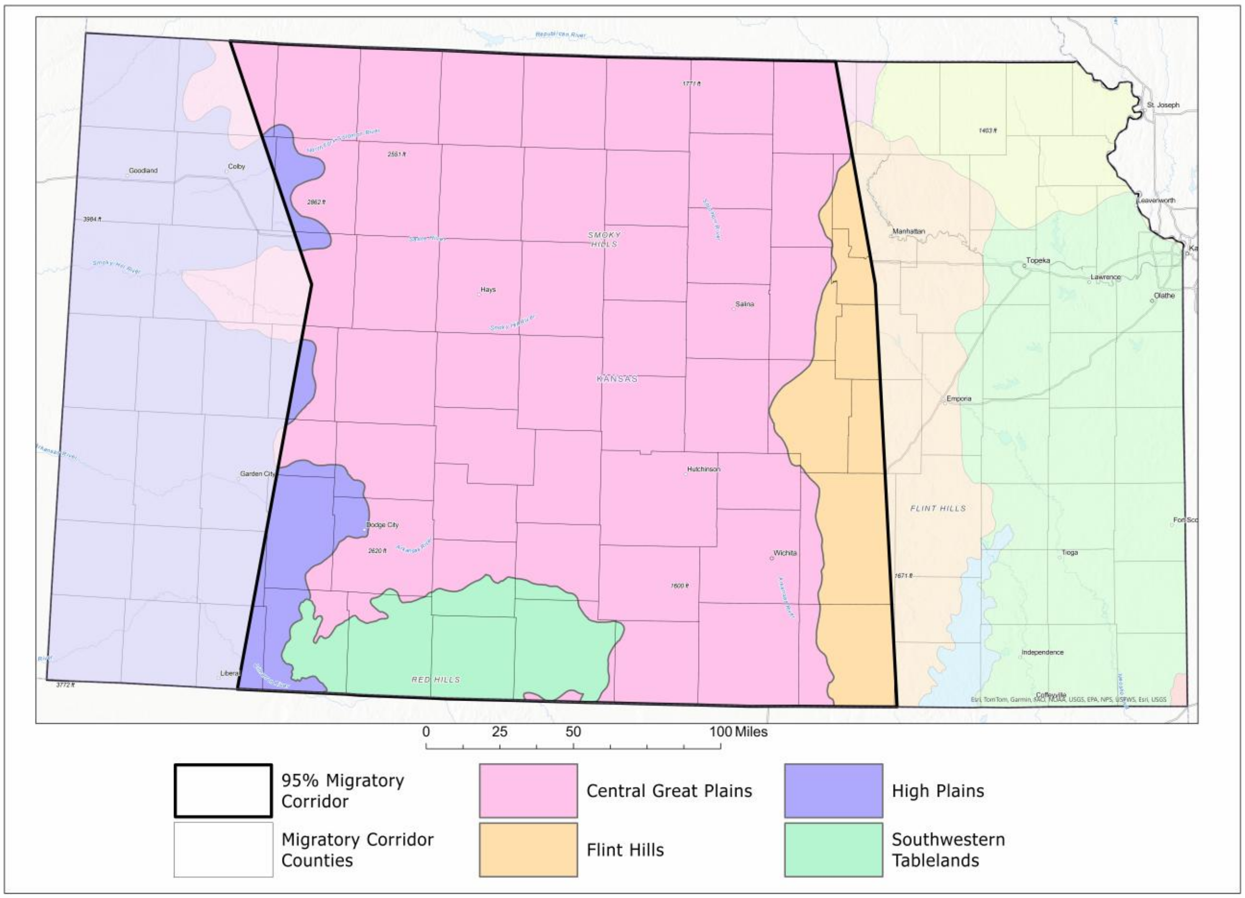
The Aransas-Wood Buffalo population is the only self-sustaining whooping crane population in the wild. It makes a biannual migration of about 4000 km (Hefley, Baasch, Tyre, & Blankenship, 2015) in the fall from its breeding ground in Wood Buffalo National Park (WBNP), Alberta, Canada, to its wintering ground in Aransas National Wildlife Refuge (ANWR) in Aransas, Texas, (Pearse A. T., et al., 2020). During its migration, the species has been observed to travel through the Canadian Prairies and the Great Plains of North America (Pearse, et al., 2015; Baasch D. M., Farrell, Pearse, Brandt, & Caven, 2019). Observational siting data have shown their presence in Alberta and Saskatchewan provinces in Canada and the states of North and South Dakota, Nebraska, Kansas, Oklahoma, and Texas, with the 75% confidence interval core corridor being narrowest in central Kansas (Pearse, et al., 2018).

The study area for this research is the entire state of Kansas, which was selected because of increased farming activities and the continuous conversion of prairie grassland into cropland. Another factor is the increase in wind energy exploration within the state, which could disrupt their migratory route and potentially cause a shift in the flyway. As an endangered bird species with highly specific habitat preferences during migration, there has also been a limited number of studies of the whooping crane habitat preferences within the state. For our initial analysis, we limited the geographic scope to the 95% confidence interval migratory corridor bounds but later expanded it to include the entire state of Kansas. The rationale behind this was to include all areas within Kansas where the probability of detection was greater than 0 (Figure 3.1).

Figure 3.1 Whooping crane GPS telemetry points from their breeding habitat in Wood Buffalo National Park to their wintering habitat in Aransas National Wildlife Refuge along the expanse of their migratory corridor from 2010 to 2016.

The state has an area of 82,278mi^2 (213,100km^2) and is the 15th largest state by area (United States Census Bureau, 2010). There are 105 counties within the state, and it has eight (8) distinct level III ecoregions, including Central Great Plains, Central Irregular Plains, Cross Timbers, Flint Hills, High Plains, Ozark Highlands, Southwestern Tablelands, and Western Corn Belt Plains (Bailey, Avers, King, & McNab, 1994). Of the 105 counties, the 95% bound of the cranes' migratory corridor sits within 60 counties and encompasses four of the eight ecoregions, with 77.8% falling within the Central Great Plains ecoregion (Figure 3.2). This ecoregion is primarily a prairie region and contains the largest area of mixed grassland with a few trees scattered across the region (Burke, et al., 1991). It is home to approximately 2,900 species of plants and over 500 animal species (World Wildlife Fund, 2024). The eastern portion of this region receives the most rain and is known as the prairie pothole region (USGS: Land Management Research Program, n.d.).

Figure 3.2 Kansas: 95% confidence interval of migratory corridor ecoregions and county boundaries.



According to the Köppen climate classification, the state's climate is generally considered continental and has three distinct climate subtypes: humid continental, semi-arid steppe, and humid subtropical (Peel, Finlayson, & McMahon, 2007). Being in the center of the continental U.S., the weather in Kansas is highly variable from hot and humid summers to cold and dry winters (Hutchinson, Jacquin, Hutchinson, & Verbesselt, 2015). The monthly average temperatures range from 0°C to 25°C in the winter and summer, respectively (Williams & Lohman, 1949). The mean annual precipitation varies across the state from over 1143mm in the southeast to less than 508mm in the southwest (Williams & Lohman, 1949). Approximately 75% of the state's annual precipitation occurs during the spring growing season (Hutchinson, Jacquin, Hutchinson, & Verbesselt, 2015). It has a north-south temperature gradient, with a hotter south and a colder north, and an east-west precipitation gradient with higher precipitation in the east and drier conditions towards the west (Goodin, Mitchell, Knapp, & Bivens, 1995, rep. 2004).

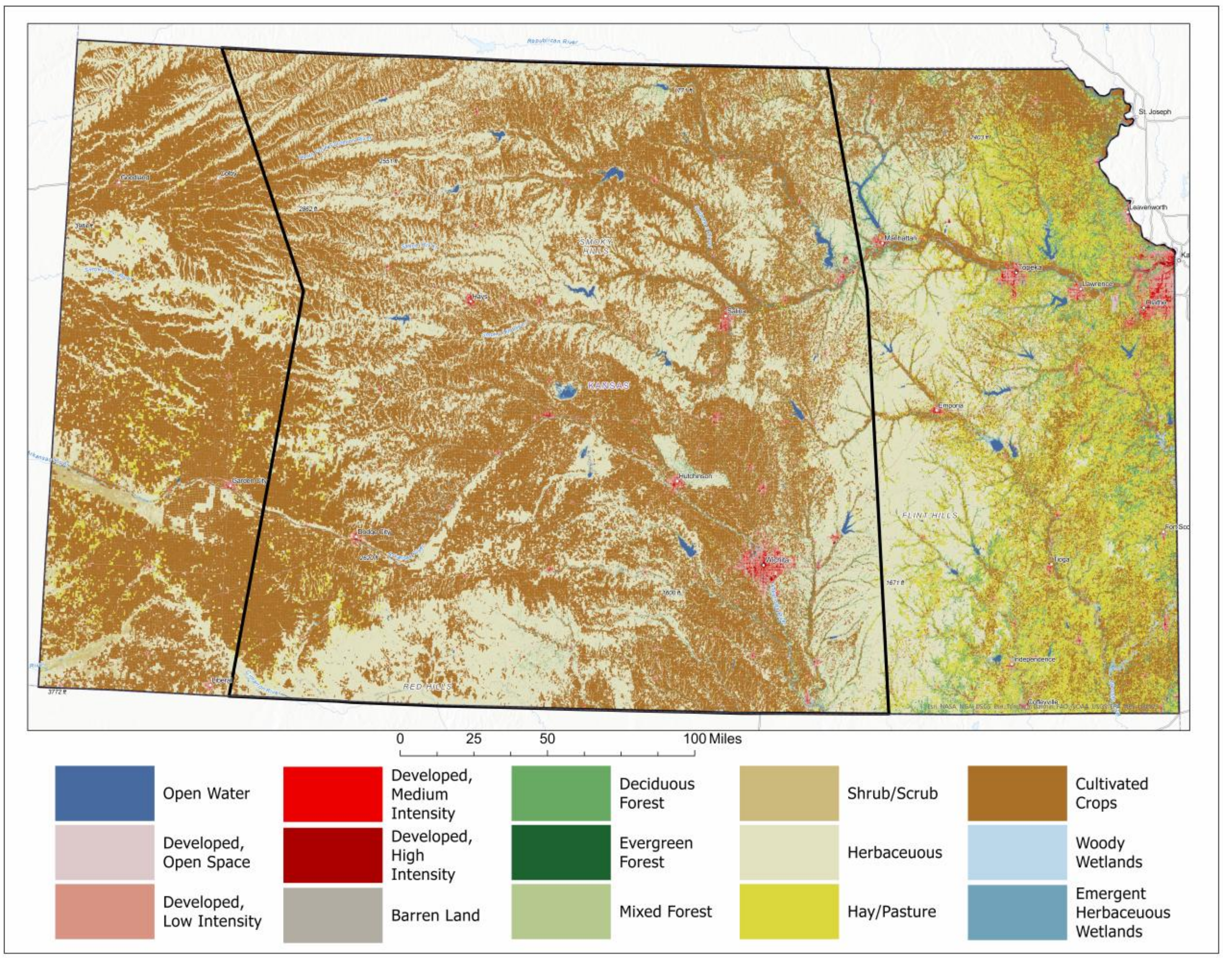
The state is best known for its agricultural and livestock production, which significantly contributes to its revenue (Kansas Department of Agriculture, n.d.). The most dominant land cover types within the state are cultivated crops with an approximate area of 92,092km² (43.3%) and herbaceous grasslands with an area of 77,914km² (36.6%) (Table 3.1). Wetland and water cover an area of 3,907km² (1.8%) within the state, primarily in the eastern and central regions (Figure 3.3). The most important wetlands and water bodies within the state are the Cheyenne Bottoms, Quivira National Wildlife Refuge, and Wilson Lake. Several open water bodies are also found, especially in the eastern portion of the state, including the Kansas River (Kaw) and several flood protection reservoirs. Between 2008 and 2021, approximately 96% of land cover within the state remained unchanged, but the land cover type with the most decrease in this period was open water, with a 9% decrease in area.

Table 3.1 Kansas landcover class area and percent cover for 2011 (Source: National Landcover Database 2011).

Land Cover Class	**Area** (km^2**)**	**% Cover**
Open Water	2,108.17	1.0%
Developed, Open Space	7,658.99	3.6%
Developed, Low Intensity	2,371.98	1.1%
Developed, Medium Intensity	578.69	0.3%
Developed, High Intensity	215.70	0.1%

Barren Land	147.92	0.1%
Deciduous Forest	7,494.68	3.5%
Evergreen Forest	31.95	0.0%
Mixed Forest	170.70	0.1%
Shrub/Scrub	888.24	0.4%
Herbaceous	77,914.57	36.6%
Hay/Pasture	19,414.52	9.1%
Cultivated Crops	92,092.60	43.3%
Woody Wetlands	1,580.99	0.7%
Emergent Herbaceous Wetlands	218.50	0.1%

Figure 3.3 Land use/land cover within the state of Kansas (Source: National Land Cover Database 2011).



Chapter 4 - Predicting Whooping Crane Stopover Habitat Preferences along the Kansas Migratory Flyway

Abstract

The whooping crane (Grus americana) is an endangered species that faces critical challenges, especially during migration. This makes identification of suitable stopover habitats necessary for its survival and recovery. This research focuses on modeling habitat suitability within the Kansas portion of the Aransas-Wood Buffalo population's migratory corridor, an area impacted by wind energy developments. We build upon recent research using machine learning algorithms to create species distribution models (SDM) for this migratory avian species.

We developed an SDM for the whooping crane using a random forest technique to inform management decisions within Kansas. The model uses six predictor variables to estimate the relationship between environmental characteristics and stopover site suitability and telemetry data from 58 tagged birds between 2010 – 2016 (n = 1253) for our observation data (presence points). In similar studies, presence-only data is commonly used by randomly generating the background data ("pseudo-absence" points), but this approach has several weaknesses. For this study, we utilized a Poisson point process method for generating pseudo-absences and generated 2000 spatially weighted points for the model.

The result was a prediction map showing areas where whooping cranes would most likely be found. The relative probability function ranged from 0.0 to 0.94, with a prediction accuracy of 92.2%. The prediction map showed that 95.23% of the study area was marked unsuitable and posed a low conflict for energy development projects. This research supports whooping crane recovery while contributing to the body of knowledge on species distribution modeling techniques to further wildlife conservation efforts.

Introduction

The whooping crane (*Grus americana*) is the rarest crane (family *Gruidae*) species and was listed in 1970 as endangered under the Endangered Species Preservation Act. This bird species is endemic to North America (French, Converse, & Austin, 2019) and faces critical challenges during its long migratory journey (Armbruster, 1990). Once, the population of whooping cranes exceeded 10,000 individuals (Canadian Wildlife Service and U.S. Fish and Wildlife Service, 2007), but by the late 1940s, only about 15 individuals remained in the wild, bringing the species close to extinction. Fortunately, through combined conservation efforts, such as habitat restoration, captive breeding programs, and different protection measures, there has been a significant increase in the crane population. Today, their numbers have risen to approximately 600 individuals in the wild (Leaverton & Fellows, 2023; U.S. Fish & WIldlife Service, 2023) . Despite these efforts, whooping cranes still face threats from land use changes, predation, and hunting pressures during migration (Pearse A. T., Metzger, Brandt, Shaffer, & Bidwell, 2021; U.S. Fish and Wildlife Service., 2009).

Migration events are the most limiting time of a migratory bird's annual life cycle (Carlisle, et al., 2009; Baasch D. , Farrell, Pearse, Brandt, & Caven, 2019). This phase is challenging for several reasons; however, the ecology of migrating birds during their stopover habitats is still not well understood (Faaborg, et al., 2010; Arzel, Elmberg, & Guillemain, 2006; Webb, Smith, Vrtiska, & Lagrange, 2010). The whooping cranes migrate in small groups, bringing rise to more "decision makers". During migration, they are exposed to several unpredictable challenges that affect their population, such as habitat loss and adverse weather conditions. Research shows that, on average, 70% of fledged mortality occurs during this period

(U.S. Fish and Wildlife Service., 2009). After hours of continuous flight, the birds' fat reserves become depleted, making stopover sites essential for successful migration (Myers, 1983). Habitat fragmentation and land-use changes have drastically reduced the availability and quality of critical stopover sites where cranes can rest and refuel during their long journeys (Baasch D. M., Farrell, Pearse, Brandt, & Caven, 2019). For migrating Whooping cranes, survival and body conditions going into breeding season depend on the decisions they make regarding stopover habitats, where factors such as habitat quality play a crucial role (Whitham, 1980; Baasch D. , Farrell, Pearse, Brandt, & Caven, 2019; Myers, 1983; Moore, Gauthreaux, Kerlinger, & Simons, 1995). High-quality stopover habitats promote the health, survival, and reproductive success of individuals within the population (Rodewald, 2015).

Many conservation strategies for the whooping crane have traditionally focused on protecting wintering and breeding habitats, as these areas are critical for the species' reproductive success and survival during the non-migratory period (Moore, Gauthreaux, Kerlinger, & Simons, 1995). While these efforts have contributed significantly to the species' recovery, they are insufficient for ensuring long-term population stability. Effective conservation must also prioritize the identification and protection of stopover habitats, which provide essential resources for rest and refueling during migration (Canadian Wildlife Service and U.S. Fish and Wildlife Service, 2007). In the past, extensive wetland loss and conversion to agricultural land across North America drastically reduced the availability of suitable stopover sites (French, Converse, & Austin, 2019), creating geographic bottlenecks for migratory birds like the whooping crane (Myers, 1983). Wetlands, which are crucial for feeding and resting thousands of migratory birds, have been especially impacted by urbanization, land-use change, and drainage for farming. This loss of habitat disproportionately affects species such as the whooping crane, which is highly specific in its habitat requirements during migration (Webb, Smith, Vrtiska, & Lagrange, 2010). Kansas lies within the whooping crane's central migratory corridor and plays a pivotal role in the species' migration. The state's remaining wetlands, including Cheyenne Bottoms and Quivira National Wildlife Refuge, serve as critical stopover sites for whooping cranes, offering food resources and safety during migration. However, these habitats are increasingly threatened by water scarcity, agricultural expansion, and urban development. Conservation efforts in Kansas are essential for addressing these threats and ensuring the availability of high-quality stopover habitats.

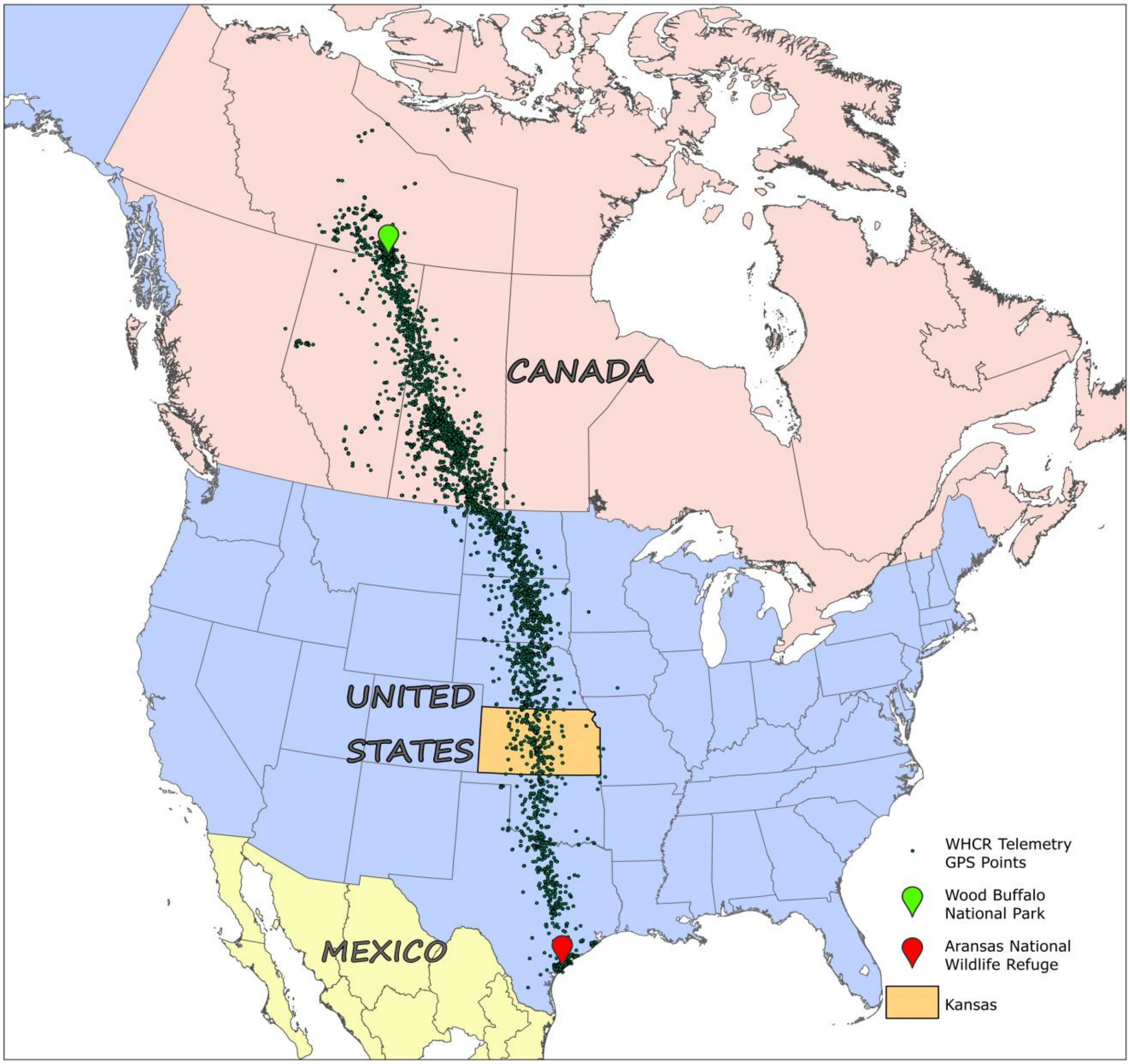
The whooping cranes' migratory corridor spans regions experiencing significant land-use changes, including the rapid expansion of wind energy infrastructure. Wind farms are increasingly recognized for their potential to reduce greenhouse gas emissions and contribute to renewable energy goals (Drewitt & Langston, 2006; Kuvlesky, et al., 2007). However, the development of these facilities within critical migratory pathways introduces new challenges for wildlife conservation. For whooping cranes, the risks are multifaceted, including collision with wind turbines and associated infrastructure, such as power lines, which are already a leading cause of mortality during migration (Lewis, Kuyt, Schwindt, & Stehn, 1992). Additionally, wind farms can disrupt migratory flight paths and lead to avoidance of nearby stopover habitats, forcing cranes to expend additional energy searching for alternative sites (U.S. Fish and Wildlife Service., 2009). These impacts underscore the need for careful siting and mitigation strategies that balance the need for renewable energy development with conserving critical migratory habitats.

Climate change exacerbates these threats by altering the availability, quality, and spatial distribution of stopover habitats. Changes in precipitation patterns, increased frequency of extreme weather events, and shifting vegetation dynamics can make wetlands and the available habitats less reliable during migration. These climate-driven changes compound the effects of habitat fragmentation and land-use alterations, amplifying the challenges faced by migratory species (Myers, 1983; Webb, Smith, Vrtiska, & Lagrange, 2010). For the whooping crane, which relies heavily on wetland ecosystems within its flyway, the combined pressures of climate change and expanding human infrastructure highlight the urgent need for integrated conservation approaches. Prioritizing habitat restoration, protecting remaining wetlands, and ensuring that renewable energy projects adhere to wildlife-friendly practices are crucial for safeguarding the species' migratory corridor.

This study aims to advance the understanding of whooping crane stopover ecology and inform conservation strategies within the Aransas-Wood Buffalo migratory flyway. Specifically, this research's objectives are to develop a predictive model that can delineate suitable habitats within the study area and investigate whether preferred stopover habitat characteristics vary spatially. To address this, we used telemetry data in a random forest model (Breiman, 2001), a machine learning approach well-suited for analyzing complex ecological relationships, to identify key environmental variables influencing whooping crane habitat selection within Kansas, a critical state in their migratory corridor. Environmental factors such as wetland cover, access to food sources, urban development, proximity to roads, and other land cover types were included to comprehensively assess habitat suitability. By comparing the relative importance of these variables between Kansas and Nebraska, we aim to determine whether significant spatial differences exist in stopover habitats across both states. Although the boundary between Kansas and Nebraska is political (and thus arbitrary) rather than natural, we compared how differences in legislative laws and arrangement of land cover types influence variable importance and habitat selection as the birds migrate between both states. For instance, Nebraska has more natural waterbodies than Kansas, and while Sandhill cranes (Grus *canadensis*), a close relative of the endangered Whooping crane (Grus *americana*), are hunted in Kansas, they are protected in Nebraska. We assessed whether these differences affect habitat preferences in each state.

The study builds on predictions that whooping cranes select areas with a higher percentage of wetlands and access to food while avoiding regions with substantial urban development. These insights provide an opportunity to refine conservation strategies, ensuring they account for regional variability in habitat preferences. Additionally, this work highlights the importance of integrating habitat modeling with land-use planning, enabling prioritization of habitat protection and restoration efforts while addressing potential conflicts with urbanization and renewable energy development along the migratory corridor.

Figure 4.1 Whooping crane GPS telemetry points from their breeding habitat in Wood Buffalo National Park to their wintering habitat in Aransas National Wildlife Refuge along the expanse of their migratory corridor from 2010 to 2016.



Methods

Study Area

The Aransas-Wood Buffalo population is the only whooping crane population in the wild. It makes a biannual migration of about 4000 km (Hefley, Baasch, Tyre, & Blankenship, 2015) in the fall from the breeding grounds in Wood Buffalo National Park (WBNP) Alberta, Canada, to wintering grounds in Aransas National Wildlife Refuge (ANWR) Aransas, Texas, (Pearse A. T., et al., 2020). During its migration, the species has been observed to travel through the Canadian Prairies and the Great Plains of North America (Pearse, et al., 2015; Baasch D. M., Farrell, Pearse, Brandt, & Caven, 2019). Observational siting data have shown their presence in Alberta and Saskatchewan provinces in Canada and the states of North and South Dakota, Nebraska, Kansas, Oklahoma, and Texas, with the 75% core corridor narrowest in central Kansas (Pearse, et al., 2018).

We selected Kansas because of increased farming activities and the continuous conversion of prairie grassland into cropland. Another factor was the increase in wind farm development in the state, which will disrupt their migratory route, potentially causing a spatial shift in the flyway. As an endangered bird species with highly specific habitat preferences during migration, there has also been limited studies of whooping crane habitat preferences within Kansas. For our initial analysis, we limited our scope to the 95% migratory corridor bounds but later expanded the spatial bounds of analysis to include the entire state of Kansas. The rationale behind this was to include all areas within Kansas where the probability of detection was greater than 0 (Figure 4.1).

Data

We acquired whooping crane sightings data (1942 – 2020) from the database compiled by the U.S. Fish and Wildlife Service (USFWS, Nebraska Field Office, unpublished data) and Whooping crane telemetry GPS data from 68 radio-tagged unique individuals from the Aransas – Wood Buffalo population from 2009 – 2017 (Pearse, et al., 2015). Because of potential biases in the observational data (Austin & Richert, 2001), we decided to use only the telemetry database, which has the most precise location points. There were records from 56 unique individuals (n = 1,253) for Kansas with an average observation per day of 4 hours; all data points were included in the analysis. According to (Belaire J. A., Kreakie, Keitt, & Minor, 2014), conservation efforts are targeted toward used habitats across the flyway. Therefore, we used all the stopover sites in the database without considering the migration season (Fall or Spring). We obtained 30m x 30m landcover classification data from the National Landcover Database (NLCD). To select the year to use for our land cover analysis, we tested to see how much of the land cover had changed during the data collection period and found that most of the area remained unchanged for 96% of the study area from 2008 to 2021. For our analysis, we therefore chose the 2011 land cover dataset because it falls within our study time period.

The habitat selection type used for this study is multi-level, single-scale habitat selection, i.e., multiple factors are assessed at a single scale within each level. A grid size of 1 km by 1 km was adopted for this study because, based on past whooping crane literature, at this scale the environmental characteristics of the whooping crane were best analyzed (Belaire J. A., Kreakie, Keitt, & Minor, 2014). Four land cover types previously associated with the whooping crane were tested as predictor variables: agricultural land, wetlands and rivers, urban areas, and roads (Table 1). To generate our covariates, we examined the percent cover of each of these variables within our 1 km^2 grid. Two additional covariates were generated to investigate how fine-scale and broad-scale landscape factors impact stopover habitats (Table 1). We developed a categorical ecotone with 16 categories from A - P for fine-scaled investigation. This category quantifies the structure of the landscape in terms of the arrangement of certain features. Each ecotone category represents the distance of each 1 km^2 cell from the nearest agricultural area and wetland in meters. This layer was added to examine if whooping cranes select for areas close to these landcover types and the threshold between these landcover types where stopover habitats start to become unfavorable. A second variable, bearing, was developed to analyze broad-scale landscape interactions. It describes the directional heading from the centroid of each cell towards the wintering ground in ANWR (Belaire J. A., Kreakie, Keitt, & Minor, 2014), providing information on how far along the migratory corridor cranes start to adhere to the center of the corridor, regardless of surrounding land cover type. It helps the model differentiate between used and available habitats. The bearing was developed with the geosphere package in R (Hijmans, Williams, & Vennes, 2011) and to avoid a bimodal distribution, 180 was subtracted from each value (Belaire J. A., Kreakie, Keitt, & Minor, 2014).

Species Distribution Modeling and Validation

A species distribution model was developed using a machine-learning approach to estimate the relative probability of use of a specific area based on its environmental characteristics and generate a suitability map within the state. The random forest method (package ‘randomForest; (Liaw & Wiener, 2002)) was chosen because it is a statistical classifier that can effectively model the non-linear and complex relationships between environmental variables, offering simple interpretations and performing better than other classification procedures (Cutler, et al., 2007). 0A random forest is a collection of decision trees that make decisions and classify data. According to (Breiman, 2001), it consists of tree-structured classifiers

$$\{h(x, \Theta_k), k = 1, \ldots\}$$

where the $\{\Theta_k\}$ are independent identically distributed random numbers. Each tree casts a unit vote for the most popular class at input x. Unlike single classification trees, which are prone to overfitting and perform poorly on new data, the random forest model combines the simplicity of decision trees with flexibility, resulting in more accurate predictions.

Information on both species' presence and absence is required to model the environmental space they can inhabit (Iturbide, et al., 2015). Getting true absence points is daunting for mobile species, especially those that migrate long distances. Therefore, pseudo-absence points are used as background data instead of true absence points. When using machine learning models, the model accuracy is impacted by the number of pseudo-absence points added to the model (Barbet-Massin, Jiguet, Albert, & Thuille, 2012). Therefore, it is essential to find the right balance between presence and pseudo-absence point. To avoid sampling bias, it is ideal to have an equally balanced sample of presence and absence points (i.e. 50/50 split) (Brizuela-Torres, Elith, Guillera-Arroita, & Briscoe, 2024) but in the absence of true absence points, (Barbet-Massin, Jiguet, Albert, & Thuille, 2012) proposed the 1/3 rule of sample balance. This rule suggests that at least 33% of the sample points are present locations. For our study, we used the Poisson Point process to generate pseudo-absences. We generated 2,000 random points across the entire study space and used these as our pseudo-absence points. We chose this number because it meets the 1/3 rule, with the sample balance of presence locations being 38.5%. We split the data into training and test sets for our model run and withheld 40% of our data during model training, ensuring each run had an equal number of presence and pseudo-absence points.

Next, we tested for multicollinearity of all the variables at $\alpha=0.05$ using a leave-one-out assessment (Sullins, et al., 2019).

We then estimated how important a variable is within the model using the mean decrease in accuracy (MDA). The mean decrease in accuracy shows how much accuracy is lost from the model when a variable is removed. The MDA doesn't have a fixed range, but in general, a higher mean decrease in accuracy shows that a variable is more important for classifying the data (Cutler, et al., 2007). Ranks of model variable importance were then estimated using the mean decrease in out-of-bag error.

We validated the model with data that wasn't used in the predictive model training. The validation was done based on the accuracy, specificity, and sensitivity of the predictive model. The area under the receiver operating curve (AUC) was also estimated and used to evaluate the predictive power of the model. It assesses the ability of the model to correctly categorize data. AUC is an indicator of a model's accuracy, and it ranges from 0 to 1, with 0.5 showing that the model was no different than random (Fielding & Bell, 1997). Finally, we generated a relative probability function map showing suitability within the study area. To test how well the probability map estimates occurrence, we overlaid the test data set over the map and then calculated how accurately the map depicted presence and pseudo-absence.

Table 4.1 Ranked Predictor Variables by Mean Decrease in Model Accuracy

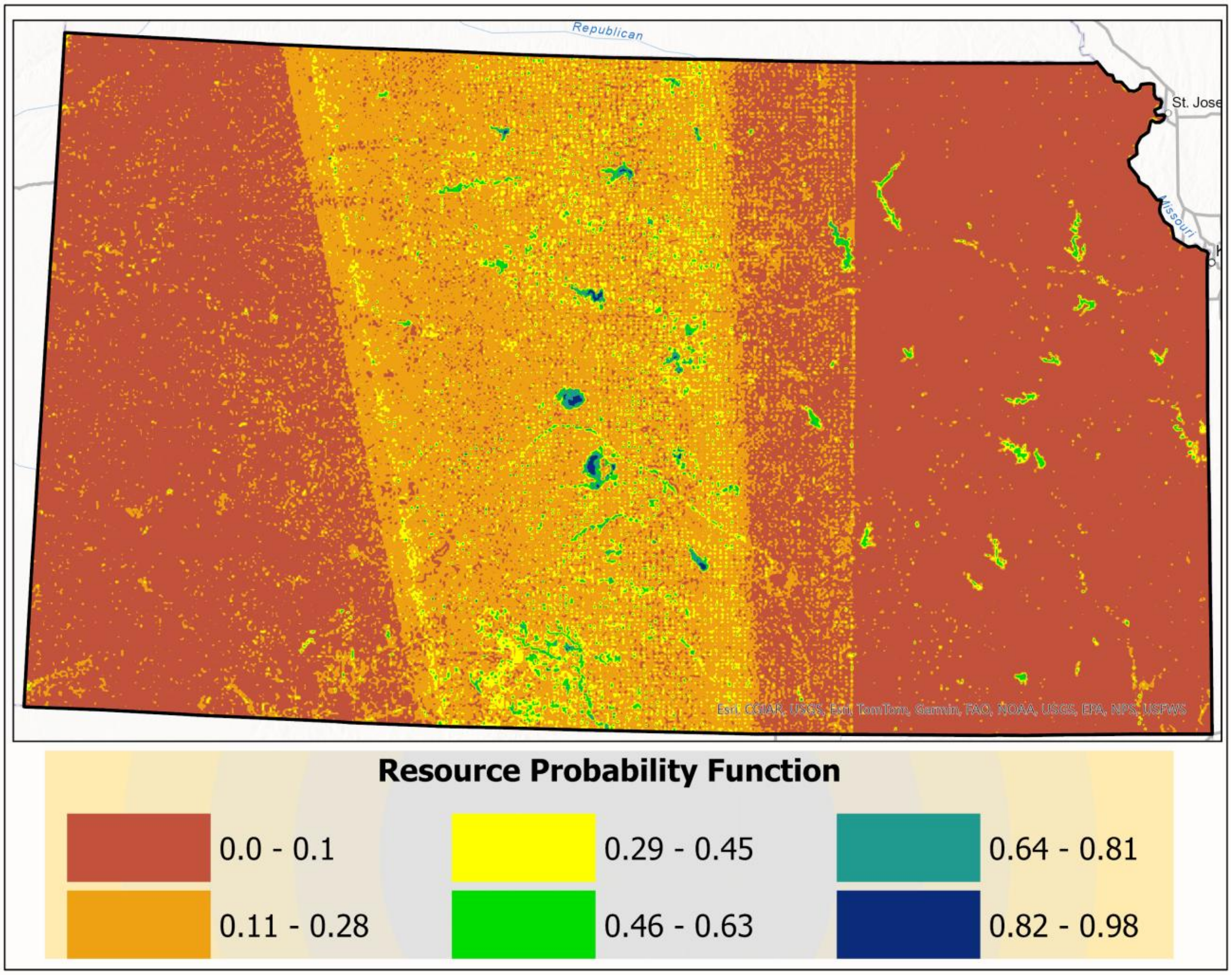
Predictor Variables	*Description*	*Mean decrease in accuracy (MDA/10)*	*Rank*
Bearing	*Directional heading between the cell and the Aransas National Wildlife Refuge in South Texas, U.S.A.*	16.28	1
Agricultural land	*All crop-based land uses (% cover in 1 km^2).*	10.64	3
Urban areas	*Urban land - defined as towns or cities with more than 100 people (% cover in 1 km^2).*	7.54	5
Wetland and water	*Wetlands and open water (% cover in 1 km^2).*	12.51	2
Roads	*Primary roads, secondary roads, and railroads (% cover in 1 km^2).*	9.57	4
Ecotone category	*A categorical variable that identifies the combined Euclidean distance from the nearest agricultural and nearest wetland area.*	6.28	6

Results

Our model effectively identified the most important environmental variables influencing whooping crane stopover habitat selection in Kansas. Bearing was shown to be the most important predictor, with a mean decrease in accuracy (MDA) score of 16.28, while wetland and water ranked second (12.51) (Table 4.1). Partial dependence plots (Figure 4.3a) indicated that the relative suitability increased as the bearing shifted to the center of the migratory flyway and that areas with intermediate to high wetland cover had higher predicted suitability. It also showed that areas with low coverage of roads and urban areas showed higher suitability, and as agricultural areas increased, there was a slow decline in suitability.

Analysis of ecotone categories further supported these findings, revealing that areas categorized as "E"—those within 100 meters of wetlands and between 500 and 1000 meters from agricultural lands—had the highest predicted suitability. The model achieved a high Area Under the Curve (AUC) score of 0.96, signaling its reliability and robust predictive power. The results show the importance of fine-scale environmental variables and broader spatial characteristics in determining suitable stopover habitats.

Figure 4.2 Reclassified map of predicted suitability of stopover habitat within the Kansas Whooping Crane migratory corridor. *Original map found in appendix B, figure 1.*



Spatial Variation Analysis –

Results revealed significant spatial differences in habitat selection drivers, which reflect underlying landscape heterogeneity between Kansas and Nebraska. When comparing the importance of variables for Kansas with the results from similar research carried out in Nebraska (Belaire J. A., Kreakie, Keitt, & Minor, 2014), spatial dynamics reveal that some variables become more important while others decrease in significance (Figure 4.3). To compare how each variable's importance contributes to the model's performance, the MDAs for both states were standardized using the formula below, and the variable's contribution was given a value from 0 to 1 (Table 4.2).

$$Standardized\ MDA = \frac{(MDA - Min\ MDA\ in\ state)}{(Max.MDA\ in\ state - Min.MDA\ in\ state)}$$

Table 4.2 Comparison of Predictor Importance Between Nebraska and Kansas Models

	NEBRASKA			KANSAS		
Predictor Variable	**MDA**	**Standardized MDA**	**Rank**	**MDA**	**Standardized MDA**	**Rank**
Bearing	37.17	1.00	**1**	16.28	1.00	**1**
Roads	31.67	0.85	**2**	9.57	0.59	**4**
Wetlands and Water	13.03	0.25	**3**	12.51	0.77	**2**
Ecotone	10.54	0.19	**4**	6.28	0.39	**6**
Agricultural Land	8.48	0.13	**5**	10.64	0.65	**3**
Urban Areas	8.21	0.12	**6**	7.54	0.46	**5**

In both states, the bearing was the most critical predictor of stopover habitat suitability, as expected in small-front migration (Berthold, 2001). This is because bearing helps capture the directions followed and their consistency across individuals and years. The availability of wetlands was more crucial in Kansas than in Nebraska, where natural wetlands are more common, with a standardized mean decrease in accuracy (MDA) score of 0.77 (Table 4.2). Model results for both states consistently identified avoidance of roads as an important factor, though this behavior was more pronounced in Nebraska (Std. MDA = 0.59 versus 0.85 in Nebraska). Urban avoidance was a stronger factor in Kansas than Nebraska (Std. MDA = 0.46 versus 0.12 in Nebraska), possibly due to more significant urbanization pressures.

Partial dependence plots also showed differences in how whooping cranes interacted with agricultural lands in both states (Figure 4.3). In Kansas, where the landscape has been intensively modified with more agricultural farming, there is a negative relationship between the proximity of agricultural lands and the probability of use, while in Nebraska, where there is less intensive agricultural land, there is a positive relationship (Belaire J. A., Kreakie, Keitt, & Minor, 2014). On a finer scale, ecotone categories contributed minimally to both regions, Nebraska more than Kansas. Still, they showed subtle spatial relationships, with Kansas habitats favoring areas closer to wetlands yet moderately distant from agricultural zones, and Nebraska habitats favoring areas closer to agricultural zones.

These spatial differences suggest cranes adapt to regional resource availability. Kansas's intensive agriculture may concentrate cranes in remnant wetlands, while Nebraska's mixed landscapes offer more flexible stopover options.

Discussion

The findings of this study indicate that outside the migratory corridor, the relative probability of use significantly decreases. Most of the western part of Kansas, which is the driest area and heavily engaged in intensive agricultural farming, has nearly zero probability of use. The center of the flyway where most of the state's wetlands, including Cheyenne Bottoms and Quivira National Wildlife Refuge, are located has the highest probability of use and should be protected as critical stopover sites. There is a sudden decrease in the relative probability of use of the eastern portion of the migratory corridor, both due to urban development and increased occurrence of outliers in that region. Only 5.14% (10,946.79 km^2) of Kansas has a medium-high relative probability of use (>= 0.3), leaving the remaining areas open to explore other development projects (Figure 4.2).

Regional differences in variable importance between Kansas and Nebraska underscore how landscape context shapes migratory behavior. The dominance of wetland cover in Kansas reflects the species' reliance on large, predictable wetland complexes in an otherwise intensive agricultural landscape. In contrast, Nebraska's more heterogeneous environment allows for greater flexibility in habitat selection, with riverine systems playing a more prominent role. These findings challenge the notion of a uniform migratory corridor and instead paint a picture of adaptive habitat use shaped by local resource availability. Conservation strategies must therefore be tailored to regional conditions, focusing on wetland protection and restoration in Kansas while maintaining connectivity among riparian corridors in Nebraska. The stronger avoidance of urban areas in Kansas suggests that development pressures may be pushing cranes into suboptimal habitats, highlighting the need for stricter land-use regulations near critical stopover sites.

Bearing, the most influential variable, indicates that on a broad scale, whooping cranes adhere to a narrow range of directional headings during their migration. Wetlands were identified as essential stopover sites, corroborating prior research highlighting this ecosystem’s role in providing food resources and resting opportunities for migratory birds. The observed avoidance of urban areas and regions with extensive road networks aligns with studies indicating that human activity disrupts wildlife behavior and habitat use. Urban expansion and infrastructure development along the migratory route reduce habitat availability and introduce risks such as collisions with power lines and light, as well as noise pollution disturbances. The gradual decline in the relative probability of use with increased agricultural land further supports the hypothesis that intensively modified landscapes pose challenges for migrating whooping cranes. However, moderate agricultural adjacency, as captured by ecotone category E (501m-1000m from agricultural land), may provide complementary benefits in proximity to wetlands (Table 4.3).

Conservation Strategies

These results have important implications for conservation planning, showing that the same conservation strategies should not be adopted for all regions along the migratory corridor. The high suitability of areas with wetland-adjacent habitats suggests that efforts should prioritize preserving and restoring wetlands, particularly those near existing agricultural landscapes, to maintain ecological functionality within the migratory corridor. Kansas, a central node within this flyway, plays a pivotal role in ensuring the cranes' successful migration and long-term survival. Climate change and renewable energy development pose additional challenges. Altered precipitation patterns and extreme weather events may further impact wetland availability. At the same time, the rapid expansion of wind farms within the corridor necessitates strategic siting to minimize disruption to crane migration. Mitigation strategies should align renewable energy initiatives with habitat conservation goals, such as buffer zones around critical wetlands and low-disturbance infrastructure designs.

Future research will explore the temporal variability in stopover habitat use, particularly in response to changing environmental conditions and anthropogenic pressures. Integrating telemetry data with long-term land use and climate projections can provide deeper insights into adaptive management strategies. By leveraging the predictive power of species distribution models, resource managers can optimize habitat conservation efforts, ensuring the protection of this species across its migratory range.

Figure 4.3 Comparing partial dependence plots for Nebraska and Kansas

a. Partial dependence plots for Nebraska　　　　b. Partial dependence plots for Kansas

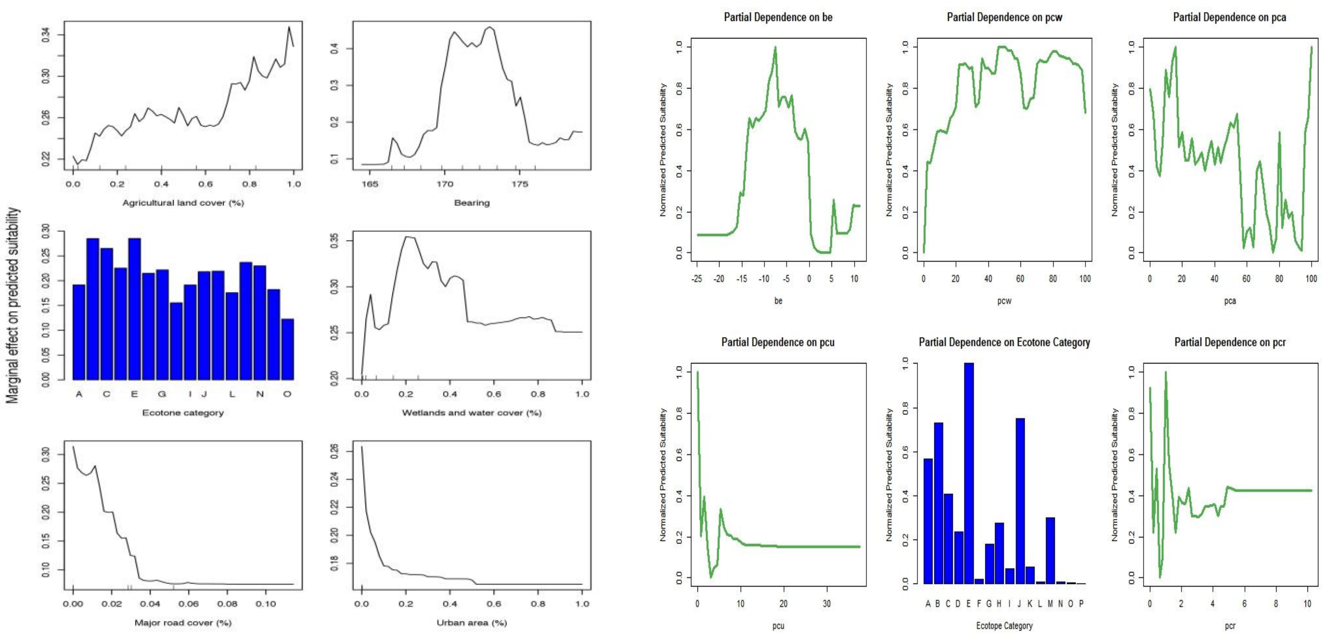


Table 4.3 Ecotone Category Rankings and Distance Thresholds to Wetland and Agricultural Areas

Code	Rank According to Importance	Distance from wetland (m)	Distance from agriculture (m)
A	**4**	0-100	0-100
B	**3**	0-100	101-500
E	**1**	0-100	501-1000
J	**2**	0-100	>1000
C	**5**	101-500	0-100
D	**7**	101-500	101-500
F	**15**	101-500	501-1000
K	**10**	101-500	>1000
G	**9**	501-1000	0-100
H	**8**	501-1000	101-500
I	**11**	501-1000	501-1000
L	**14**	501-1000	>1000
M	**6**	>1000	0-100
N	**12**	>1000	101-500
O	**13**	>1000	501-1000
P	**16**	>1000	>1000

Chapter 5 - Mapping Shifting Corridors: Spatial and Temporal Dynamics of Whooping Crane (*Grus americana*) Stopover Habitat in Kansas and Implications for Wind Energy Development

Abstract

Understanding how endangered species interact with dynamic landscapes is key to good conservation planning. This study presents an improved random forest model to assess temporal and spatial changes in whooping crane (Grus americana) stopover habitat use in the Kansas segment of the Central Flyway. We added spatial (latitude, longitude) and temporal (date) variables to the model to see how the habitat suitability changes over time.

We created habitat suitability maps for specific user-defined dates and seasonal time intervals from 2010 to 2016. We analyzed changes in characteristics of habitat preferences over migratory seasons (Spring and Fall) and between various years. A wind resource suitability map was created using wind power density data from the National Renewable Energy Laboratory (NREL). We overlaid this wind potential map with the predicted high-suitability stopover habitat areas (probability > 0.6) to see where they overlap. This analysis showed areas of low habitat impact with high wind development potential, so priority for development can be placed on low-risk zones.

We analyzed current turbine conflict zones by applying 5 km buffers around wind turbines from data derived from the U.S. Wind Turbine Database to account for potential displacement and collision risk. The final outputs are seasonal habitat suitability maps, high-potential wind development zones, and spatial conflict maps to help with habitat-sensitive wind

energy siting. Our results outline a comprehensive approach for expanding renewable energy while conserving a critically endangered species.

Introduction

Migratory corridors are critical for the survival of endangered species like the whooping crane (*Grus americana*), which relies on specific stopover habitats to rest and refuel during its long journey between breeding and wintering grounds, and understanding how it selects stopover habitat is important for its conservation. Kansas is a crucial part of the whooping crane's central migratory corridor. Wetlands like Cheyenne Bottoms and Quivira National Wildlife Refuge are where these birds stop to refuel and find safety during migration. But water shortages, agriculture, and urban development are increasingly threatening those habitats. Anthropogenic pressures fragment habitats, reduce resource availability, and introduce collision risks, making it imperative to map and monitor corridor dynamics to inform conservation strategies. To keep those stopover locations available—and healthy— the state needs more conservation efforts.

Despite the extensive research that has been done on stopover habitat selection of the whooping crane, there is still a significant knowledge gap, especially along the Kansas migratory corridor. Prior studies have primarily focused on broad-scale habitat preferences across the Central Flyway (Pearse, et al., 2018; Harrell & Bidwell, 2020), often overlooking finer spatial and temporal variations critical for targeted conservation efforts. Habitat suitability models have traditionally been built using GIS-based methods (Kaminski, Comer, Garner, Hung, & Calkins, 2013). But there has been a gap in research that combines high-resolution spatial data with the latest machine learning techniques—like Random Forest (Cutler, et al., 2007). Kansas is a potential geographic bottleneck for the species, which means we need a more detailed approach to refine conservation strategies and inform how we manage habitats in the state.

Previous research, as detailed by (Okonye, Unpublished Thesis), employed a Random Forest model to assess habitat suitability for whooping cranes along the Kansas migratory flyway, identifying key environmental predictors such as wetland cover, bearing, and proximity to urban areas. This work provided a foundational understanding of stopover site selection within the flyway, highlighting the importance of wetlands and the avoidance of human-modified landscapes. However, the model was limited to a static spatial framework and did not account for temporal variability in habitat use, which is crucial for addressing seasonal and interannual changes in migration patterns. Extending this analysis to incorporate spatial and temporal dimensions is essential for a holistic understanding of corridor dynamics. Seasonal shifts in resource availability, climate variability, and evolving land-use patterns necessitate a model that can adapt to these changes. Furthermore, comparing habitat drivers across states like Kansas and Nebraska, regions with differing agricultural intensity and wetland distributions, can reveal how landscape heterogeneity influences migratory behavior.

The primary objectives of this study are to enhance habitat suitability modeling by integrating spatial-temporal variables to improve predictions of stopover site selection across seasons and years, analyze shifts in variable importance across space to uncover regional differences in habitat selection, visualize corridor dynamics through time-series maps for spring and fall migrations, evaluate site suitability for wind energy development, and analyze potential conflicts between existing wind turbines and the suitable habitats. By addressing these goals, this study aims to bridge the gap between ecological research and applied conservation, offering actionable insights for protecting Whooping Cranes while supporting sustainable land-use planning.

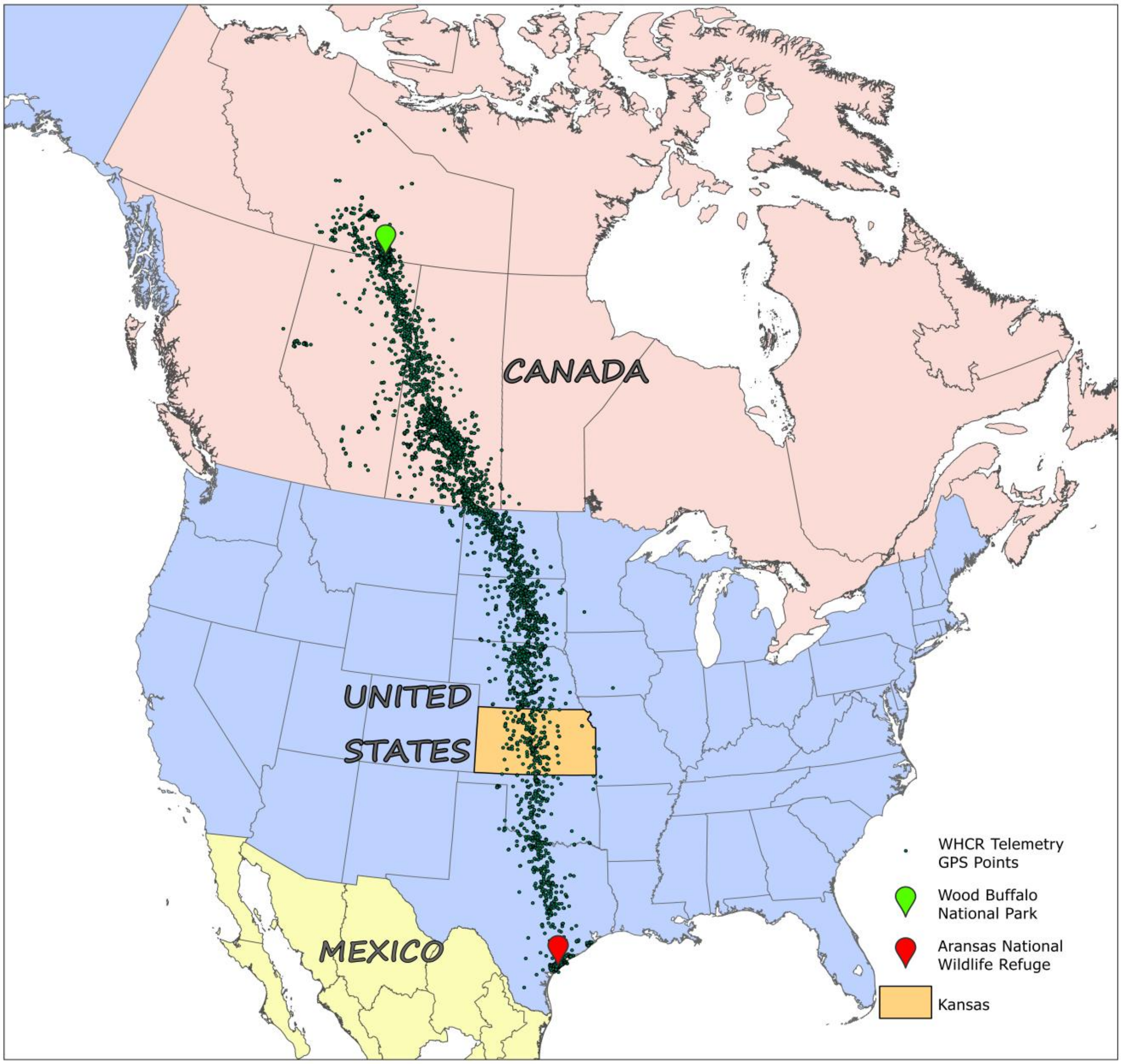
Methods

Study Area

The Aransas-Wood Buffalo population is the only whooping crane population in the wild. It makes a biannual migration of about 4000 km (Hefley, Baasch, Tyre, & Blankenship, 2015) in the fall from its breeding ground in Wood Buffalo National Park (WBNP) Alberta, Canada, to its wintering ground in Aransas National Wildlife Refuge (ANWR) in Aransas, Texas, (Pearse A. T., et al., 2020). During its migration, the species has been observed to travel through the Canadian Prairies and the Great Plains of North America (Pearse, et al., 2015; Baasch D. M., Farrell, Pearse, Brandt, & Caven, 2019). Observational siting data have shown their presence in Alberta and Saskatchewan provinces in Canada and the states of North and South Dakota, Nebraska, Kansas, Oklahoma, and Texas, with the 75% core corridor narrowest in central Kansas (Pearse, et al., 2018).

We selected Kansas because of increased farming activities and the continuous conversion of prairie grassland into cropland. Another factor was the uprise in wind farm development in the state, which could disrupt their migratory route, potentially causing a shift in the flyway. As an endangered bird species with a highly specific habitat preference during migration, there has also been limited study of whooping crane habitat preference within the state. For our initial analysis, we limited our scope to the 95% migratory corridor bounds but later expanded our scope to include the entire state of Kansas. The rationale behind this was to include all areas within Kansas where the probability of detection was greater than 0 (Figure 5.1).

Figure 5.1 Whooping crane GPS telemetry points from their breeding habitat in Wood Buffalo National Park to their wintering habitat in Aransas National Wildlife Refuge along the expanse of their migratory corridor from 2010 to 2016.



The state is best known for its agricultural and livestock production, which significantly contributes to its revenue (Kansas Department of Agriculture, n.d.). The most dominant land cover types within the state are cultivated crops with an approximate area of 92,092km² (43.3%) and herbaceous grasslands with an area of 77,914km² (36.6%) (Table 5.1). Wetland and water cover an area of 3,907km² (1.8%) within the state, primarily in the eastern and central regions. The most important wetlands and water bodies within the state are the Cheyenne Bottoms, Quivira National Wildlife Refuge, and Wilson Lake. Several open water landcover types are also found, especially in the eastern portion of the state, including the Kansas River (Kaw). Between 2008 and 2021, approximately 96% of land cover within the state remained unchanged, but the land cover type with the most decrease in this period was open water, with a 9% decrease in area.

Table 5.1 Kansas Landcover class area and percent cover for 2011.

Land Cover Class	**Area (km^2)**	**% Cover**
Open Water	2,108.17	1.0%
Developed, Open Space	7,658.99	3.6%
Developed, Low Intensity	2,371.98	1.1%
Developed, Medium Intensity	578.69	0.3%
Developed, High Intensity	215.70	0.1%
Barren Land	147.92	0.1%
Deciduous Forest	7,494.68	3.5%
Evergreen Forest	31.95	0.0%
Mixed Forest	170.70	0.1%
Shrub/Scrub	888.24	0.4%
Herbaceous	77,914.57	36.6%
Hay/Pasture	19,414.52	9.1%
Cultivated Crops	92,092.60	43.3%
Woody Wetlands	1,580.99	0.7%
Emergent Herbaceous Wetlands	218.50	0.1%

Data

We used a telemetry dataset augmented with spatial-temporal variables. Whooping Crane occurrence data (2009–2017) were obtained from GPS-tagged individuals (n = 68) (Pearse, et al., 2015). There were records from 56 unique individuals (n = 1,253) for Kansas; all data points were included in the analysis. We generated 2,000 random points across the entire study space and used these as our pseudo-absence points (background data). Similar to the work done by (Okonye, Unpublished Thesis), we maintained a grid size of 1 km by 1 km to capture the environmental characteristics of the whooping crane. Land cover covariates, including wetland extent, agricultural land, urban areas, and road density, were sourced from the National Land Cover Database (NLCD). Bearing, which is the directional heading from the centroid of each cell toward the wintering ground in ANWR, was used to analyze broad-scale landscape interactions, while ecotone, as defined by (Okonye, Unpublished Thesis), was generated to investigate how fine-scale landscape factors impact stopover habitats.

New variables—latitude, longitude, and date—were incorporated to capture spatial gradients and seasonal trends. Date information was transformed from the Gregorian calendar date format to numeric values, and values were assigned by calculating the number of days since the Unix Epoch, R's default origin (1970-01-01). Random dates, within the study period, were generated and assigned to the pseudo-absence points. Wind power density data (W/m^2), produced by the National Renewable Energy Laboratory (NREL), was obtained from ESRI's Living (Davis, et al., 2023) and compared with the classified power density map for Kansas obtained from Data Basin https://databasin.org/datasets/. The two datasets showed similar information, and the density map from Data Basin was chosen for the analysis because the power classes had already been classified by the National Renewable Energy Laboratory (NREL).

All variables were standardized to ensure consistency across datasets. Spatial covariates were resampled to a 1 km^2 grid to align with the scale of the study. Multicollinearity among predictors was assessed at α=0.05 using a leave-one-out assessment (Sullins, et al., 2019).

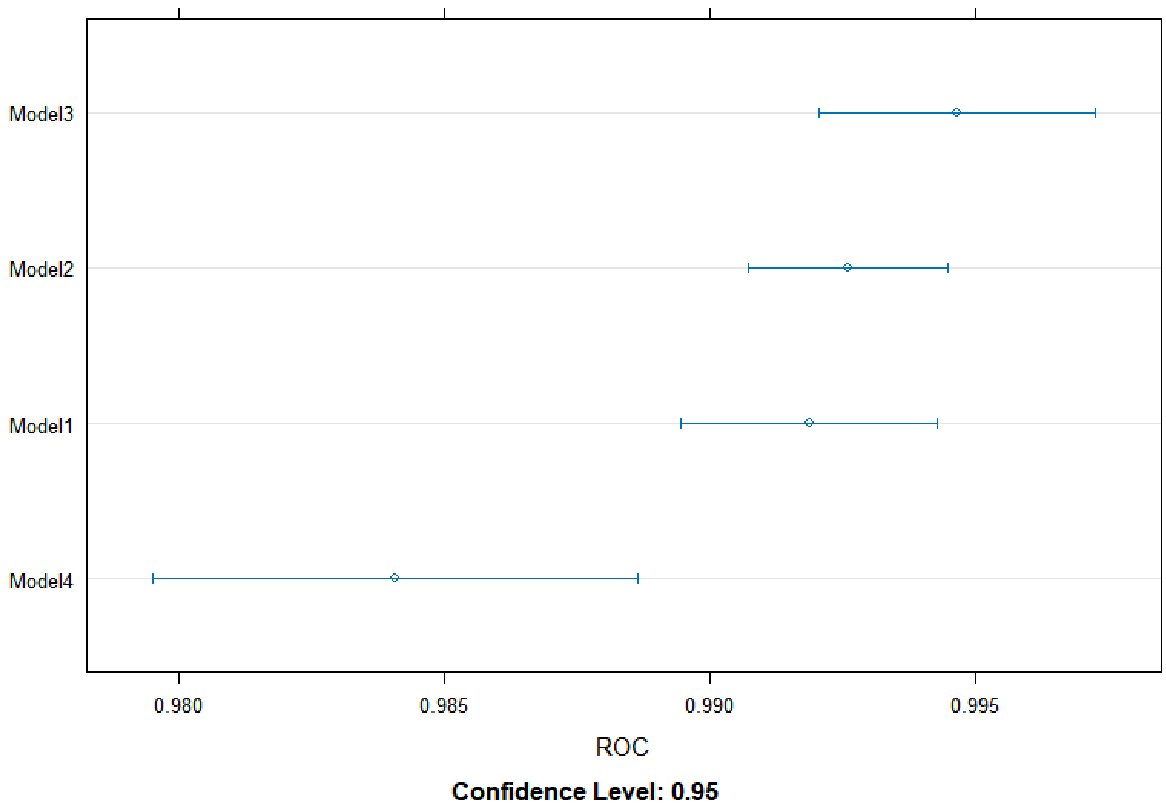
Species Distribution Model Improvement

For this study, we improved on the model developed by (Okonye, Unpublished Thesis) with the inclusion of spatial and temporal covariates, while fine-tuning model hyperparameters. The Random Forest algorithm was retained for its ability to handle non-linear relationships and complex interactions. The dataset was split into training (60%) and testing (40%) subsets, stratified by observation type and season to ensure balanced representation. A systematic model selection process was employed to identify the optimal combination of predictors (Table 5.2). This approach was used to find the most parsimonious model that does not fit noise. It allowed us to test the model parameters and select the model with the best error component. A 10-fold cross-validation was carried out, and the mean AUC was used to determine which of the parameter sets perform best. We then tested to see if the difference in AUC between the model parameters was significant (Figure 5.3), then chose the model with a high AUC and the fewest parameters (simpler model). To avoid overfitting, we carried out an independent test with a null/simpler model.

Table 5.2 Performance metrics and predictor variables for four habitat suitability models. Each model includes a subset of spatial and temporal predictors, with corresponding mean AUC, sensitivity, and specificity values based on 10-fold cross-validation.

Models	**Variables**	**Mean AUC**	**Mean Sensitivity**	**Mean Specificity**
Model 1	Ecotone, %cover of agricultural land, %cover of urban areas, %cover of wetlands, %cover of roads, Bearing, Longitude, Latitude, Date	0.9918703	0.9690	0.9433460
Model 2	Ecotone, %cover of agricultural land, %cover of wetlands, Bearing, Longitude, Latitude, Date	0.9926006	0.9695	0.9497333
Model 3	%cover of wetlands, Bearing, Longitude, Latitude, Date	0.9946432	0.9650	0.9681206
Model 4	%cover of wetlands, Bearing, Longitude	0.9840819	0.9290	0.9425333

Figure 5.2 95% confidence intervals (CIs) around the ROC scores for each model



The inclusion of latitude and longitude enabled the model to detect fine-scale spatial patterns of habitat selection, while date variables captured seasonal shifts in habitat use. Spatial coordinates revealed gradients in habitat suitability, with higher probabilities near known wetland complexes. These enhancements enabled the model to generate dynamic predictions, such as probability maps for user-specified dates and interannual corridor shifts. Performance was evaluated using AUC, accuracy, and out-of-bag error. Comparative analyses between Kansas and Nebraska were used to assess regional differences in variable importance, providing insights into landscape-specific habitat preferences.

Wind Resource and Site Suitability Analysis

To assess potential areas for wind energy development while minimizing impacts on Whooping Crane migration corridors, we integrated habitat suitability predictions with wind resource data. Wind resource data developed by the National Renewable Energy Laboratory (NREL), which provides wind power classification at 50m above ground level across the continental United States, was used. This level above ground was chosen because it represents standard wind turbine installation. The original vector-based wind power data, classified on a 1-7 scale (1 = poor, 7 = superb), were converted to a 1 km^2 resolution raster to match the scale of our habitat suitability analysis. There were only 6 classes of power density for Kansas (scale of 1-6). Following U.S. Department of Energy guidelines, we considered areas with wind class 4 (fair) or above as potentially viable for commercial wind development, as these represent the minimum threshold for economically feasible energy production.

The habitat suitability map generated by the Random Forest model provided continuous probability values (0-1) for crane stopover likelihood across the study area. To delineate suitable versus unsuitable areas, we established two classification thresholds with distinct ecological rationales. The first, Lowest Presence Threshold, identified unsuitable areas, as those with predicted values below the minimum suitability score observed at known crane stopover sites. The second threshold used a 10% omission rate, classifying 90% of known stopover sites as suitable while allowing a margin for error.

Using spatial overlay techniques, we combined wind resource and habitat suitability layers to categorize areas based on development potential and conservation priority. We then developed a suitability ranking system for wind energy development. Areas with both high wind resources (class $\geq$ 4) and low predicted crane use (below LPT) were assigned the highest priority for development, while those with good wind resources but overlapping moderate-to-high habitat suitability were flagged as exclusion or higher-risk zones requiring mitigation measures (Table 5.3).

Table 5.3 Priority Zoning Based on Wind Potential and Whooping Crane Habitat Conflict Risk

Priority Zone	Definition	Total Land Area km^2 (Percent of Study Area)
Priority 1	Areas with fair or better wind potential with unsuitable stopover areas as designated by the lowest presence threshold; areas are of the lowest risk for conflict with WHCR.	91,587 (43.1%)
Priority 2	Areas with fair or better wind potential with unsuitable stopover areas as designated by the 10% omission error threshold; areas involve a slightly higher risk for conflict with WHCR.	46,040 (21.67%)
Exclusion Zone	Areas with an overlap of fair or better wind potential with predicted stopover habitat for whooping cranes designated by the 10% omission error threshold; areas involve the greatest risk of conflict with WHCR.	24,408 (11.49%)
Unranked	Inadequate wind resource potential	50,456 (23.75%)

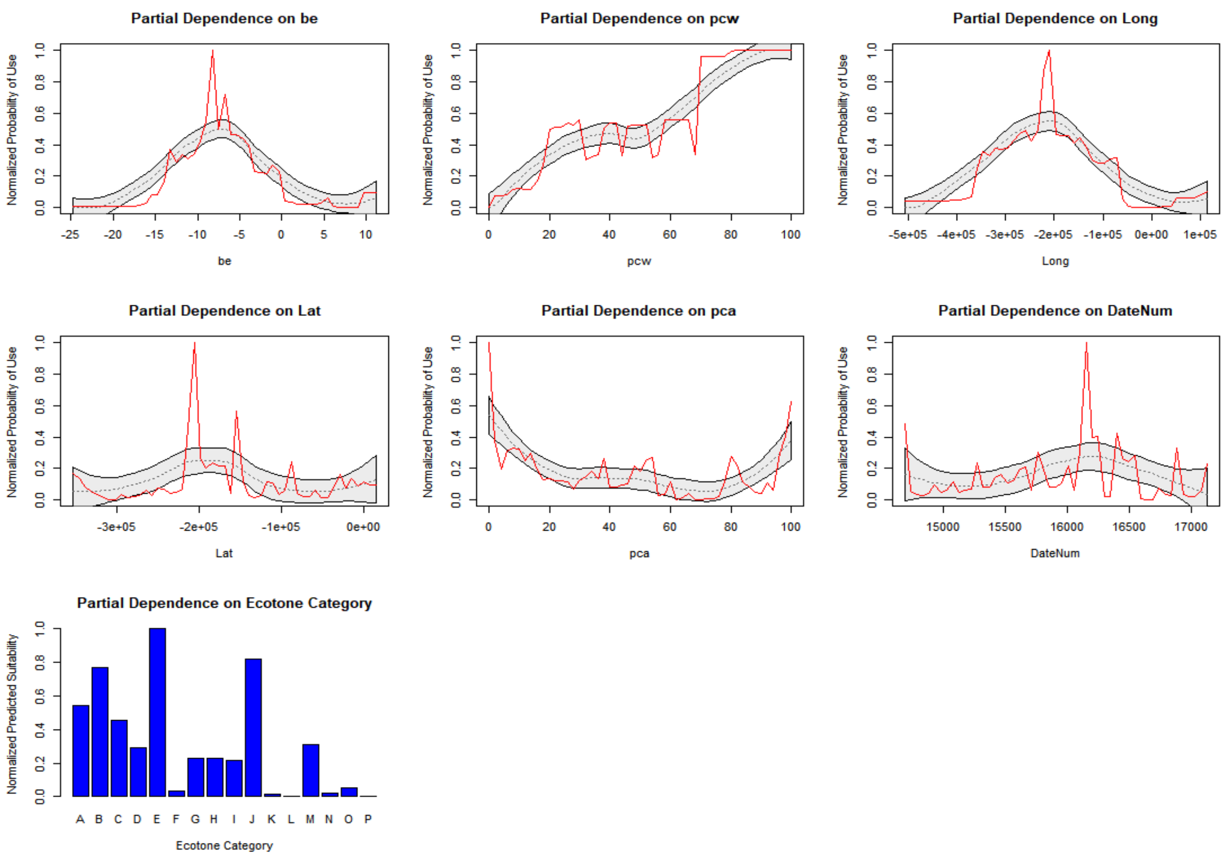
Conflict Analysis with Existing Wind Infrastructure

To evaluate current overlaps between wind energy infrastructure and critical crane habitats, we incorporated data from the U.S. Wind Turbine Database, which provides georeferenced locations of all utility-scale turbines in the study area. We analyzed the spatial distribution of turbines relative to medium- to high-suitability stopover habitats (probability > 0.4). Proximity buffers of 5 km were applied to each turbine to account for both direct collision risk and potential displacement effects, as cranes may avoid areas near wind infrastructure even if not directly at risk of collision.

Results

The enhanced Random Forest model demonstrated significant improvements in predictive performance compared to the original framework. By incorporating spatial-temporal variables, the model achieved an AUC score of 0.98, representing a 2% increase over the previous version. This heightened accuracy was particularly evident in the model's ability to distinguish between suitable and unsuitable habitats during validation testing, where it correctly classified 94% of presence and pseudo-absence points over the previous 90%. The temporal components proved especially valuable, contributing a 5% boost in predictive power by capturing seasonal variations in habitat use that were previously unaccounted for (Figure 5.3).

Figure 5.3 Partial dependency plots of predictor variables showing individual effects on predicted suitability



Temporal Analysis

The inclusion of a temporal variable detected seasonal trends, with wetland reliance increasing in the spring migration (Table 5.4) and adherence to the center of the migratory corridor being a top priority in Fall (Figure 5.4). The model generated probability maps for specific dates and seasons, enabling real-time corridor monitoring. For example, maps for spring 2015 showed concentrated suitability aligned with wetland clusters, while fall 2015 revealed a streamlined and concentrated corridor aligned with the center of the flyway (Figure 5.5).

Analysis on how variables change from one year to the next reveals a change in preference depending on climatic conditions during migration. From 2010 to 2012, we saw a shift in wetland importance. In 2010, when there were normal precipitation conditions, wetlands were not as important as they were in 2012 (Table 5.5), which was a drought year in Kansas. We see cranes actively select for wetlands as a result of the drier conditions in the state in 2012 (Figure 5.6). As a result, we see a narrowing of the migratory corridor in 2012 (Figure 5.7)

Table 5.4 Change in Mean Decrease in Accuracy from Spring 2015 to Fall 2015.

Variables	Spring 2015	Fall 2015
Longitude	*22.50*	*27.43*
Latitude	*21.07*	*15.33*
Bearing	*21.72*	*26.72*
% Cover of Wetlands	*22.99*	*19.53*
% Cover of Agric Land	*19.72*	*12.29*
% Cover of Urban Areas	*10.33*	*12.05*
% Cover of Roads	*15.27*	*13.15*
Ecotone Categories	*10.15*	*17.64*

Figure 5.4 Variations in variable importance between migration seasons (Spring and Fall)

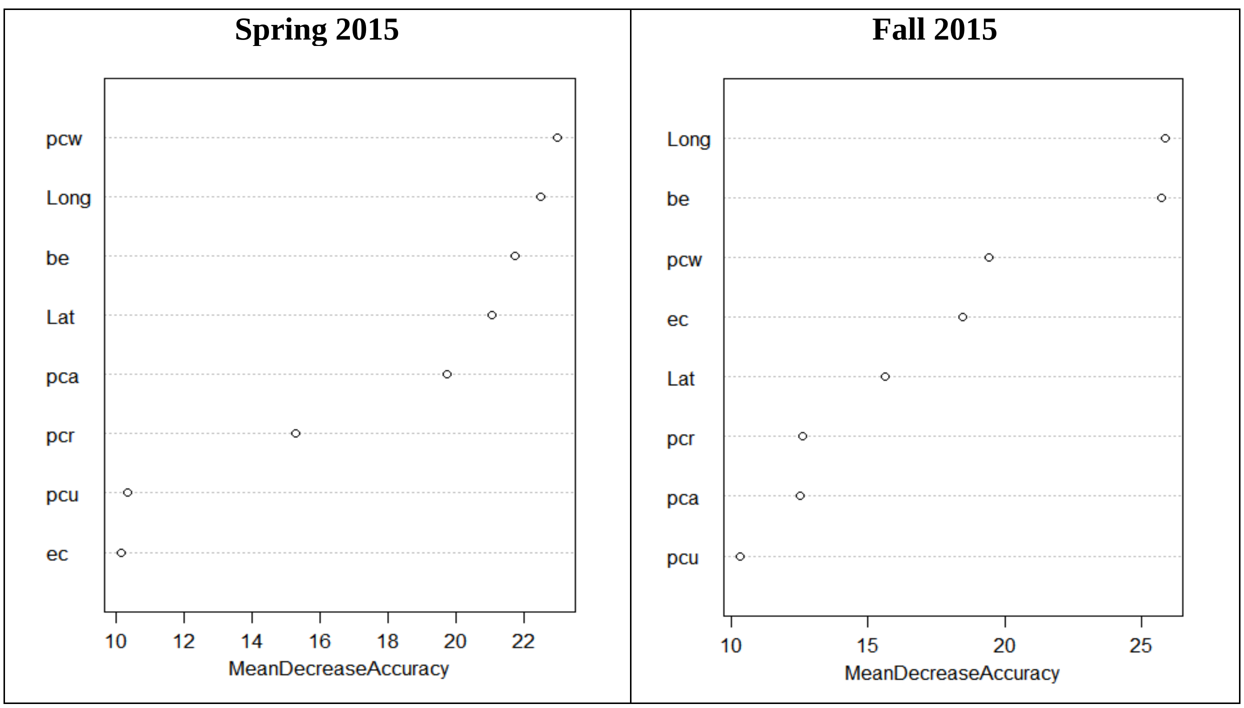


Figure 5.5 Comparison between Spring and Fall migration. A) shows the relative probability of use in Spring 2015. B) shows the relative probability of use in Fall 2015.

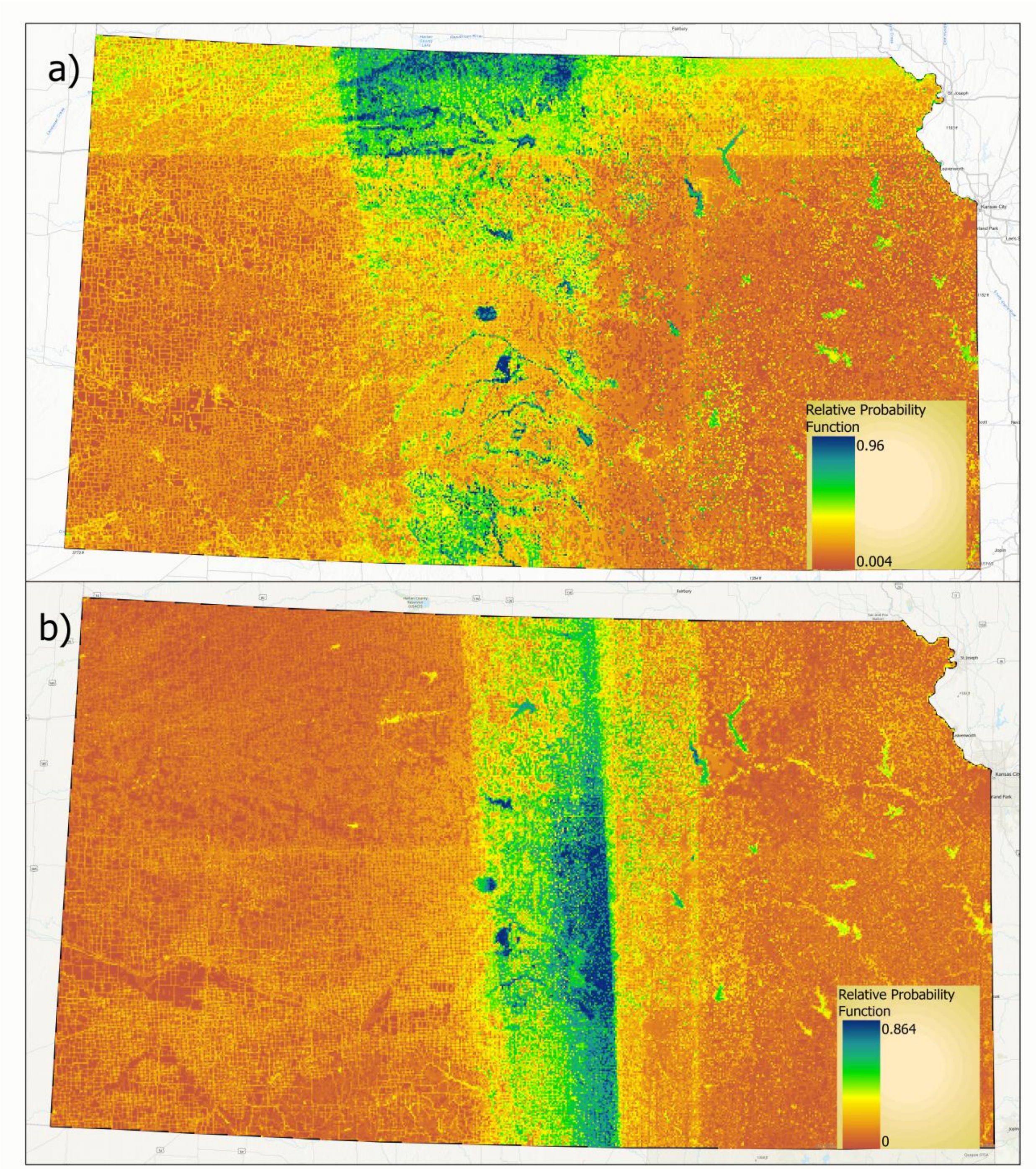


Table 5.5 Change in Mean Decrease in Accuracy from 2010 to 2012.

Variables	Year 2010	Year 2012
Longitude	*34.77*	*42.46*
Latitude	*26.17*	*29.05*
Bearing	*31.54*	*40.89*
% Cover of Wetlands	*15.51*	*48.18*
% Cover of Agric Land	*22.10*	*29.79*
% Cover of Urban Areas	*13.77*	*13.77*
% Cover of Roads	*15.80*	*20.96*
Ecotone Categories	*14.84*	*22.12*

Figure 5.6 Variations in variable importance between years (2010 and 2012).

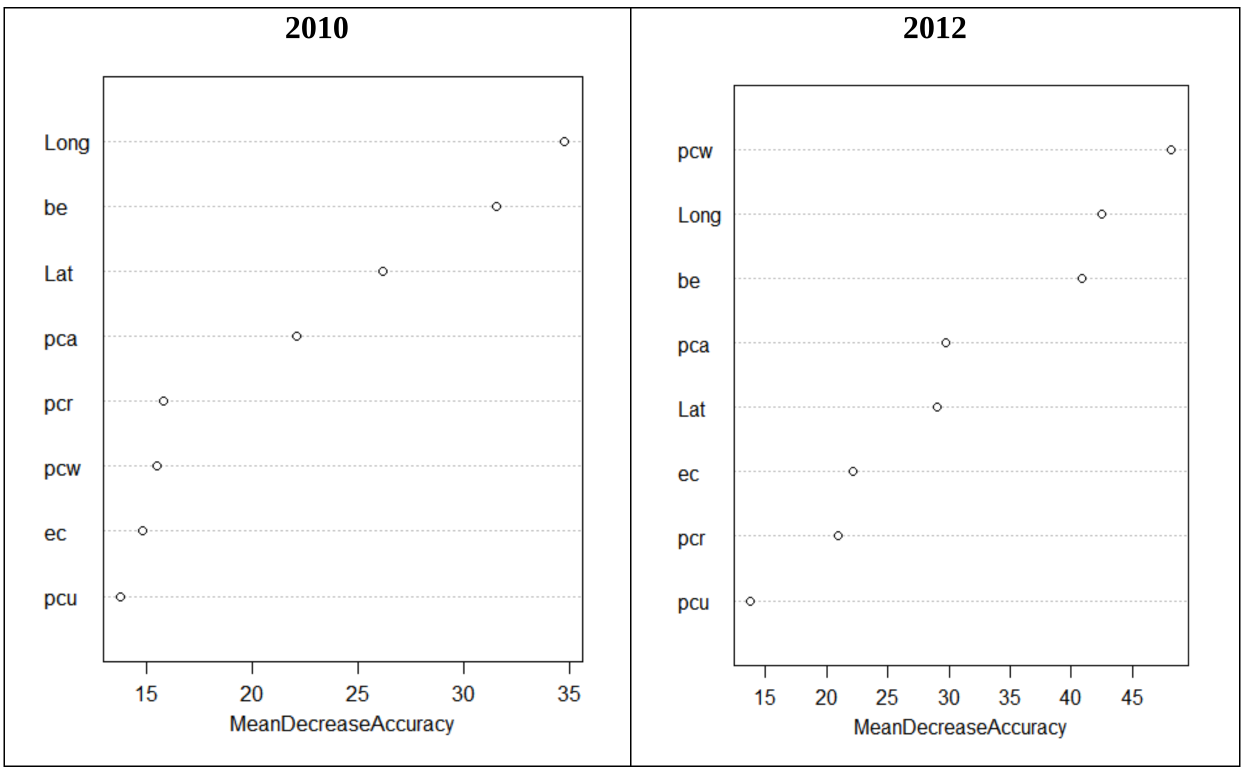
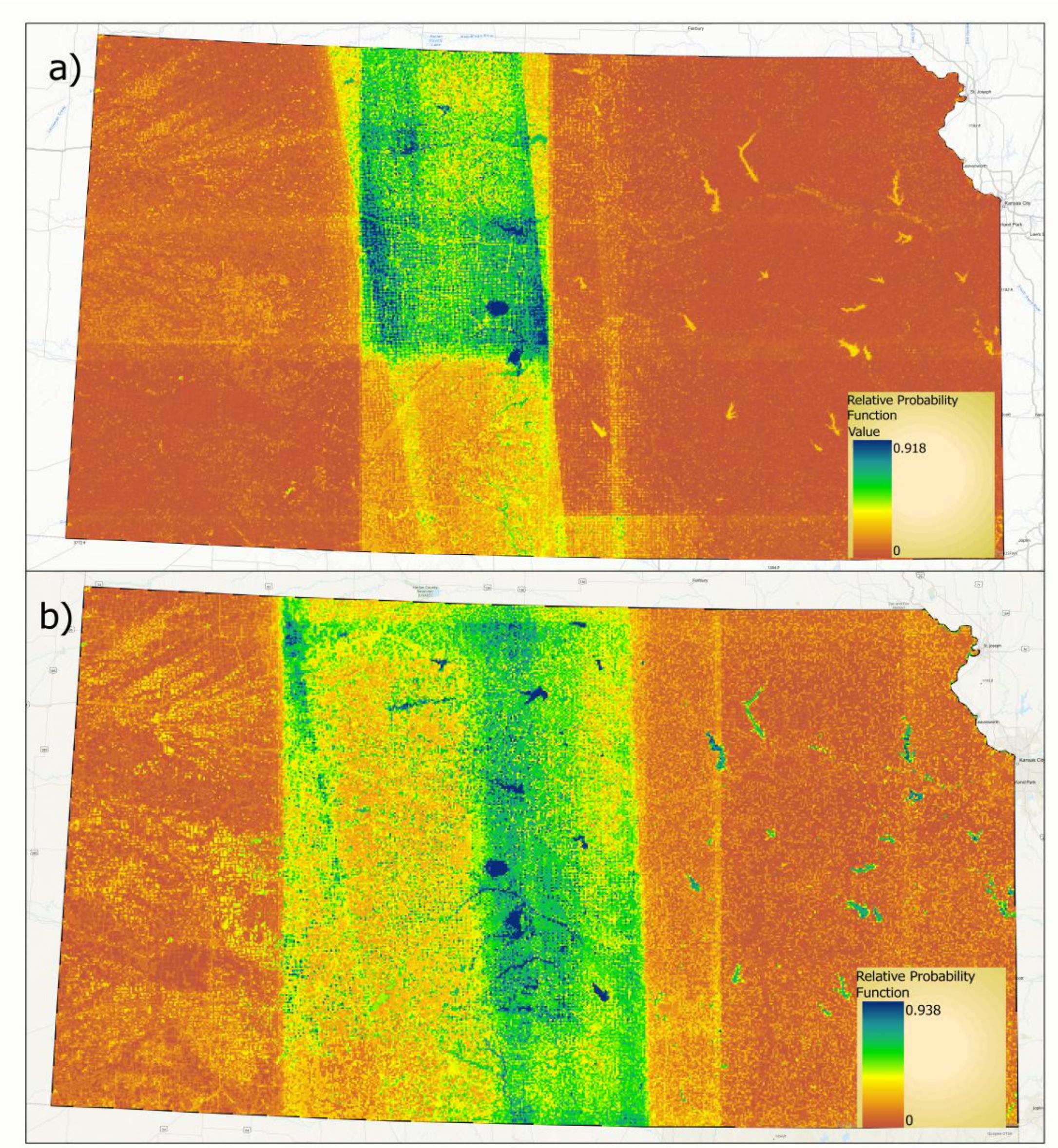
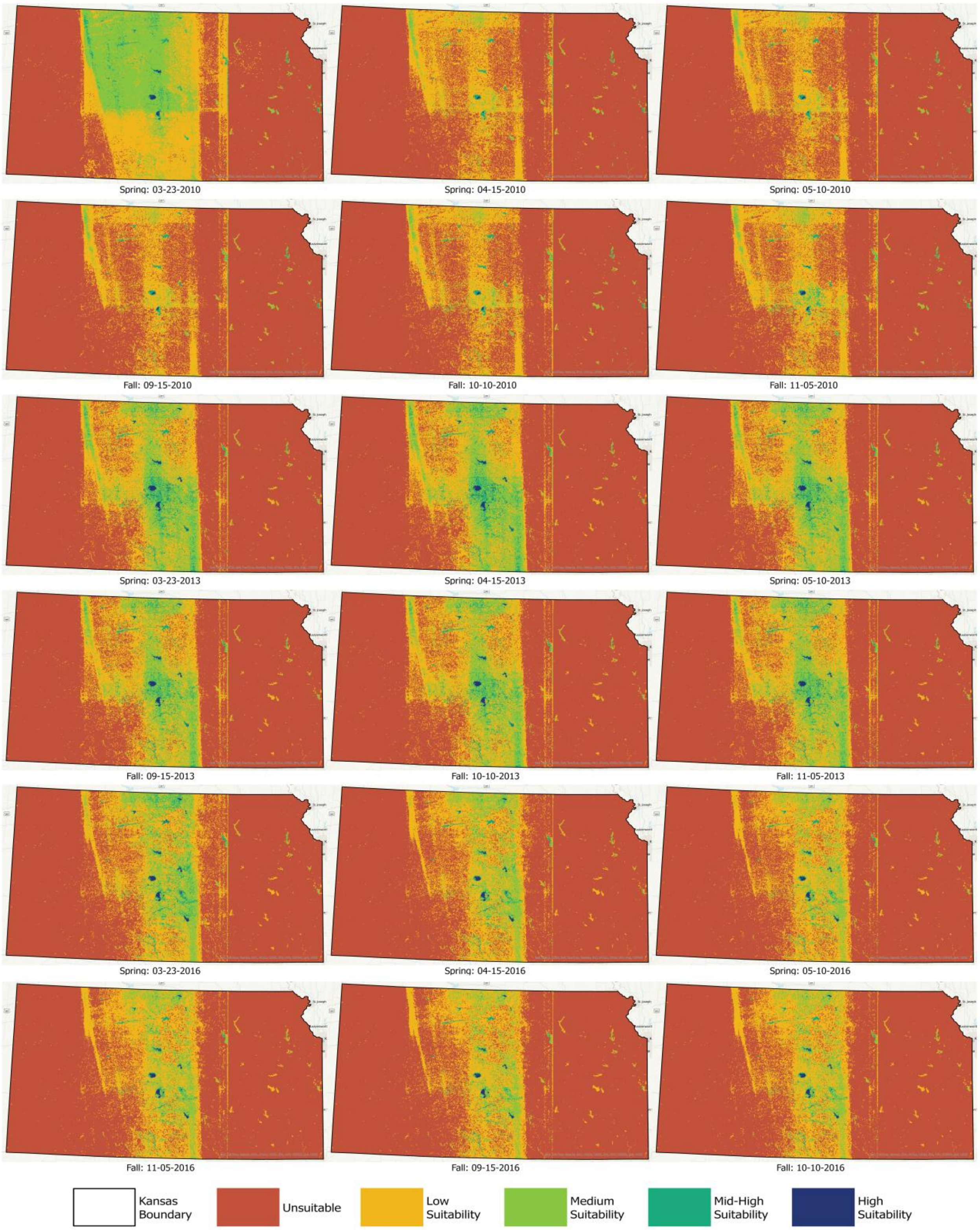


Figure 5.7 Comparison between years. A) shows the relative probability of use in 2010. B) shows the relative probability of use in 2012.



The time-series maps from 2010 to 2016 showed a gradual northward displacement of the core migratory flyway, with particularly pronounced shifts following severe drought years in 2012 and 2013 (Figure 5.5). These dry periods corresponded with fragmented habitat patterns and reduced wetland availability in the southern portions of the flyway. Seasonal comparisons revealed that spring migrations typically followed broader corridors than fall journeys, potentially due to more favorable wind conditions or greater flexibi lity in timing.

Figure 5.8 Time Series Maps (2010–2016) at 3-Year Intervals. *Original images can be found in Appendix C.*

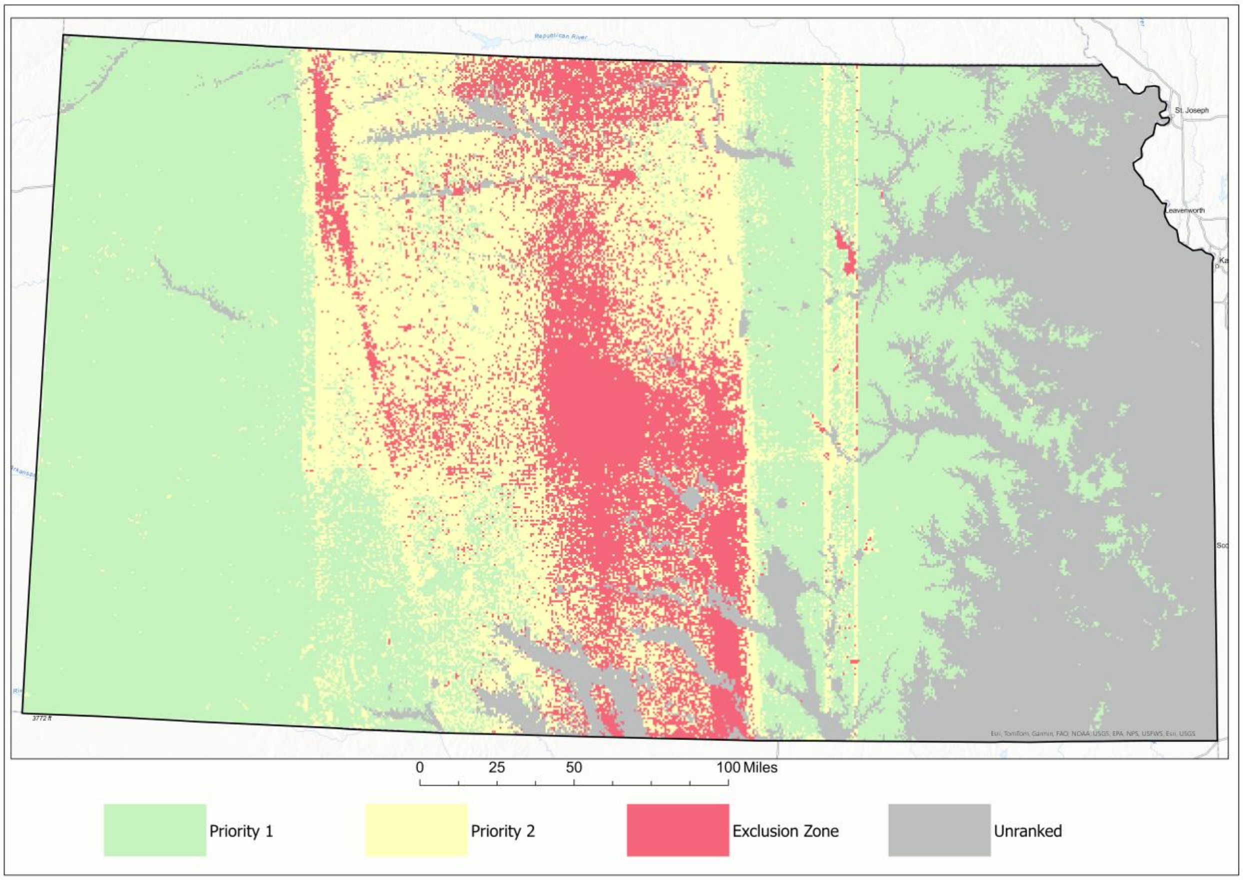


Wind Resource and Site Suitability Analysis

The analysis revealed significant spatial variation in the overlap between wind energy potential and Whooping Crane habitat suitability across Kansas. Large portions of the state's western region, characterized by intensive agriculture and limited wetland cover, showed both medium-high wind resources (> 300 W/m²) and low predicted habitat suitability for Whooping Cranes (probability of use < 0.14). Approximately 91,587km² (43.1% of the state) met these criteria, representing prime locations for low-impact wind energy development (Figure 5.6). These areas were predominantly located in the High Plains ecoregion, where consistent wind patterns and open landscapes offered favorable conditions for turbines while posing minimal risk to crane populations.

When applying a more moderate threshold for habitat suitability (probability of use < 0.378), an additional 46,040km² (21.67% of the state) became available for consideration, bringing the total suitable area to 137,627 km² (64.8% of the state). This expansion included marginal agricultural zones with intermediate wind potential (400–600 W/m²), where careful site planning could further minimize ecological disruption. Notably, these areas avoided critical wetland complexes, which remained high-priority exclusion zones due to their consistent use by migrating cranes. Eastern Kansas exhibited limited opportunities for wind development, as higher habitat suitability values frequently coincided with moderate wind resources. Only 6% of this region met the criteria for low-impact development, primarily in fragmented cropland patches adjacent to urban centers.

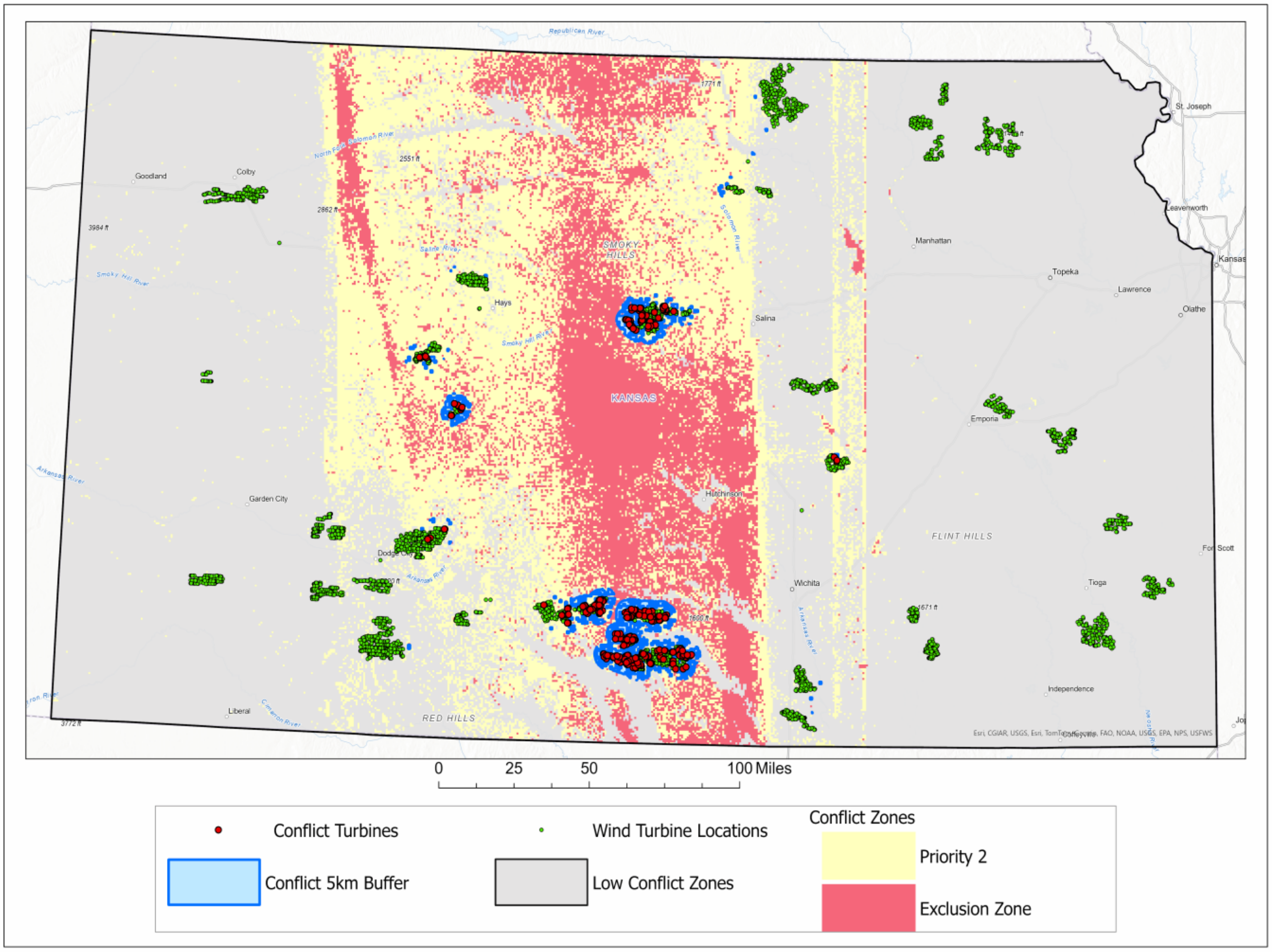
Figure 5.9 Wind-Power Site Suitability Ranking within the State



Conflict Analysis with Existing Wind Infrastructure

Our analysis of existing wind turbine locations relative to medium-high suitability whooping crane habitats revealed significant spatial overlap in portions of the Central Flyway. Of the 4,395 operational turbines identified within the study area through the U.S. Wind Turbine Database, 344 (7.83%) were located within 5 km of habitats classified as medium- to high-probability stopover sites (suitability > 0.4) (Figure 5.7). For instance, the Spearville Wind Farm, one of the largest in the state, lies adjacent to key stopover sites along the Arkansas River, raising concerns about cumulative impacts on migratory pathways. The spatial distribution of conflicts showed distinct patterns when examined by habitat type. There were no wetland-associated high-risk installations, but turbines in agricultural areas (n = 195) and herbaceous grasslands (n = 143) demonstrated lower per-unit conflict, as these landscapes generally had lower baseline habitat suitability.

Figure 5.10 Areas of wind turbine conflict



Temporal analysis of turbine installation dates revealed an increasing trend in habitat conflicts, with 83.43% of high-risk turbines commissioned after 2010. This coincides with the period of most rapid wind energy expansion in the Great Plains and suggests that recent development has occurred without systematic consideration of migratory corridor impacts.

Discussion

The enhanced model's ability to incorporate both spatial and temporal dimensions represents a significant advancement in understanding Whooping Crane migratory ecology. By integrating latitude, longitude, and date variables, we've moved beyond static snapshots of habitat suitability to capture the dynamic nature of migration corridors. This temporal resolution revealed critical patterns that would otherwise remain obscured, particularly the northward shift in corridor use following drought years and the seasonal expansion and contraction of stopover sites. These findings carry important implications for conservation planning in an era of climate change, where shifting precipitation patterns and more frequent extreme weather events may increasingly disrupt traditional migratory pathways. The model's high predictive performance (AUC = 0.98) demonstrates that these spatiotemporal variables substantially improve our ability to forecast habitat use under changing environmental conditions.

The application of this modeling framework extends beyond Whooping Cranes to inform conservation of other migratory species facing similar challenges. The methods developed here could be adapted for species ranging from shorebirds to waterfowl, though careful consideration must be given to differences in habitat requirements and movement ecology. However, several limitations temper the immediate applicability of these results. The reliance on presence-only data may bias predictions toward frequently used areas while overlooking potentially suitable but unoccupied habitats. The 1 km^2 resolution of land cover data, while appropriate for broad-scale patterns, may miss fine-scale habitat features important for stopover site selection. Future research should incorporate higher-resolution remote sensing data and experimental validation of habitat preferences to address these limitations.

Perhaps most importantly, this study demonstrates how ecological modeling can directly inform land-use planning and policy decisions. The spatial overlap analysis between crane habitats and wind resources provides a blueprint for balancing renewable energy development with species conservation. By identifying specific areas where wind potential is high and habitat suitability is low, we've created a practical tool for minimizing conflicts. However, realizing this potential will require close collaboration between conservation biologists, energy developers, and policymakers to implement science-based siting guidelines and mitigation measures. As renewable energy expansion continues across the Central Flyway, such integrated approaches will be essential for achieving both climate goals and biodiversity conservation targets.

Looking forward, this research points to several promising directions for advancing migratory species conservation. Incorporating real-time tracking data could enable dynamic corridor mapping that responds to annual environmental conditions. Expanding the temporal scope to include climate change projections would help anticipate future shifts in habitat suitability. Most crucially, these scientific advances must be paired with stronger policy frameworks and stakeholder engagement to ensure that modeling insights translate into on-the-ground conservation outcomes. The whooping crane's recovery story demonstrates what's possible when science, policy, and public support converge. This study aims to build on that legacy by providing the tools to navigate an increasingly complex conservation landscape.

Conservation Strategies

The findings of this study provide a robust foundation for proactive conservation planning, which offers strategies that can be put to action to safeguard whooping crane habitats while accommodating the growing demands of renewable energy development. These results have important implications for conservation planning, showing that Whooping Cranes demonstrate behavioral plasticity in their habitat selection, therefore, the same conservation strategies should not be adopted for all regions along the migratory corridor. The high suitability of areas with wetland-adjacent habitats suggests that efforts should prioritize preserving and restoring wetlands, particularly those near existing agricultural landscapes, to maintain ecological functionality within the migratory corridor.

By integrating dynamic habitat suitability models with wind resource data, this research identifies critical stopover sites that must be prioritized for protection, as well as areas where wind energy projects could be developed with minimal ecological disruption. The spatial-temporal approach reveals how migratory corridors shift in response to environmental changes, enabling managers to anticipate and mitigate future conflicts. For instance, the identification of high-probability habitats in Kansas emphasizes the need for stringent protection in these regions, including buffer zones and restrictions on infrastructure development.

Wind energy developers can leverage the study's suitability maps to guide project siting, ensuring turbines are placed in areas with low predicted crane activity. The analysis highlights western Kansas as optimal for low-impact development, where high wind potential coincides with low habitat suitability. However, even in these zones, precautionary measures—such as turbine shutdowns during peak migration periods and the use of radar systems to detect approaching flocks—can further reduce risks. Collaboration between conservationists, policymakers, and energy companies is essential to implement these strategies effectively. Policies that mandate pre-construction habitat assessments and incentivize wildlife-friendly siting practices can help balance renewable energy goals with species protection.

Chapter 6 - Synthesis Conclusion

This research aimed to improve our understanding of whooping crane stopover habitat by creating a spatiotemporal model to evaluate habitat suitability in Kansas Building on an earlier habitat suitability model for Nebraska, the study addressed four related objectives including (1) determining environmental predictors of whooping crane, (2) modeling spatiotemporal variation in stopover habitat selection across Kansas using advanced machine learning, (3) comparing habitat drivers between the two states to understand regional differences in landscape use, and (4) combining wind energy potential mapping with habitat suitability to find low-impact areas for development. These objectives came from gaps in the existing literature, particularly the lack of dynamic, fine-scale models that account for both seasonal migration and interannual habitat change, especially in Kansas. By combining machine learning, geospatial analysis, and conservation science, this work fills an important knowledge gap in stopover ecology and provides a data-driven framework to balance species conservation with renewable energy development.

The new model with spatial (latitude, longitude) and temporal (seasonal date) variables had much better predictive ability (AUC = 0.98) than the static model. Spatial analysis showed fundamental differences in habitat selection, with wetland cover being the dominant variable for habitat suitability in Kansas and distance away from roads being more important in Nebraska, reflecting landscape-driven adaptations. Temporally, drought triggered a northward corridor shift post-2013, showing climate sensitivity. Most importantly, overlay analysis found 91,587 km² of high wind potential areas (class ≥3) overlapped with low suitability crane habitats, mostly in western Kansas. With wind resource data, low-conflict zones were identified where wind energy development can occur with minimal ecological impact.

Whooping cranes rely on a network of ephemeral and variable habitats, therefore static conservation models fail to capture the complexity of their spatial ecology. By incorporating time-sensitive and location-specific predictors and predicting habitat suitability across space and time, resource managers can proactively safeguard wetlands while managing agricultural landscapes to reduce displacement. Identifying drought-sensitive habitats allows for pre-emptive management of alternative stopover sites before water shortages occur. The strong avoidance of urban areas (Std. MDA 0.46 in Kansas) means we need to strength management around critical wetlands and the nuanced relationship with agriculture (moderate use near wetlands but avoidance of intensive fields) means we have opportunities for working lands conservation programs. Protecting migratory corridors through this kind of modeling ensures not only the survival of endangered species but also the ecosystem services supported by intact wetland and grassland systems. This study shows the value of geospatial tools in identifying “ecological traps” (e.g., suitable habitats next to turbines and powerlines) and prioritizing restoration sites. This shifts conservation from reactive to proactive, so habitat can be resilient in the face of land use and climate change.

Kansas is a key player in the national transition to renewable energy, especially with the expansion of wind farms across the prairie. This study showed that it is possible to reconcile biodiversity conservation with clean energy development. The wind energy suitability overlay was a practical tool to identify areas of high energy potential that don’t overlap with critical stopover habitats. This is the concept of “coexistence landscapes”, where infrastructure planning incorporates ecological priorities from the onset. The conflict analysis between wind turbines and crane habitats showed that 7.83% of existing turbines in Kansas are within 5 km of high suitability zones. To improve coexistence, a three-tiered approach is proposed: (1) Strategic siting by directing wind farms to pre-identified low-impact areas, (2) seasonal curtailments that reduce turbine operation during peak migrations (April and October), and (3) ecological buffers based on a 5 kilometer no-development zones around critical wetlands. This can protect cranes and provides regulatory certainty for energy companies navigating endangered species compliance to ensure important ecological thresholds are respected.

While the model achieved strong performance, certain limitations should be considered while interpreting results. First, the spatial resolution of the environmental layers ($1km^2$), while appropriate for landscape-scale analysis, may not capture fine-scale habitat features important for crane selection, like isolated prairie potholes that are emergency stopovers. Second, telemetry data, though precise, overrepresent adult survival and may underestimate juvenile habitat preferences. Third, generated pseudo-absence points may introduce potential bias. Fourth, the wind infrastructure dataset is comprehensive but may not capture all planned or small-scale developments and lacks operational details (e.g., turbine height) that affect collision risk. Lastly, the temporal window (2010-2016) may not fully reflect recent climatic variability or development trends. The model assumes current land use patterns will persist, while climate projections suggest radical wetland shifts in the Great Plains (Xu, et al., 2024). While these limitations don't invalidate the findings, they emphasize the need for continuous and adaptive frameworks that incorporate uncertainty.

Future research should include high-resolution environmental data to increase model resolution and validation by showing fine-scale vegetation structure preferences. Expanding the model to include climate projections will give foresight into corridor shifts under future scenarios. Applying this method to the entire Central Flyway or other at-risk migratory species will test generalizability and increase conservation impact. Finally, evaluating the real-world effectiveness of habitat-informed siting decisions—via post-installation monitoring of wind facilities—will provide critical feedback for adaptive management.

As pressure to meet renewable energy targets while conserving biodiversity increases, spatially explicit, evidence-based tools like this are more important than ever. This research shows that conservation isn't a constraint on development, but can instead be a guiding principle for better land use. It shows how interdisciplinary collaborations, combining geography, ecology, and renewable energy planning, can coexist. By mapping the exact intersections between crane habitats and energy infrastructure, we've moved beyond blanket opposition to renewable energy and towards smart siting that serves both climate and biodiversity goals. The path forward isn't through less technology or more wilderness, but through better geography - the science of how we organize our shared space in ways that honor ecological connections while meeting human needs.

References

Allen, R. P. (1952). *The Whooping Crane* (3rd ed.). New York 28, New York, United States of America: National Audubon Society.

American Bird Conservancy. (2021, March 17). *Wind Turbines Deter Whooping Cranes From Stopover Sites, Study Confirms*. Retrieved from American Bird Conservancy: https://abcbirds.org/news/wind-turbines-deter-whooping-cranes-from-stopover-sites-study-confirms/

Amici, V., Eggers, B., Geri, F., & Battisti, C. (2013, May 09). Habitat Suitability and Landscape Structure: A Maximum Entropy Approach in a Mediterranean Area. *Landscape Research, 40*(2), 208-225. doi:10.1080/01426397.2013.774329

Andrén, H. (1994, Decenmber). Effects of Habitat Fragmentation on Birds and Mammals in Landscapes with Different Proportions of Suitable Habitat: A Review. *Oikos, 71*(3), 355-366. Retrieved from https://doi.org/10.2307/3545823

Armbruster, M. J. (1990). *Characterization of Habitat Used by Whooping Cranes During Migration.* U.S. Department of the Interior . Springfield, VA : U.S> Fish and Wildlife Service.

Arzel, C., Elmberg, J., & Guillemain, M. (2006, April). Ecology of spring-migrating Anatidae: A review. *Journal of Ornithology, 147*(2), 167-184. Retrieved from http://dx.doi.org/10.1007/s10336-006-0054-8

Austin, J. E., & Richert, A. L. (2001). *comprehensive review of observational and site evaluation data of migrant whooping cranes in the United States, 1943–99.* Jamestown, North Dakota: U.S. Geological Survey, Northern Prairie Wildlife Research Center .

Austin, J. E., & Richert, A. L. (2005). Patterns of Habitat Use by Whooping Cranes During Migration: Summary form 1977-1999 Site Evaluation Data. *Proceedings of the Ninth North American Crane Workshop* (pp. 79-104). Sacramento, California: North American Crane Working Group.

Austin, J., & Richert, A. (2001). *A Comprehensive Review of Observational and Site Evaluation Data of the Migrant Whooping Crane.* Northern Prairie Wildlife Research Center. Reston: U.S. Geological Survey. Retrieved from https://pubs.usgs.gov/unnumbered/93805/report.pdf

Austin, J., Morrison, K., & Harris, J. (2018). *Cranes and Agriculture: A Global Guide for Sharing the Landscape.* Wisconsin, USA: The International Crane Foundation.

Austin, J., Morrison, K., & Harris, J. (2018). *Cranes and Agriculture: A Global Guide for Sharing the Landscape.* Baraboo, Wisconsin, USA: International Crane Foundation.

Baasch, D. M., Farrell, P. D., Pearse, A. T., Brandt, D. A., & Caven, A. J. (2019). Diurnal habitat selection of migrating Whooping Crane in the Great Plains. *USGS Northern Prairie Wildlife Research Center*, *14*(1), 1-16. doi:https://doi.org/10.5751/ACE-01317-140106

Baasch, D. M., Farrell, P. D., Pearse, A. T., Brandt, D. A., Caven, A. J., Harner, M., . . . Metzger, K. (2019). Diurnal habitat selection of migrating Whooping Crane in the Great Plains. *USGS Northern Prairie Wildlife Research Center, 14*(1), 1-16. doi:https://doi.org/10.5751/ACE-01317-140106

Baasch, D., Farrell, P., Pearse, A., Brandt, D., & Caven, A. (2019). Diurnal Habitat Selection of migrating Whooping Crane in the Great Plains. *Avian Conservation and Ecology, 14*(1). doi:10.5751/ACE-01317-140106

Bailey, R. G., Avers, P., King, T., & McNab, W. (1994). *Ecoregions and Subregions of the United States [Map].* Washington, D.C., U.S: Department of Agriculture–Forest Service. doi:10.3133/70250183

Barbet-Massin, M., Jiguet, F., Albert, C. H., & Thuille, W. (2012, January 19). Selecting pseudo-absences for species distribution models: how, where and how many? *Methods in Ecology and Evolution, 3*(2), 327-338. Retrieved from https://doi.org/10.1111/j.2041-210X.2011.00172.x

Becker, E., Carretta, J., Forney, K., Barlow, J., Brodie, S., Hoopes, R., . . . Hazen, E. (2020, May 11). Performance evaluation of cetacean species distribution models developed using generalized additive models and boosted regression trees. *Ecology and Evolution*, 5759-84. Retrieved from https://doi.org/10.1002/ece3.6316

Belaire, A. J., Kreakie, B. J., Keitt, T., & Minor, E. (2013, July 17). Predicting and Mapping Potential Whooping Crane Stopover Habitat to Guide Site Selection for Wind Energy Projects. *Conservation Biology, 28*(2), 541-550. doi:10.1111/cobi.12199

Belaire, A. J., Kreakie, B. J., Keitt, T., & Minor, E. (2014, July 17). Predicting and Mapping Potential Whooping Crane Stopover Habitat to Guide Site Selection for Wind Energy Projects. *Conservation Biology, 28*(2), 541-550. doi:10.1111/cobi.12199

Belaire, J. A., Kreakie, B. J., Keitt, T., & Minor, E. (2014, April). Predicting and mapping potential Whooping Crane stopover habitat to guide site selection for wind energy projects. *Conservation Biology, 28*(2), 541-50. doi:10.1111/cobi.12199

Belgiu, M., & Drăguţ, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS Journal of Photogrammetry and Remote Sensing, 114*, 24-31. Retrieved from https://doi.org/10.1016/j.isprsjprs.2016.01.011

Berthold, P. (2001). *Bird Migration: A General Survey.* New York: Oxford University Press. Retrieved from https://doi.org/10.1093/auk/119.3.874

Bidwell, M., & Conkin, J. (2023). *Recovery and Ecology of Endangered Whooping Cranes: Monitoring of the Aransas-Wood Buffalo Population during the 2021 Breeding Season.* Government of Canada.

Booth, T. (1985, September). A new method for assisting species selection. *The Commonwealth Forestry Review, 64*(3), 241-250. Retrieved from https://www.jstor.org/stable/42608049

Breiman, L. (2001). Random forests. *Machine Learning, 45*(1), 5-32.

Brizuela-Torres, D., Elith, J., Guillera-Arroita, G., & Briscoe, N. (2024, January 16). Dealing with sampling bias and inferring absence data to improve distribution models of a widely distributed vulnerable marsupial. *Austral Ecology, 49*(1), e13474. Retrieved from https://doi.org/10.1111/aec.13474

Burke, I., Kittel, T., Lauenroth, W., Snook, P., Yonker , C., & Parton , W. (1991, November). Regional Analysis of the Central Great Plains: Sensitivity to climate variability. *BioScience, 41*(10), 685-692. Retrieved from https://doi.org/10.2307/1311763

Canadian Wildlife Service and U.S. Fish and Wildlife Service. (2007). *International recovery plan for the whooping crane.* Albuquerque, New Mexico: Ottawa: Recovery of Nationally Endangered Wildlife (RENEW), and U.S. Fish and Wildlife Service.

Carlisle, J. D., Skagen, S. K., Kus, B. E., Van Riper III, C., Paxtons, K. L., & Kelly, J. F. (2009, May 1). Landbird Migration in the American West: Recent Progress and Future Research Directions. *The Condor, 111*(2), 211-225. Retrieved from https://doi.org/10.1525/cond.2009.080096

Caven, A., Pearse, A., Brandt, D., Harner, M., Wright, G., Baasch, D., . . . Lacy, A. (2022). WHooping Crane Stay Length in Relation to Stopover Site Characteristics. *PROCEEDINGS OF THE NORTH AMERICAN CRANE WORKSHOP, 15*, 6-33.

Caven, A., Rabbe, M., & Malzahn, J. (2020). Trends in the occurrence of large Whooping Crane groups during migration in the great plains, USA. *Heliyon, 6*(4), e03549. doi:10.1016/j.heliyon.2020.e03549

Chuprunov, A., & Fazekas, I. (2009, March 11). Strong laws of large numbers for random forests. *Acta Mathematica Hungarica, 124*, 59-71. Retrieved from https://doi.org/10.1007/s10474-009-8150-x

Coxen, C., Frey, J., Carleton, S., & Collins, D. (2017, July). Species distribution models for a migratory bird based on citizen science and satellite tracking data. *Global Ecology and Conservation, 11*, 298-311. Retrieved from https://doi.org/10.1016/j.gecco.2017.08.001

Cressie , N. (1990, April). The origins of kriging. *Mathematical Geology, 22*, 239252. Retrieved from https://doi.org/10.1007/BF00889887

Cutler, R. D., Edwards, J. T., Beard, K. H., Cutler, A., Hess, K. T., Gibson, J., & Lawler, J. J. (2007, December). Random Forests for Classification in Ecology. *Ecology, 88*(11), 2783-2792. doi:10.1890/07-0539.1

Davis, N., Badger, J., Hahmann, A., Hansen, B., Mortensen, N., Kelly, M., . . . Drummond, R. (2023). The Global Wind Atlas: A High-Resolution Dataset of Climatologies and Associated Web-Based Application. *Bulletin of the American Meteorological Society, 104*(8), E1507-E1525. Retrieved from https://doi.org/10.1175/BAMS-D-21-0075.1

Drew, A., Wiersma, Y., & Huettmann, F. (2010). *Predictive Species and Habitat Modeling in Landscape Ecology.* New York: Springer. doi:10.1007/978-1-4419-7390-0

Drewitt, A. L., & Langston, R. H. (2006, March 27). Assessing the impacts of wind farms on birds. *Ibis, 148*(1), 149-172.

Ellis, K. S., Pearse, A. T., Brandt, D. A., Bidwell, M. T., Harrell, W., Butler, M. J., & Burg, M. P. (2022, August 12). Balancing future renewable energy infrastructure siting and associated habitat loss for migrating whooping cranes. *Frontiers in Ecology and Evolution*, 1-17. doi:10.3389/fevo.2022.931260

Environment Canada. (2007). *Recovery Strategy for the Whooping Crane (Grus americana) in Canada.* Ottawa, Canada: Environment Canada.

Faaborg, J., Holmes, R. T., Anders, A. D., Bildstein, K. L., Dugger, K. M., Gauthreaux, S. A., . . . Merk. (2010, March). Conserving migratory land birds in the new world: do we know enough? *Ecological Applications, 20*(2), 398–418. doi:10.1890/09-0397.1.

Farm Service Agency. (2023, March). Retrieved from U.S. Deoartment of Agriculture: https://www.fsa.usda.gov/sites/default/files/documents/202301-FSA-KSNEOK-SAFE-FactSheet_web.pdf#:~:text=The%20playa%20wetlands%20being%20restored%20will%20provide,will%20increase%20recharge%20to%20the%20Ogallala%20Aquifer.

Fielding, A. H., & Bell, J. F. (1997). A review of methods for the assessment of prediction errors in conservation presence/absence models. *Environmental Conservation, 24,* 38-49.

Fontsere, C., Speak, S. A., Caven, A. J., Rodríguez, J. A., Wang, X., Pacheco, C., . . . D., E. (2024). Persistent genomic erosion in whooping cranes despite demographic recovery. *BioRxiv*, 11.

French, J. J., Converse, S. J., & Austin, J. E. (2019). Whooping Cranes Past and Present. *Whooping Cranes: Biology and Conservation*, 3-14. Retrieved from https://doi.org/10.1016/B978-0-12-803555-9.00001-3

Geary, M., Fielding, A., McGowan, P., & Marsden, S. (2015, November 16). Scenario-Led Habitat Modelling of Land Use Change Impacts on Key Species. *PLoS One, 10*(11), e142477. Retrieved from https://doi.org/10.1371/journal.pone.0142477

Glenn, T., Stephan, W., & Braun, M. (1999, October). Effects of a Population Bottleneck on Whooping Crane Mitochondrial DNA Variation. *Conservation Biology, 13*(5), 1097-1107.

Goetzman, M. (2024, 01 25). *Whooping Cranes*. Retrieved from Michael Goetzman: https://goetzman.com/2024/01/25/whooping-cranes/

Golden, K., Hemingway, B., Frazier, A., Scholtz, R., Harrell, W., Davis, C., & Fuhlendorf, S. (2022, April 19). Spatial and temporal predictions of whooping crane (Grus americana) habitat along the US Gulf Coast. *Conservation Science and Practice, 4*(6), e12696. Retrieved from https://doi.org/10.1111/csp2.12696

Goodin, D., Mitchell, J., Knapp, M., & Bivens, R. (1995, rep. 2004). *Climate and Weather Atlas of Kansas: An Introoduction.* Lawrence, Kansas: Kansas Geological Survey.

Guisan, A., & Zimmermann, N. E. (2000, December 05). Predictive habitat distribution models in ecology. *Ecological Modelling, 135*(2-3), 147-186. Retrieved from https://doi.org/10.1016/S0304-3800(00)00354-9

Guo, X., Coops, N., Gergel, S., Bater, C., Nielsen, S., Stadt, J., & Drever, M. (2018, January 20). Integrating airborne lidar and satellite imagery to model habitat connectivity dynamics for spatial conservation prioritization. *Landscape Ecology*, *33*, 491-511. Retrieved from https://link.springer.com/article/10.1007/s10980-018-0609-0

Hands, H. (2024, January 22). *Wind Energy: A Wildlife Biologist's Take*. Retrieved from Climate and Energy: https://climateandenergy.org/2024/01/22/wind-energy-a-wildlife-biologists-take/

Harrell, W., & Bidwell, M. (2019). *Report on Whooping Crane Recovery Activities (2012 breeding season-2013 spring migration).* U.S. Fish and Wildlife Service.

Harrell, W., & Bidwell, M. (2020). Climate impacts on whooping crane migration: A review of weather patterns and habitat availability. *Ecological Applications, 30*(4), e02145.

Hebblewhite, M., & Haydon, D. (2010, July 20). Distinguishing technology from biology: a critical review of the use of GPS telemetry data in ecology. *Philosophical Transacrtions B, 365*(1550), 2303-312. Retrieved from https://doi.org/10.1098/rstb.2010.0087

Hefley, T. J., Baasch, D. M., Tyre, A. J., & Blankenship, E. E. (2015, January 14). Use of opportunistic sightings and expert knowledge to predict and compare Whooping Crane stopover habitat. *Conservation Biology*, *29*(5), 1337-1346. doi:10.1111/cobi.12515

Heisman, R. (2019, March 04). *A High-wire Act to Protect Whooping Cranes from Powerlines*. Retrieved from American Bird Concervancy: https://abcbirds.org/blog/preventing-whooping-crane-collisions/#:~:text=The%20Peril%20of%20Powerlines,to%20do%20good%20for%20birds.

Hengla, T., Sierdsema, H., Radovic, A., & Dilo, A. (2009, July 23). Spatial prediction of species' distributions from occurrence-only records: combining point pattern analysis, ENFA and regression-kriging. *Ecological Modelling*, 3499-511. doi:10.1016/j.ecolmodel.2009.06.038

Heumann, B., Walsh, S., Verdery, A., McDaniel, P., & Rindfuss, R. (2012, August 22). Land Suitability Modeling Using a Geographic Socio-Environmental Niche-Based Approach: A Case Study from Northeastern Thailand. *Annals of the Association of American Geographers, 103*(4), 764-784. Retrieved from https://doi.org/10.1080/00045608.2012.702479

Hijmans, R. J., Williams, E., & Vennes, C. (2011). *Geosphere: spherical trigonometry*. Retrieved from R package version 1.2–18: (http://CRAN.R-project.org/package=geosphere)

Hijmans, R., & Graham, C. (2006, October 20). The ability of climate envelope models to predict the effect of climate change on species distributions. *Global Change Biology*, 2272-2281. Retrieved from https://doi.org/10.1111/j.1365-2486.2006.01256.x

Hoban, S., Bruford, M. W., Funk, W. C., Galbusera, P., Griffith, M. P., Grueber, C. E., . . . Lopes-Fernandes, M. (2021). Global Commitments to Conserving and Monitoring Genetic Diversity Are Now Necessary and Feasible. *BioScience, 71*(9), 964-76.

Hopkins, L., Hallman, T., Kilbride, J., Robinson, W., & Hutchinson, R. (2022, February 16). A Comparison of Remotely Sensed Environmental Predictors for Avian Distributions. *Landscape Ecology, 37*, 997-1016. Retrieved from https://link.springer.com/article/10.1007/s10980-022-01406-y

Huang, B., & Boutros, P. (2016, September 01). The parameter sensitivity of random forests. *BMC Bioinformatics, 17*(331). doi:10.1186/s12859-016-1228-x

Hutchinson, J., Jacquin, A., Hutchinson, S., & Verbesselt, J. (2015). Monitoring vegetation change and dynamics on U.S. Army training lands using satellite image time series analysis. *Journal of Environmental Management, 150*, 355-366. Retrieved from http://dx.doi.org/10.1016/j.jenvman.2014.08.002

International Crane Foundation. (2021). *Whooping crane conservation.* Retrieved from International Crane Foundation: https://savingcranes.org/

International Crane Foundation and Muraviovka Park for Sustainable Land Use. (2010). *Cranes, Agriculture and Climate Change.* (J. Harris, Ed.) Baraboo, Wisconsin: International Crane Foundation.

Iturbide, M., Bedia, J., Herrera, S., Hierro, O., Pinto, M., & Gutiérrez, J. M. (2015, May). A framework for species distribution modelling with improvedpseudo-absence generation. *Ecological Modelling, 312*, 166-174. Retrieved from http://dx.doi.org/10.1016/j.ecolmodel.2015.05.018

Johns, B. W. (1992). Preliminary identification of whooping crane staging areas in prairie Canada. *Proceedings 1988 North American Crane Workshop* (pp. 61-66). Lake Wales, Florida: North American Crane Working Group.

Johns, B., Stehn, T., & Windingstad, R. (2005). Migration pathways of whooping cranes: A review of tracking studies. *Proceedings of the North American Crane Workshop, 11,* 1-10.

Johns, B., Woodsworth, E., & Driver, E. (1997). Habitat Use by Migrant Whooping Cranes in Saskatchewan. *Proceedings of the North American Crane Workshop* (pp. 123-131). Saskatchewan, Canada: North American Crane Group.

Jones, M. (2005). *Endangered Species Act and Incentives for Private Landowners.* U.S. Fish and Wildlife Service, U.S. Department of the Interior. Washington, D.C.: U.S. Government. Retrieved 2025, from https://www.doi.gov/ocl/endangered-species-act#:~:text=Two%20key%20purposes%20of%20the,species%20ecosystems%20may%20be%20conserved.

Kačergytė, I., Arlt, D., Berg, A., Żmihorski, M., Knape, J., Rosin, Z. M., & Pärt, T. (2021, May). Evaluating created wetlands for bird diversity and reproductive success. *Biological Conservation, 257,* 109084. Retrieved from https://doi.org/10.1016/j.biocon.2021.109084

Kaminski, D., Comer, C., Garner, N., Hung, I.-K., & Calkins, G. (2013, September 19). Using GIS-based, regional extent habitat suitability modeling to identify conservation priority areas: A case study of the Louisiana black bear in east Texas. *Journal of Wildlife Management, 77*(8), 1639-1649. Retrieved from https://doi.org/10.1002/jwmg.611

Kansas Department of Agriculture. (n.d.). *Kansas Agriculture*. Retrieved from agriculture.ks.gov: https://www.agriculture.ks.gov/kansas-agriculture

Kansas Department of Wildlife & Parks. (2023, March). *Kansas Department of Wildlife & Parks.* Retrieved from Kansas Outdoors: https://ksoutdoors.com/Services/Threatened-and-Endangered-Wildlife/All-Threatened-and-Endangered-Species/WHOOPING-CRANE

Kramer-Schadt, S., Niedballa, J., Pilgrim, J., Schröder, B., Lindenborn, J., Reinfelder, V., . . . Wilting, A. (2013, July 02). The importance of correcting for sampling bias in MaxEnt species distribution models. *Diversity and Distribution, 19*(11), 1366-79. Retrieved from https://doi.org/10.1111/ddi.12096

Kuvlesky, W. P., Brennan, L. A., Morrison, M. L., Boydston, K. K., Ballard, B. M., & Bryant, F. C. (2007, November). Wind Energy Development and Wildlife Conservation: Challenges and Opportunities. *Journal of Wildlife Management, 71*(8), 2487-2498.

Kuyt, E. (1992). *Aerial radio-tracking of whooping cranes migrating between Wood Buffalo National Park and Aransas National Wildlife Refuge, 1981-84.* Ottawa, Ontario, Canada: Canadian Wildlife Service.

Leaverton , C., & Fellows, V. (2023, August 22). *Whooping Cranes: Reflecting on 50 Years of ESA Protection and Habitat Conservation with Our Partners*. Retrieved from U.S. Fish & Wildlife Service Website: https://www.fws.gov/story/2023-08/whooping-cranes-reflecting-50-years-esa-protection-and-habitat-conservation#:~:text=In%20response%2C%20the%20whooping%20crane,of%201966%2C%20the%20ESA's%20predecessor.

Lees, A., Haskell, L., Allinson, T., Bezeng, S., Burfield, I., Renjifo, L., . . . Butchart, S. (2022). State of the World's Birds. *Annual Review of Environment and Resources*, 231-260. Retrieved from https://doi.org/10.1146/annurev-environ-112420-014642

Lee-Yaw, J., McCune, J., Pironon, S., & Sheth, S. (2021, December 21). Species distribution models rarely predict the biology of real populations. *Ecography,* e05877. Retrieved from https://doi.org/10.1111/ecog.05877

Lehnen, S., Sesnie, S., Butler, M., Pearse, A., & Metzger, K. (2024, January 18). Management implications of habitat selection by whooping cranes (Grus americana) on the Texas coast. *Ecosphere*, 1-19. doi:10.1002/ecs2.4820

Lewis, J. C. (1995). Whooping crane (Grus americana). *The Birds of North America, 153,* 28 pp.

Lewis, J. C., Kuyt, E., Schwindt, K. E., & Stehn, T. V. (1992). Mortality in fledged whooping cranes of the Aransas/Wood Buffalo population. *Proceedings of 1988 North American Crane Workshop* (pp. 145-148). Lake Wales, Florida: in D. A. Wood, editor. Proceedings of 1988 North American Crane workshop. State of Florida Game and Fresh Water Fish Commission.

Li, J., & Heap, A. (2011, July 4). A review of comparative studies of spatial interpolation methods in environmental sciences: Performance and impact factors. *Ecological Informatics, 6*(3), 228-241. Retrieved from https://doi.org/10.1016/j.ecoinf.2010.12.003

Liaw, A., & Wiener, M. (2002, December 03). Classification and Regression by randomForest. *R News, 2*, pp. 18-22.

Liu, C., Newell, G., & White, M. (2015). On the selection of thresholds for predicting species occurrence with presence-only data. *Ecology and Evolution,* 337-348.

Liverman, D. (1999, March). Geography and the Global Environment. *Annals of the Association of American Geographers, 89*(1), 107-120. Retrieved from https://www.jstor.org/stable/2564037

Londe, D. (2023). *Climate change causes declines and greater extremes in wetland inundation in a region important for wetland birds.* Dryad. doi:https://doi.org/10.5061/dryad.wwpzgmsqv

MacArthur, R., & Wilson, E. (1967). *The Theory of Island Biogeography.* Princeton, New Jersey: Princeton University Press.

McDuie, F., Casazza, M., Overton, C., Herzog, M., Hartman, A., Peterson, S., . . . Ackerman, J. (2019, February 25). GPS tracking data reveals daily spatio-temporal movement patterns of waterfowl. *Movement Ecology, 7*(6). Retrieved from https://doi.org/10.1186/s40462-019-0146-8

Mellin, C., Mengersen, K., Bradshaw, C., & Caley, M. (2014, November 01). Generalizing the use of geographical weights in biodiversity modelling. *Global Ecology and Biogeography, 23*(11), 1314-1323. doi:DOI: 10.1111/geb.12203

Meretsky, V. J., Atwell, J. W., & Hyman, J. B. (2011). Migration and Conservation: Frameworks, Gaps, and Synergies in Science, Law, and Management. *Environmental Law, 41*(2), 447-534.

Mielke, K., Claassen, T., Busana, M., Heskes, T., Huijbregts, M., Koffijberg, K., & Schipper, A. (2020, July 16). Disentangling drivers of spatial autocorrelation in species distribution models. *Ecography, 43,* 1741-51. doi:10.1111/ecog.05134

Moore, F. R., Gauthreaux, S. A., Kerlinger, P., & Simons, T. R. (1995). Habitat Requirements During Migration: Important Link In Conservation . In T. E. Martin, & D. M. Finch, *Ecology And Management Of Neotropical Migratory Birds: A Synthesis and Review of Critical Issues* (pp. 121-144). New York: Oxford University Press.

Myers, J. P. (1983). Conservation of migrating shorebirds: staging areas, geographic bottlenecks, and regional movements. *Migration and Conservation, 37*(1), 23-25.

Niemuth, N., Ryba, A., Pearse, A., Kvas, S., Brandt, D., Wangler, B., . . . Carlisle, M. (2018, April 1). Opportunistically collected data reveal habitat selection by migrating Whooping Cranes in the U.S. Northern Plains. *The Condor,* 343-356. Retrieved from https://doi.org/10.1650/CONDOR-17-80.1

Okonye, I. (Unpublished Thesis). *Predicting Whooping Crane Stopover Habitat Preferences along the Kansas Migratory Flyway.*

Oppel, S., Meirinho, A., Ramírez, I., Gardner, B., O'Connell, A., Miller, P., & Louzao, M. (2012, December). Comparison of five modelling techniques to predict the spatial distribution and abundance of seabirds. *Biological Conservation, 156*, 94-104. Retrieved from https://doi.org/10.1016/j.biocon.2011.11.013

Pearce, J., & Ferrier, S. (2000, September 03). Evaluating the predictive performance of habitat models developed using logistic regression. *Ecological Modelling, 133*(3), 225-245. Retrieved from https://doi.org/10.1016/S0304-3800(00)00322-7

Pearse, A. T., Brandt, D. A., Harrell, W. C., Metzger, K. L., Baasch, D. M., & Hefley, T. J. (2015, January). Whooping Crane Stopover Site Use Intensity Within the Great Plains. *USGS professional paper*, 1-24. doi:DOI: 10.3133/ofr20151166

Pearse, A. T., Metzger, K. L., Brandt, D. A., Bidwell, M. T., Harner, M. J., Baasch, D. M., & Harrell, W. (2020, March). Heterogeneity in migration strategies of Whooping Cranes. *The Condor, 122*(1), 1-15. Retrieved from https://doi.org/10.1093/condor/duz056.

Pearse, A. T., Metzger, K. L., Brandt, D. A., Shaffer, J. A., & Bidwell, M. T. (2021, April). Migrating Whooping Cranes avoid wind-energy infrastructure when selecting stopover habitat. *Ecological Applications , 31*(5). doi:10.1002/eap.2324

Pearse, A. T., Rabbe, M., Juliusson, L. M., Bidwell, M. T., Craig-Moore, L., Brandt, D. A., & Harrell, W. (2018, February 15). Delineating and identifying long-term changes in the whooping crane (Grus americana) migration corridor. *PLoS ONE, 13*(2), 1-15. Retrieved from https://doi.org/10.1371/journal.pone.0192737

Pearse, A., Caven, A., Baasch, D., Bidwell, M., Conkin, J., & Brandt, D. (2024, April 25). Flexible migration and habitat use strategies of an endangered waterbird during hydrological drought. *Conservation Science and Practice, 6*(5), 1-18. doi:10.1111/csp2.13120

Peel, M., Finlayson, B., & McMahon, T. (2007, October 11). Updated world map of the Köppen-Geiger climate classification. *Hydrology and Earth System Sciences, 11*, 1633-1644. Retrieved from https://doi.org/10.5194/hess-11-1633-2007

Phillips, S., Anderson, R., & Schapire, R. (2006, January 25). Maximum entropy modeling of species geographic distributions. *Ecological Modelling, 190*(3), 230-259. Retrieved from https://doi.org/10.1016/j.ecolmodel.2005.03.026

Phillips, S., Dudík, M., Elith, J., Graham, C., Lehmann, A., Leathwick, J., & Ferrier, S. (2009, January 01). Sample selection bias and presence-only distribution models: implications for background and pseudo-absence data. *Ecological Applications, 19*(01), 181-197. Retrieved from https://doi.org/10.1890/07-2153.1

Prasad , A., Iverson , L., & Liaw , A. (2006, March 15). Newer Classification and Regression Tree Techniques: Bagging and Random Forests for Ecological Prediction. *Ecosystems, 9*, 181-199. doi:10.1007/s10021-005-0054-1

Riggio, J., Jr., A. E., Cook, H., Greef, E. d., Karp, D. S., & Truan, M. L. (2023, February). Long-term monitoring reveals the impact of changing climate and habitat on the fitness of cavity-nesting songbirds. *Biological Conservation*, 109885. Retrieved from https://doi.org/10.1016/j.biocon.2022.109885

Rodewald, A. D. (2015). Demographic Consequences of Habitat. In M. L. Morrison, & H. A. Mathewson, *Wildlife Habitat Conservation: concepts, challenges, and solutions* (pp. 19-34). Baltimore: Johns Hopkins University Press.

Row, J., Holloran, M., & Fedy, B. (2022, May 19). Quantifying the temporal stability in seasonal habitat for sage-grouse using regression and ensemble tree approaches. *Ecosphere, 13*(5), e4034. Retrieved from https://doi.org/10.1002/ecs2.4034

Runge, C., Watson, J., Butchart, S., Hansonr, J., Possingham, H., & Fuller, R. (2015, December 4). Protected areas and global conservation of migratory birds. *Science, 350*(6265), 1255-1258. doi:10.1126/science.aac9180

Sadoti, G., Pollock, M., Vierling, K., Albright, T., & Strand, E. (2014, April 01). Variogram models reveal habitat gradients predicting patterns of territory occupancy and nest survival among vesper sparrows. *Wildlife Biology, 20*(2), 97-107. Retrieved from https://doi.org/10.2981/wlb.13056

Sime, M. J., Thompson, H. L., Szyszkoski, E. K., Zimorski, S. E., Dellinger, T. A., & Schmidt, S. M. (2024, June 4). Power-Line Collisions in Reintroduced Whooping Cranes (Grus americana). *Southeastern Naturalist*, 194-211. Retrieved from https://doi.org/10.1656/058.023.0205

Stehn, T. (2011). Reproductive success of whooping cranes: A review of nesting and chick survival. *Journal of Wildlife Management, 75*(5), 987-1001.

Stehn, T. V., & Haralson-Strobel, C. L. (2014). An Update on Mortality of Fledged whooping Crane in the Aransas/Wood Buffalo Population. *Proceedings of the North American Crane Workshop*, 372. Retrieved from https://digitalcommons.unl.edu/nacwgproc/372

Stehn, T., & Wassenich, T. (2008). Whooping Crane Collisions with Power Lines: an Issue Paper. *Proceedings of North American Crane Workshop, 10*, 25-36. Retrieved from http://digitalcommons.unl.edu/nacwgproc/203

Stehn, T., & Wassenich, T. (2008). Whooping Crane Collisions with Power Lines: an Issue Paper. *Proceedings of the Tenth North American Crane Workshop* (pp. 25-36). Zacatecas, Mexico: North American Crane Working Group.

Sullins, D., Haukos, D., Lautenbach, J., Lautenbach, J., Robinson, S., Rice, M., . . . Hagen, C. (2019, August 11). Strategic conservation for lesser prairie-chickens among landscapes of varying anthropogenic influence. *Biological Conservation, 238*, 108213. Retrieved from https://doi.org/10.1016/j.biocon.2019.108213

Tacha, M., Bishop, A., & Brei, J. (2010). Development of the Whooping Crane Tracking Project Geographic Information System. *Proceedings of the North American. 11*, pp. 98-104. North American Crane Working Group. Retrieved from https://digitalcommons.unl.edu/nacwgproc/144?utm_source=digitalcommons.unl.edu%2Fnacwgproc%2F144&utm_medium=PDF&utm_campaign=PDFCoverPages

The International Crane Foundation. (2024, December). *Whooping Crane Eastern Population Update - December 2024*. Retrieved from Saving Cranes Website: https://savingcranes.org/news/resources/whooping-crane-eastern-population-update-december-2024/#:~:text=The%20current%20estimated%20population%20size,Illinois%2C%20and%2031%20in%20Indiana.

The International Crane Foundation. (n.d.). *A Risky Climate for Cranes, Wetlands and Our World.* Retrieved from savingcranes.org: https://savingcranes.org/news/resources/a-risky-climate-for-cranes-wetlands-and-our-world/

Thompson, H. L., Glass, M. S., Wellington, M. M., Boardman, K. H., & Olsen, G. H. (2022). Effects of Release Techniques on Parent-Reared Effects of Release Techniques on Parent-Reared Whooping Cranes In The Eastern Migratory Population Whooping Cranes In The Eastern Migratory Population . *Proceedings of the North American Crane Workshop* , 53-71.

Thompson, H. L., Gordon, N., Bolt, D., Lee, J., & Szyszkoski, E. (2022). Twenty-Year Status of The Eastern Migratory Whooping Crane Reintroduction. *Proceedings of the North American Crane Workshop, 15*, 34-52. Retrieved from https://digitalcommons.unl.edu/nacwgproc/386/

Thompson, H., Caven, A., Hayes, M., & Lacy, A. (2021, Aug 11). Natal dispersal of Whooping Cranes in the reintroduced Eastern Migratory Population. *Ecology and Evolution, 11*(18), 12630-38.

Tirpak, J., Jones-Farrand, D., Thompson, F., Twedt, D., Baxter, C., Fitzgerald, J., & Uihlein III, W. (2010, December 13). Assessing Ecoregional-Scale Habitat Suitability Index Models for Priority Landbirds. *Journal of Wildlife Management, 73*(8), 1307-1315. Retrieved from https://doi.org/10.2193/2008-125

Turner, M. G. (1989, November). Landscape Ecology: The Effect of Pattern on Process. *Annual Review of Ecology, Evolution, and Systematics, 20*, 171-197. Retrieved from https://doi.org/10.1146/annurev.es.20.110189.001131

U.S. Fish & Wildlife Service. (2023, May 23). *2023 Wintering Whooping Crane Count*. Retrieved from U.S. Fish & WIldlife Service: https://www.fws.gov/press-release/2023-05/2023-wintering-whooping-crane-count

U.S. Fish & WIldlife Service. (2023, May 23). *2023 Wintering Whooping Crane Count*. Retrieved from U.S. Fish & WIldlife Service: https://www.fws.gov/press-release/2023-05/2023-wintering-whooping-crane-count

U.S. Fish & Wildlife Service. (2024, March 22). *Continued Decline of Wetlands Documented in New U.S. Fish and Wildlife Service Report*. Retrieved from www.fws.gov: https://www.fws.gov/press-release/2024-03/continued-decline-wetlands-documented-new-us-fish-and-wildlife-service-report

U.S. Fish & Wildlife Service. (2024, Jan 25). *Whooping Crane*. Retrieved from U.S. Fish & Wildlife Service: https://www.fws.gov/species/whooping-crane-grus-americana

U.S. Fish and Wildlife Service. (2003). *Endangered Species Act of 1973 (As Amended through the 108th Congress).* Washington, D.C.: U.S. Department of the Interior. Retrieved from https://www.fws.gov/media/endangered-species-act

U.S. Fish and Wildlife Service. (n.d.). *Whooping Crane (Grus americana)*. Retrieved from U.S. Fish and Wildlife Service: https://www.fws.gov/species/whooping-crane-grus-americana

U.S. Fish and Wildlife Service. (2009). *Whooping Cranes and Wind Development.* Regions 2 and 6: An Issue Paper. U.S. Fish and Wildlife Service.

United States Census Bureau. (2010, January 1). *State Area Measurements and Internal Point Coordinates*. Retrieved from census.gov: https://www.census.gov/geographies/reference-files/2010/geo/state-area.html

Urbanek, R., & Lewis, J. (n.d.). Whooping Crane (Grus americana), version 2.0. In The Birds of North America. *Cornell Lab of Ornithology*. (P. G. Rodewald, Ed.) Ithaca, New York, USA.

Urbanek, R., Zimorski, S., & Wellington, M. (2010). Captive breeding and reintroduction of whooping cranes: A review of population trends. *Endangered Species Update*, *28*(3), 78-85.

USGS: Land Management Research Program. (n.d.). *America's Grasslands: Great Plains and Pothole Prairies.* Retrieved February 18, 2025, from U.S. Geological Survey: https://www.usgs.gov/programs/land-management-research-program/americas-grasslands-great-plains-and-pothole-prairies#:~:text=America%27s%20grasslands%20are%20in%20the,%2C%20Black%2Dfoot%20ferret%29.

Vartanian, J., & Conkin, J. (2023). *Whooping Crane Recovery Activities* . Annual Report on Whooping Crane Recovery.

Vest, J. L., Haukos, D. A., Niemuth, N. D., Setash, C. M., Gammonley, J. H., Devries, J. H., & Dahlgren, D. K. (2023). Waterfowl and Wetland Birds. In L. B. McNew, D. K. Dahlgren, & J. L. Beck (Eds.), *Rangeland Wildlife Ecology and Conservation* (pp. 417-469). Tucson: Springer, Cham. doi:https://doi.org/10.1007/978-3-031-34037-6_13

Walker, J., Balling, R., Briggs, J., Katti, M., Warren, P., & Wentz, E. (2008, January). Birds of a feather: Interpolating distribution patterns of urban birds. *Computers, Environment and Urban Systems, 32*(1), 19-28. Retrieved from https://doi.org/10.1016/j.compenvurbsys.2007.02.001

Watershed Institute, Inc. (2013). *Potentially Suitable Habitat Assessment for the Whooping Crane.* Topeka, Kansas: The Watershed Institute.

Wauchope, H., Shaw, J., Varpe, Ø., Lappo, E., Boertmann, D., & Lancto, R. (2016, May 19). Rapid climate-driven loss of breeding habitat for Arctic migratory birds. *Global Change Biology*, 1-10. doi:10.1111/gcb.13404

Webb, E. B., Smith, L. M., Vrtiska, M. P., & Lagrange, T. G. (2010). Effects of Local and Landscape Variables on Wetland Bird Habitat Use During Migration Through the

Rainwater Basin. *Journal of Wildlife Management, 74*(1), 109-119. doi:10.2193/2008-577

Whitham, T. G. (1980, April). The Theory of Habitat Selection: Examined and Extended Using Pemphigus Aphids. *The American Naturalist, 115*(4), 449-466. Retrieved from http://www.jstor.org/stable/2460478

Williams, C., & Lohman, S. (1949). *Geology and Ground-water Resources of a Part of South-central Kansas.* Lawrence, Kansas: University of Kansas Publications.

World Wildlife Fund. (2024). *Great Plains*. Retrieved from www.worldwildlife.org: https://www.worldwildlife.org/places/great-plains#:~:text=This%20sweeping%20landscape%20in%20the%20heart%20of,tens%20of%20thousands%20of%20species%20of%20insects.

Xu, D., Bisht, G., Tan, Z., Sinha, E., Di Vittorio, A., Zhou, T., . . . Leung, L. (2024, March 18). Climate change will reduce North American inland wetland areas and disrupt their seasonal regimes. *Nature Communications, 15*, 2438. Retrieved from https://doi.org/10.1038/s41467-024-45286-z

Zhu, W., Jia, S., Lü, A., & Yan, T. (2012, March 07). Analyzing and modeling the coverage of vegetation in the Qaidam Basin of China: The role of spatial autocorrelation. *Journal of Geographical Sciences, 22*, 346-358. Retrieved from https://doi.org/10.1007/s11442-012-0931-4

Zimmerman, B., & Bierregaard, R. (1986, March). Relevance of the Equilibrium Theory of Island Biogeography and Species-Area Relations to Conservation with a Case from Amazonia. *Journal of Biogeography, 13*(2), 133-143. Retrieved from https://doi.org/10.2307/2844988

Appendix A - Scripts

R Script for Bearing Calculation

```
# Load required packages
library(geosphere)

# Load table with cell and wintering habitat coordinates
data <-
read.csv("D:/KDWP_WhoopingCrane/HabitatAssessment_Belaire_New/HabitatAssessment_Bel
aire/Tables/BearingTable.csv", header=TRUE, sep=",")
#
D:\KDWP_WhoopingCrane\HabitatAssessment_Belaire_New\HabitatAssessment_Belaire\Table
s

# Create bearing function from using geosphere package
# p1 = wintering ground and p2 = cell centroid
f <- function(x, output) {
  p1 = c(x["POINT1_X"], x["POINT1_Y"])
  p2 = c(x["POINT_X"], x["POINT_Y"])
  return(bearing(p1, p2))
}

# Apply bearing function to each row in the input, then add it to the dataframe
bearing <- apply(data, 1, f)
data2 <- data.frame(bearing)

# Write an output csv file that can be joined in GIS
write.csv(data2,
"D:/KDWP_WhoopingCrane/HabitatAssessment_Belaire_New/HabitatAssessment_Belaire/Tabl
es/OutputBearings.csv")
```

R Script for Ecotone Classification

```
# Load required libraries
library(pacman)
p_load(tidyverse, readr)

# Read CSV file
WHCRMCGridCell_dist <-
read.csv("D:/KDWP_WhoopingCrane/HabitatAssessment_Belaire_New/HabitatAssessment_Bel
aire/Tables/WHCR_KS_GridCell_Dist.csv")

# Display structure of the data frame
str(WHCRMCGridCell_dist)

# Convert columns to numeric
WHCRMCGridCell_dist <- WHCRMCGridCell_dist %>%
  mutate(DistanceWetlands = as.numeric(DistanceWetlands),
         DistanceAgric = as.numeric(DistanceAgric))

# Define a function to categorize distances
categorize_distance <- function(DistanceWetlands, DistanceAgric) {
  ifelse(DistanceWetlands >= 0 & DistanceWetlands <= 100,
         ifelse(DistanceAgric >= 0 & DistanceAgric <= 100, "A",
                ifelse(DistanceAgric > 100 & DistanceAgric <= 500, "B",
                       ifelse(DistanceAgric > 500 & DistanceAgric <= 1000, "E", "J"))),
         ifelse(DistanceWetlands > 100 & DistanceWetlands <= 500,
                ifelse(DistanceAgric >= 0 & DistanceAgric <= 100, "C",
                       ifelse(DistanceAgric > 100 & DistanceAgric <= 500, "D",
                              ifelse(DistanceAgric > 500 & DistanceAgric <= 1000, "F", "K"))),
                ifelse(DistanceWetlands > 500 & DistanceWetlands <= 1000,
```

```
                    ifelse(DistanceAgric >= 0 & DistanceAgric <= 100, "G",
                          ifelse(DistanceAgric > 100 & DistanceAgric <= 500, "H",
                                ifelse(DistanceAgric > 500 & DistanceAgric <= 1000, "I", "L"))),
                    ifelse(DistanceAgric >= 0 & DistanceAgric <= 100, "M",
                          ifelse(DistanceAgric > 100 & DistanceAgric <= 500, "N",
                                ifelse(DistanceAgric > 500 & DistanceAgric <= 1000, "O", "P"))))))
}

# Create a new column 'ecotone_code'
ecotone <- WHCRMCGridCell_dist %>%
  #select(-(6:33)) %>%
  mutate(ecotone_code = categorize_distance(DistanceWetlands, DistanceAgric))



write_csv(ecotone, file =
"D:/KDWP_WhoopingCrane/HabitatAssessment_Belaire_New/HabitatAssessment_Belaire/Tabl
es/ecotone.csv")
```

R Script for Turbine Proximity Analysis

```
library(pacman)
p_load(tidyverse, sf, lubridate, adehabitatHS, lme4, lmerTest, amt, ggplot2, broom.mixed)

wksp <- "C:/Users/ifeom/OneDrive - Kansas State University/Desktop/New Research Stuff to
Merge with SSD Drive/HabitatAssessment_Belaire"

# Load data
# Combine path correctly
crane_path <- file.path(wksp, "Tables/Final RF Variables.csv")
```

```
cranes <- read.csv(crane_path, header=TRUE, sep=",") %>%
  st_as_sf(coords = c("Longitude", "Latitude"), crs = 4326) %>%
  st_transform(32614) # UTM zone for study area

turbine_path <- file.path(wksp, "Tables/TurbinesinHighSuitableAreas.shp")

turbines <- st_read(turbine_path)

# Classify crane points by turbine proximity
cranes <- cranes %>%
  mutate(
    NearTurbine = lengths(st_within(., turbines)) > 0,
    Season = ifelse(month(DateTime) %in% 3:5, "Spring", "Fall")
  )

# Calculate use rate (locations/km²)
use_rates <- cranes %>%
  group_by(Season, NearTurbine) %>%
  summarise(
    Locations = n(),
    Area_km2 = ifelse(first(NearTurbine),
                  sum(st_area(turbines))/1e6,
                  total_study_area - sum(st_area(turbines))/1e6),
    UseRate = Locations/Area_km2
  )
```

R Script for Habitat Suitability Analysis

```
library(pacman)
```

```
p_load(tidyverse, randomForest, caret, caTools, raster, sf, pROC, verification, rfUtilities, tools,
ROCR)


########################################
########################################
########## Import Data
########################################
########################################

# WC_data <-
read.csv("G:/KDWP_WhoopingCrane/HabitatAssessment_Belaire_New/HabitatAssessment_Bel
aire/Tables/Final RF Variables.csv", header=TRUE, sep=",")
WC_data <- read.csv("C:/Users/ifeom/OneDrive - Kansas State University/Desktop/New
Research Stuff to Merge with SSD Drive/HabitatAssessment_Belaire/Tables/Final RF
Variables.csv", header=TRUE, sep=",")
head(WC_data)


########################################
########################################
########## Create Time Variable
########################################
########################################


# Define the date range and calculate the number of days
start_date <- as.Date("2010-03-23")
end_date <- as.Date("2016-11-25")
num_days <- as.numeric(difftime(end_date, start_date, units = "days"))
```

```
# Generate random numbers from 1 to 2435
set.seed(123)
random_days <- sample(1:num_days, size = 2000, replace = TRUE)


#Convert the random numbers to actual dates
random_dates <- start_date + random_days


# Create data frame for pseudo-absence points with their assigned random dates
pseudo_absence_date <- data.frame(
  OID_ = 1:2000,
  random_date = random_dates
)
head(pseudo_absence_date)


#convert time column to date format
WC_data$TIME_OM <- as.Date(WC_data$TIME_OM, format = "%m/%d/%Y")
str(WC_data)


# Merge the pseudo-absence dates into WC_data based on OID
WC_data <- WC_data %>%
  left_join(pseudo_absence_date, by = "OID_") %>%
  mutate(
    obs_date = coalesce(as.Date(random_date), as.Date(TIME_OM))  # Ensure Date format &
prioritize random_date
  ) %>%
  dplyr::select(-OID_, -TIME_OM, -random_date)  # Remove the original columns
```

```
head(WC_data)



#######################################
#######################################
########## Tidy Data
######################################
#######################################

# Transform data types
WC_data <- as.data.frame(WC_data) %>%
  mutate(
    sd = as.factor(ifelse(Obs_Type %in% c("A", "Absent", "Absence"), "Absent", "Present")), #sd
is specie distribution

    ec = as.factor(ecotone_code),
    pca = as.factor(Percent_cover_Agric),
    pcu = as.factor(Percent_cover_Urban),
    pcw = as.factor(Percent_cover_Wetland),
    pcr = as.factor(Percent_cover_Road),
    be = as.factor(bearing),
    Date = as.Date(obs_date),
    Long = as.factor(Longitude),
    Lat = as.factor(Latitude)
    ) %>%
  dplyr::select(-(1:10))
str(WC_data)



# Convert ecotone categories to numbers
WC_data$ec <- as.factor(match(WC_data$ec, LETTERS[1:16]))
```

```
head(WC_data)
str(WC_data)



# Adding Season variable
wcDataframe_season <- WC_data %>%
  mutate(
    Date = as.Date(Date),  # Keep as Date type
    season = case_when(
      month(Date) %in% 3:5 ~ "Spring",
      month(Date) %in% 9:11 ~ "Fall",
      month(Date) %in% 6:8 ~ "Summer",
      TRUE ~ "Winter"))

# Replace NA values
# Convert factor columns to numeric and replace NA values with 0
wcDataframe_season <- wcDataframe_season %>%
  mutate(
    DateNum = as.numeric(as.Date(Date)),
    season = as.factor(as.character(season)),
    pca = as.numeric(as.character(pca)),
    pcu = as.numeric(as.character(pcu)),
    pcw = as.numeric(as.character(pcw)),
    pcr = as.numeric(as.character(pcr)),
    be = as.numeric(as.character(be)),
    Long = as.numeric(as.character(Long)),
    Lat = as.numeric(as.character(Lat))
  ) %>%
  mutate(
    DateNum = replace_na(DateNum, 0),
    season = replace_na(season, 0),
```

```
    pca = replace_na(pca, 0),
    pcu = replace_na(pcu, 0),
    pcw = replace_na(pcw, 0),
    pcr = replace_na(pcr, 0),
    be = replace_na(be, 0),
    Long = replace_na(Long, 0),
    Lat = replace_na(Lat, 0)
  ) %>%
  dplyr::select(-Date)


str(wcDataframe_season)

# Remove Season Variable
wcDataframe <- wcDataframe_season %>%
  dplyr::select(-season)

str(wcDataframe)

# Set Seed
set.seed(1234)

################################################################################
##################################
####                                                            ####
####                Random Forest Model: Belaire Model for Kansas                ####
####                  Variables: Be, PCA, PCW, PCU, PCR, Ec                  ####
####                                                            ####
################################################################################
##################################
```

```
########################################
########################################
##### Select Required Variables
########################################
########################################

WcD_Belaire <- wcDataframe %>%
  dplyr::select(-(8:10))
str(WcD_Belaire)

# Set up the formula for random forest
formula <- sd ~ pcu + pcw + pca + pcr + ec + be

# Split the data into training and testing sets
trainIndex <- createDataPartition(WcD_Belaire$sd, p = 0.75, list = FALSE)
trainData <- WcD_Belaire[trainIndex, ]
testData <- WcD_Belaire[-trainIndex, ]

########################################
########################################
##### Building the Random Forest model
########################################
########################################

# Check for NA Values and view summary of data
colSums(is.na(WcD_Belaire))
summary(WcD_Belaire)

# Fit the Random Forest model
(SDmodel <- randomForest(formula,
                         data = trainData,
```

```
                    importance = TRUE,
                    Proximity = TRUE,
                    Positive = "Present",
                    ntree = 500))

#Plot variable Importance
importance(SDmodel)
varImpPlot(SDmodel, main = "Species Distribution Model", scale = TRUE)

########################################
########################################
####### Optimizing the Model
########################################
########################################

# Optimum nTrees
# Plotting the error rates for each tree based on a matrix within the model called err.rate
head(SDmodel$err.rate, 5)

oob.error.data <- data.frame(
  Trees = rep(1:nrow(SDmodel$err.rate), times = 3),
  Type = rep(c("OOB", "Present", "Absent"), each = nrow(SDmodel$err.rate)),
  Error = c(SDmodel$err.rate[ , "OOB"],
           SDmodel$err.rate[ , "Present"],
           SDmodel$err.rate[ , "Absent"])
)

oob.error.data %>%
  ggplot(aes(Trees, Error)) +
  geom_line(aes(color = Type))
```

```
# making model with nTrees
(SDmodelnT <- randomForest(sd ~ .,
                          data = trainData,
                          ntree = 1000,
                          importance = TRUE,
                          Proximity = TRUE))

# to see if plotting with nT is better, plot error rate
oob.error.data1 <- data.frame(
  Trees = rep(1:nrow(SDmodelnT$err.rate), times = 3),
  Type = rep(c("OOB", "Present", "Absent"), each = nrow(SDmodelnT$err.rate)),
  Error = c(SDmodelnT$err.rate[ , "OOB"],
            SDmodelnT$err.rate[ , "Present"],
            SDmodelnT$err.rate[ , "Absent"])
)

oob.error.data1 %>%
  ggplot(aes(Trees, Error)) +
  geom_line(aes(color = Type))

# Optimum Variables per node
oob.values <- vector(length = 10)

for (i in 1:10) {
  temp.model <- temp.model <- randomForest(sd ~ ., data = trainData, mtry=i, ntree=1500)
  oob.values[i] <- temp.model$err.rate[nrow(temp.model$err.rate),1]
}

oob.values #print out the different oob error values and the one with the lowest value is the
number of variables that works best.
```

```
########################################
########################################
####### Final Random Forest Model.
########################################
########################################

## find the minimum error
min(oob.values)
## find the optimal value for mtry...
mtryV <- which(oob.values == min(oob.values))
## create a model for proximities using the best value for mtry
(SDmodel_Belaire <- randomForest(sd ~ .,
                        data = trainData,
                        ntree = 1001,
                        proximity = TRUE,
                        importance = TRUE,
                        mtryV = mtryV))

importance(SDmodel_Belaire)
varImpPlot(SDmodel_Belaire, main = "Species Distribution Model", scale = TRUE)

########################################
########################################
##### Making Predictions
########################################
########################################

# Predict probabilities on the test set
testData$Predicted <- predict(SDmodel_Belaire, testData, type = "prob")[, "Present"]

# Convert the predicted probabilities to "Absent" or "Present" based on a threshold
```

```
testData$PredictedClass <- ifelse(testData$Predicted > 0.5, "Present", "Absent")
testData$PredictedClass <- factor(testData$PredictedClass, levels = c("Absent", "Present"))


# Evaluate model performance
(cm <- confusionMatrix(data = testData$PredictedClass,
                       reference = testData$sd,
                       positive = "Present"))

# Extract the confusion matrix table
cm_table <- as.table(cm$table)

# Convert the table to a data frame
cm_df <- as.data.frame(cm_table)

# Plot confusion matrix
ggplot(data = cm_df, aes(x = Reference, y = Prediction, fill = Freq)) +
  geom_tile() +
  geom_text(aes(label = Freq), color = "white", size = 5) +
  scale_fill_gradient(low = "brown", high = "darkslateblue") +
  labs(x = "Actual Class", y = "Predicted Class") +
  theme_minimal()

########################################
########################################
####### Plotting AUC Curve
########################################
########################################
par(pty = "s")

# Plot the ROC curve using the test set response and predicted probabilities
```

```
ROC <- roc(testData$sd, testData$Predicted, percent = TRUE,
           levels = c("Absent", "Present"), legacy.axes=TRUE)
ROC

str(ROC)

AUC_Plot <- plot.roc(ROC, col = "#00008B", lwd = 4, print.auc = TRUE,
                     xlab="False Positive Percentage", ylab="True Postive Percentage")

par(pty = "m")

########################################
########################################
##### Plotting Partial Dependence Plots
########################################
########################################
########################################
# Function to normalize a vector to a 0-1 scale
normalize <- function(x) {
  (x - min(x, na.rm = TRUE)) / (max(x, na.rm = TRUE) - min(x, na.rm = TRUE))
}

# Get importance of variables and sort them
imp <- importance(SDmodel)
impvar <- rownames(imp)[order(imp[, 1], decreasing = TRUE)]

# Define labels for ecotone category (A-P)
ecotone_labels <- LETTERS[1:16]  # Creates A-P

# Set up the plot layout
op <- par(mfrow = c(2, 3))
```

```
# Loop through each variable and plot
for (i in seq_along(impvar)) {
  if (impvar[i] == "ec") {
    # Handle categorical variable (ecotone category) as a bar plot
    mean_values <- tapply(predict(SDmodel, trainData, type = "prob")[, "Present"],
                          trainData[[impvar[i]]], mean)

    # Normalize the values
    mean_values <- normalize(mean_values)

    # Barplot with custom ecotone labels (A-P)
    barplot(mean_values,
            names.arg = ecotone_labels,  # Replace numbers with A-P
            main = "Partial Dependence on Ecotone Category",
            xlab = "Ecotope Category",
            ylab = "Normalized Predicted Suitability",
            col = "blue")
  } else {
    # Generate partial dependence data
    pd_data <- partialPlot(SDmodel, trainData, impvar[i], which.class = "Present", smooth =
"loess", plot = FALSE)

    # Normalize y-values
    pd_data$y <- normalize(pd_data$y)

    # Plot the normalized partial dependence plot
    plot(pd_data$x, pd_data$y, type = "l", col = "#4daf4a", lwd = 3,
         main = paste("Partial Dependence on", impvar[i]),
         xlab = impvar[i],
         ylab = "Normalized Predicted Suitability")
```

```
  }
}

# Reset plot layout
par(op)
##########################################
##########################################
####### Habitat Suitability Map
##########################################
##########################################

# Load the raster layers
urban_raster <- raster("C:/Users/ifeom/OneDrive - Kansas State University/Desktop/New Research Stuff to Merge with SSD Drive/HabitatAssessment_Belaire/Raster Data/Pcr.tif")
wetland_raster <- raster("C:/Users/ifeom/OneDrive - Kansas State University/Desktop/New Research Stuff to Merge with SSD Drive/HabitatAssessment_Belaire/Raster Data/pcw.tif")
agric_raster <- raster("C:/Users/ifeom/OneDrive - Kansas State University/Desktop/New Research Stuff to Merge with SSD Drive/HabitatAssessment_Belaire/Raster Data/pca.tif")
road_raster <- raster("C:/Users/ifeom/OneDrive - Kansas State University/Desktop/New Research Stuff to Merge with SSD Drive/HabitatAssessment_Belaire/Raster Data/pcr.tif")
ecotone_raster <- raster("C:/Users/ifeom/OneDrive - Kansas State University/Desktop/New Research Stuff to Merge with SSD Drive/HabitatAssessment_Belaire/Raster Data/ec.tif")
bearing_raster <- raster("C:/Users/ifeom/OneDrive - Kansas State University/Desktop/New Research Stuff to Merge with SSD Drive/HabitatAssessment_Belaire/Raster Data/be.tif")
Longitude_raster <- raster("C:/Users/ifeom/OneDrive - Kansas State University/Desktop/New Research Stuff to Merge with SSD Drive/HabitatAssessment_Belaire/Raster Data/Long.tif")
Latitude_raster <- raster("C:/Users/ifeom/OneDrive - Kansas State University/Desktop/New Research Stuff to Merge with SSD Drive/HabitatAssessment_Belaire/Raster Data/Lat.tif")

# Stack the rasters
```

```
env_var <- stack(urban_raster, wetland_raster, agric_raster, road_raster, ecotone_raster,
bearing_raster)
names(env_var) <- c("pcu", "pcw", "pca", "pcr", "ec", "be")

# Predict the suitability/probability of occurrence across the landscape
suitability_map <- predict(env_var, SDmodel_Belaire, type = "prob", index = 2, progress =
"window")

# Plot the suitability map
plot(suitability_map, main = "Whooping Crane Habitat Suitability Map")

# Save the suitability map
# writeRaster(suitability_map,
"G:/KDWP_WhoopingCrane/HabitatAssessment_Belaire_New/HabitatAssessment_Belaire/Rast
er Data/SuitabilityMap_Belaire.tif", format = "GTiff", overwrite = TRUE)
writeRaster(suitability_map, "C:/Users/ifeom/OneDrive - Kansas State University/Desktop/New
Research Stuff to Merge with SSD Drive/HabitatAssessment_Belaire/Raster Data/Suitability
Map - Belaire/RelativeProbabilityFunction_Belaire_2011_1km2.tif", format = "GTiff",
overwrite = TRUE)

###############################################
###############################################
######### Identify Habitats as Binary Variable
###############################################
###############################################
rm(env_var) #Remove stack to free up some memory

# Occurrence thresholds
occurrence.threshold(SDmodel_Belaire, trainData[,sel.vars], class="Present", p = seq(0.1, 0.9,
0.02), type = "delta.ss")
```

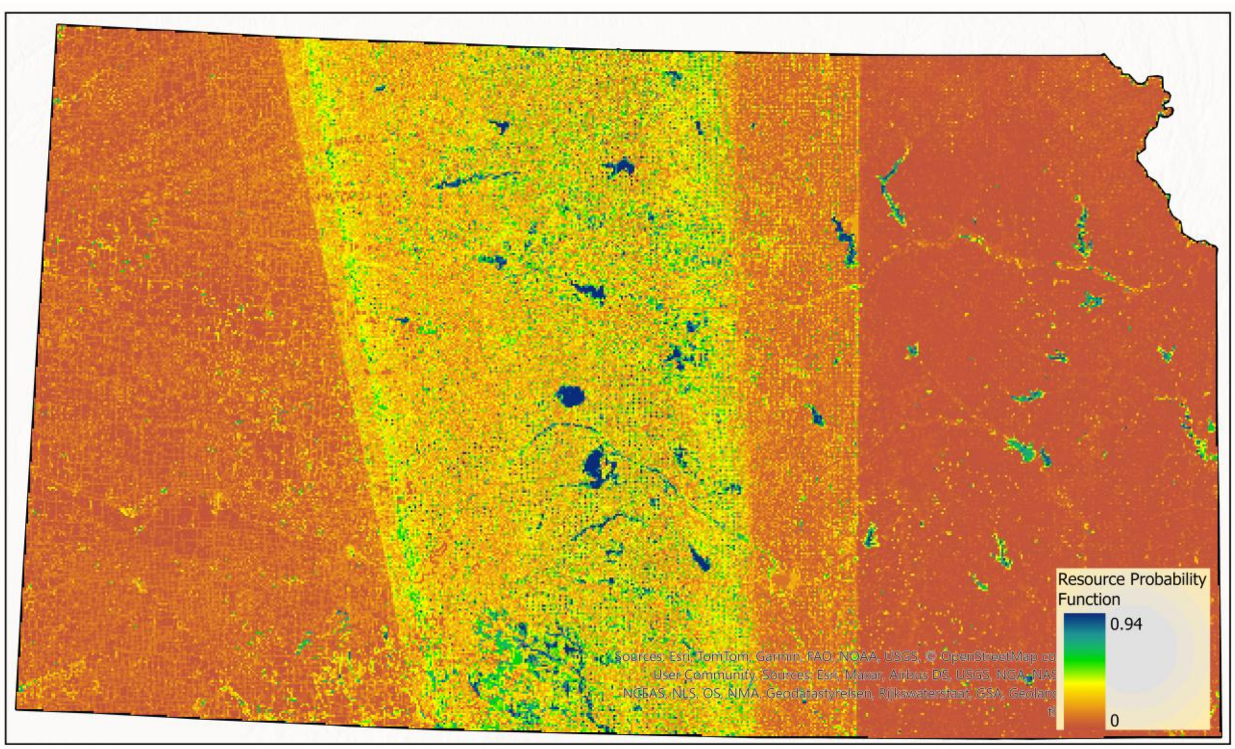
```
occurrence.threshold(SDmodel_Belaire, trainData[,sel.vars], class="Present", p = seq(0.1, 0.9, 0.02), type = "kappa")

occurrence.threshold(SDmodel_Belaire, trainData[,sel.vars], class="Present", p = seq(0.1, 0.7, 0.02), type = "sum.ss")

# change raster to binary layer
rbinary <- r

# set based on occurrence threshold from summed sensitivity and specificity above to create binary(1 or 0) habitat map
rbinary[rbinary >= 0.4] <- 1
rbinary[rbinary < 0.4] <- 0

# double check
head(rbinary)
plot(rbinary)
rbinary[rbinary == 0] <- NA
writeRaster(rbinary, "C:/Users/ifeom/OneDrive - Kansas State University/Desktop/New Research Stuff to Merge with SSD Drive/HabitatAssessment_Belaire/Raster Data/Suitability Map - Belaire/RelativeProbabilityFunction_Binary.tif", format = "GTiff", overwrite = TRUE)
```

Appendix B - Supporting Images

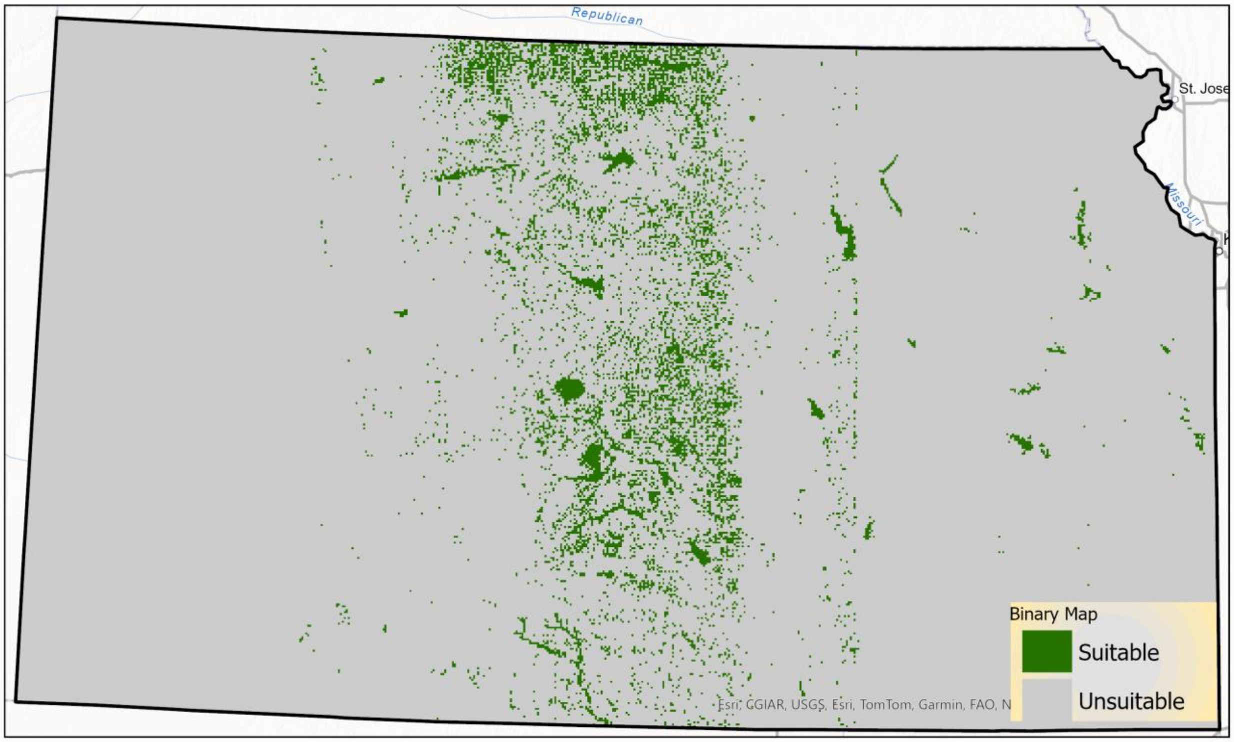
The original maps from the habitat suitability modeling using both models (the Belaire model for Kansas and the Improved Model) are attached. In this section of the Appendix, we have included the prediction maps of both models, binary maps showing suitable areas (RPF ≥ 0.4), AUC plots, partial dependence plots, and plots of variable importance. The threshold for the binary map was derived by using the random forest model to assess habitat suitability based on occurrence data. The function occurrence. threshold() was used to find the optimal threshold for classifying presence based on predicted possibilities. Our result was an optimal threshold of 0.38, but we rounded up to 0.4 as our suitability threshold.

Results from Belaire Model for Kansas

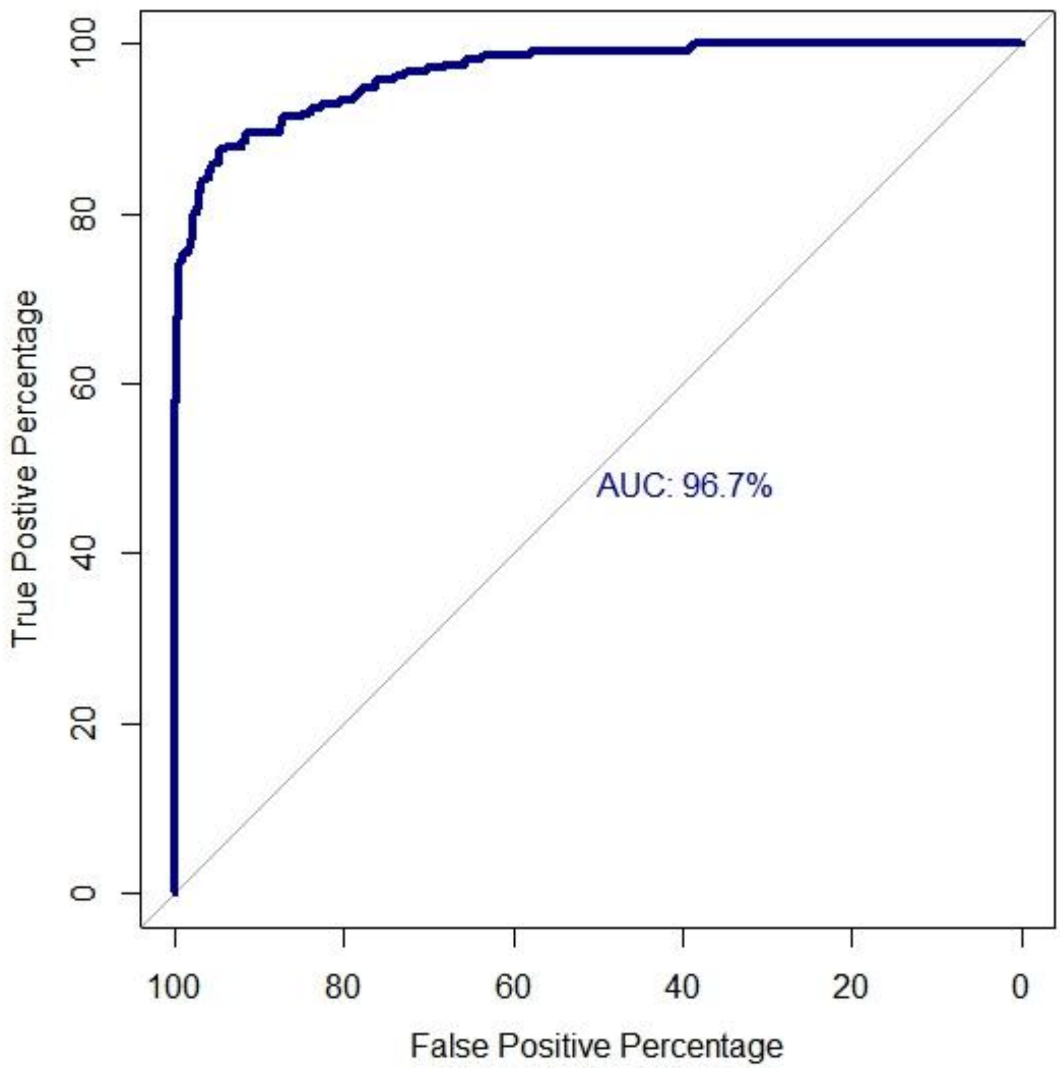
Appendix Figure B.1 Prediction map for the study area using Belaire's model for Kansas**.**



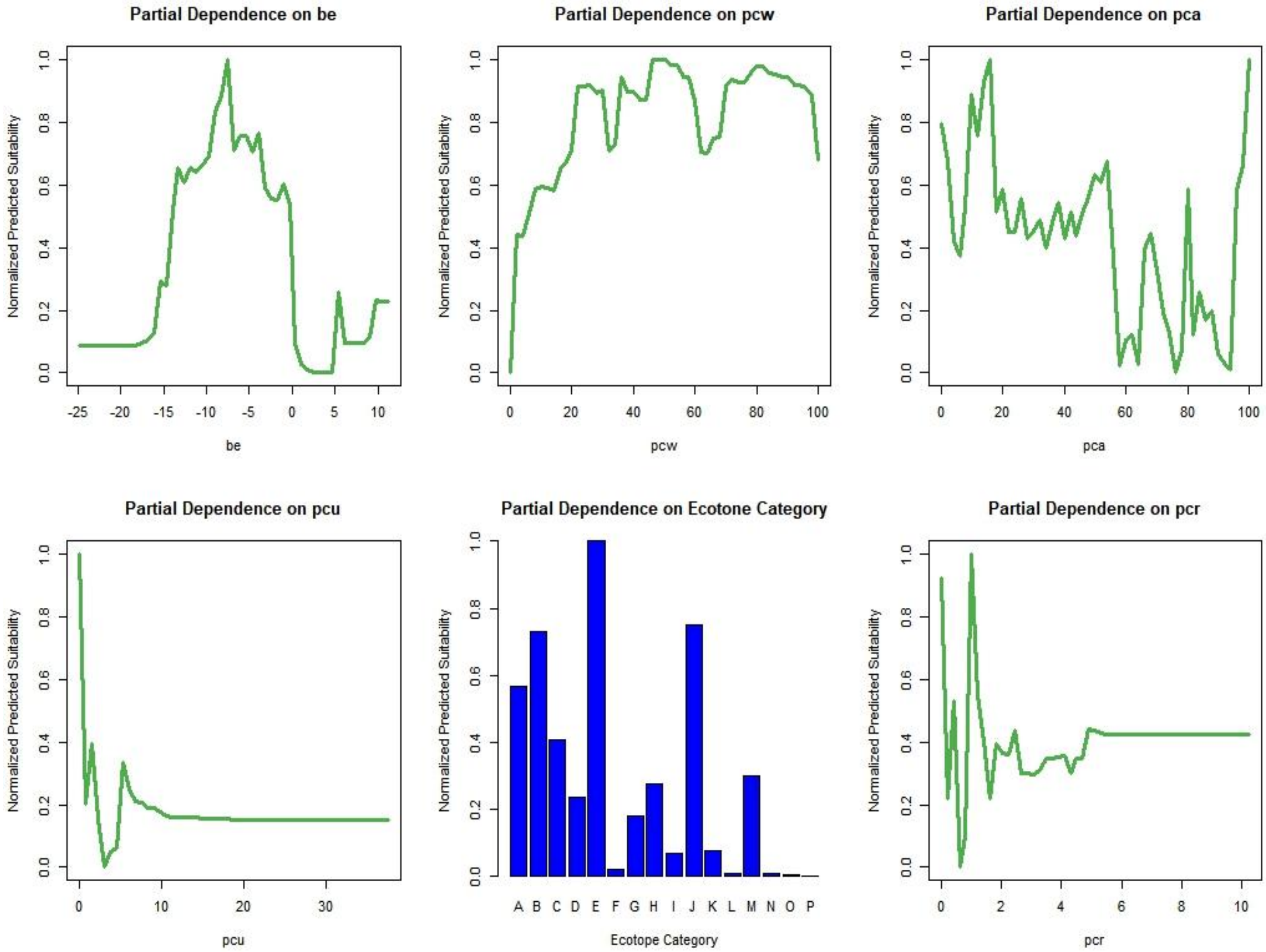
Appendix Figure B.2 Binary map of occurrence threshold for the study area.



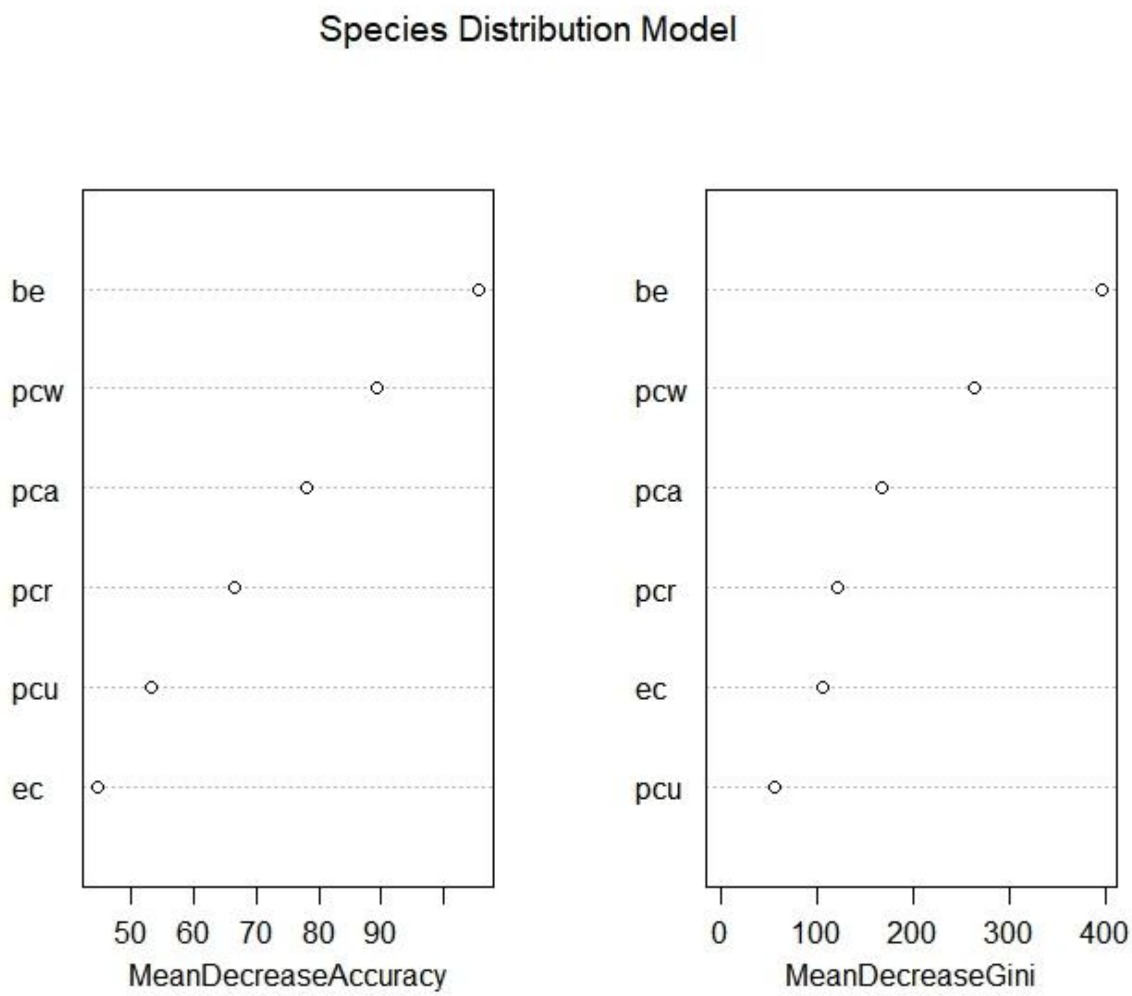
Appendix Figure B.3 Area Under the receiver Curve Plot.



Appendix Figure B.4 Partial Dependence Plot arranged in decreasing order of importance.



Appendix Figure B.5 Variable Importance plots.

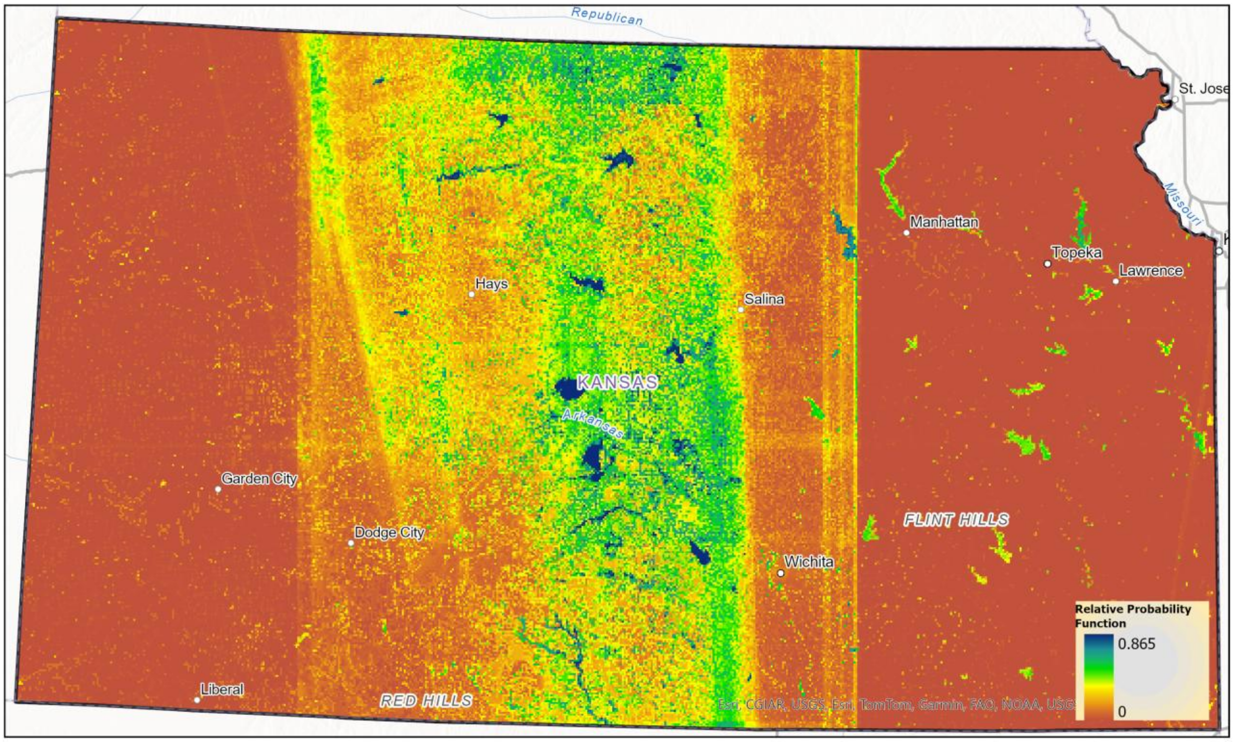


Improved Model Results

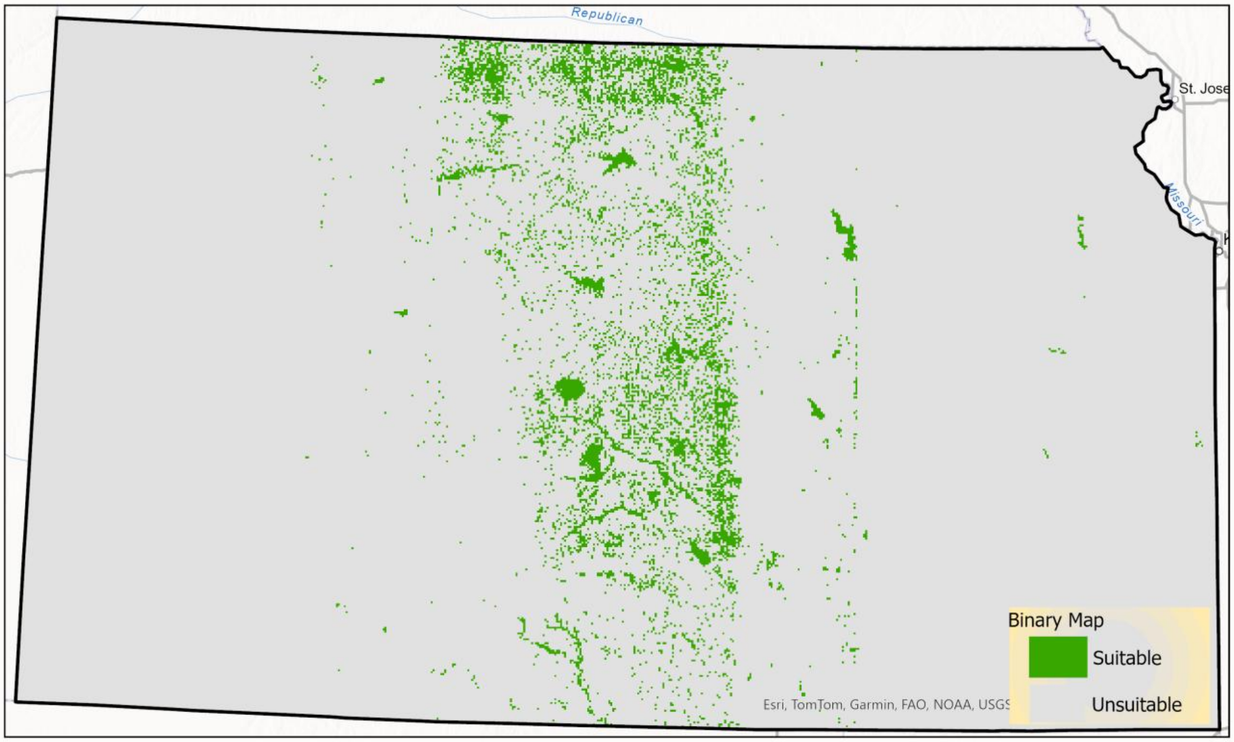
Selected Variables:

The improved model included seven variables, including bearing, percent cover of wetland, percent cover of agricultural land, longitude, latitude, date, and ecotone categories.

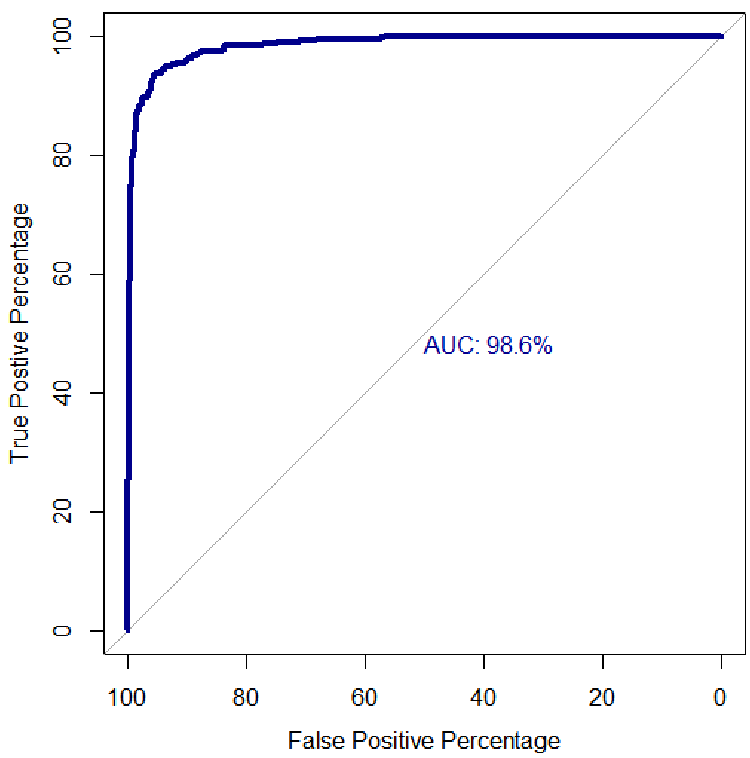
Appendix Figure B.6 Prediction map for the study area.



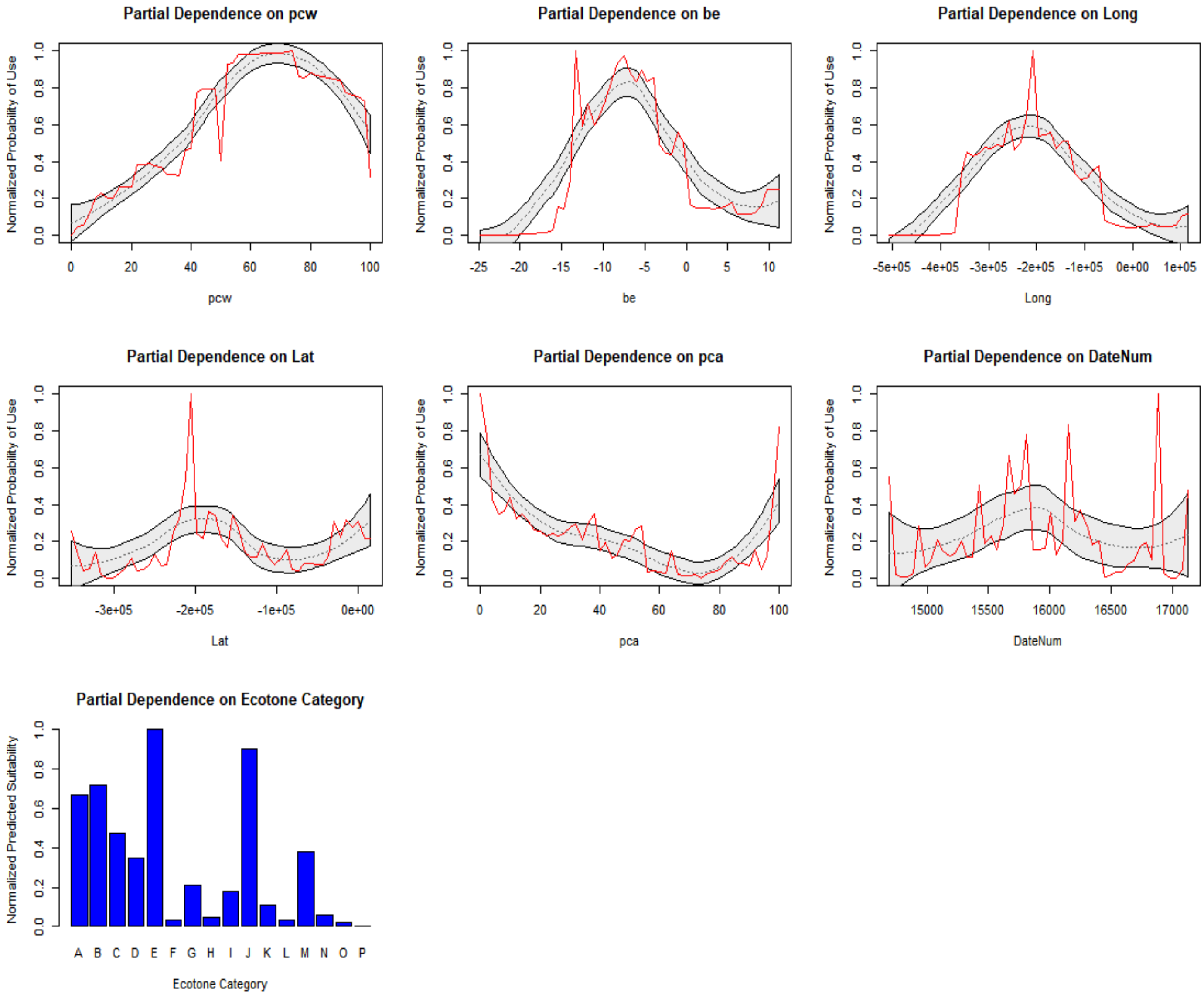
Appendix Figure B.7 Binary map of occurrence threshold for the study area.



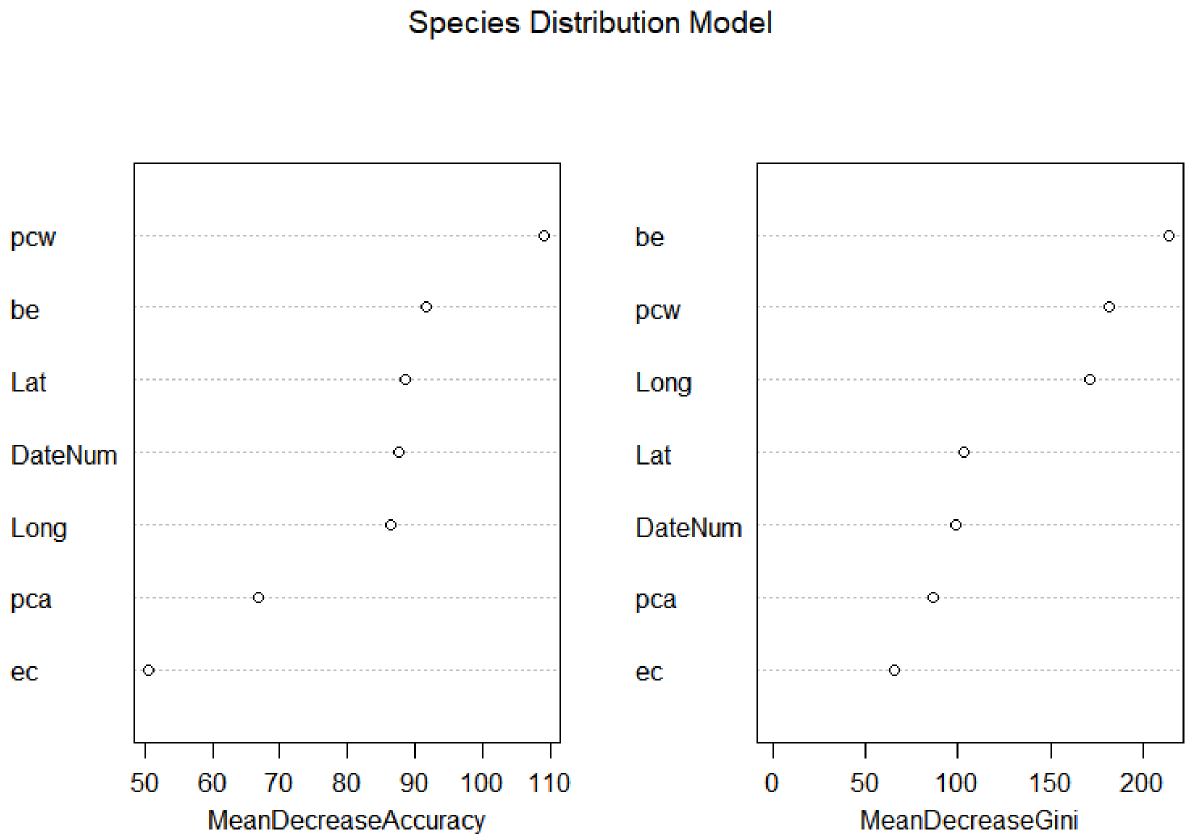
Appendix Figure B.8 Area Under the receiver Curve Plot.



Appendix Figure B.9 Partial Dependence Plot arranged in decreasing order of importance.



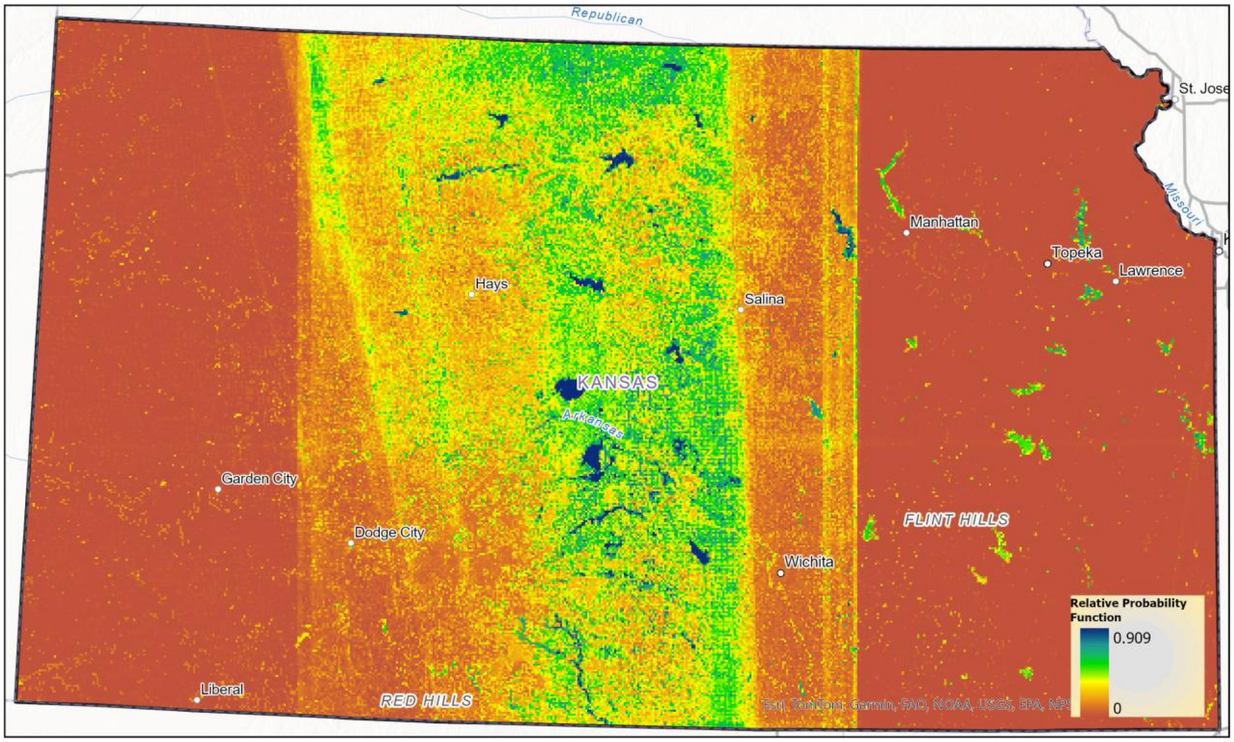
Appendix Figure B.10 Variable Importance plots.



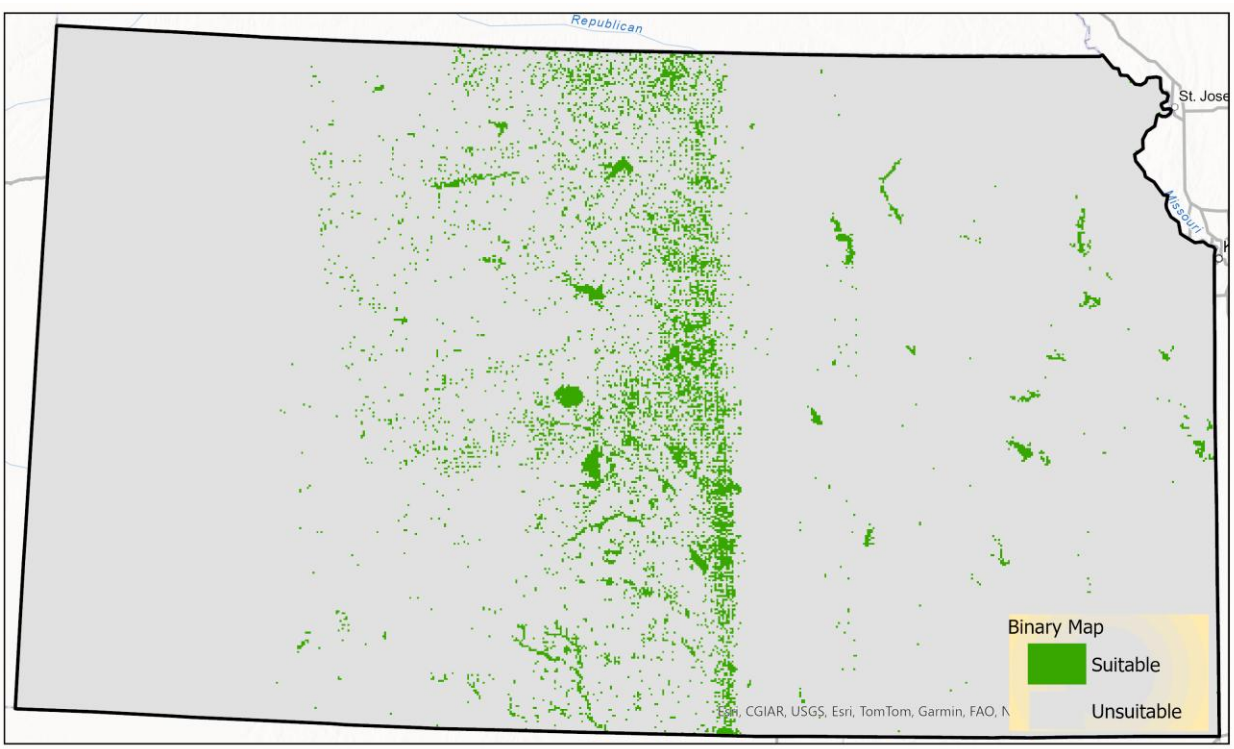
All Variables:

Next all variables were included in the Model to see how they all contribute to habitat prediction. All nine variables included are bearing, percent cover of wetland, percent cover of agricultural land, percent cover of urban areas, percent cover of roads, longitude, latitude, date, and ecotone categories

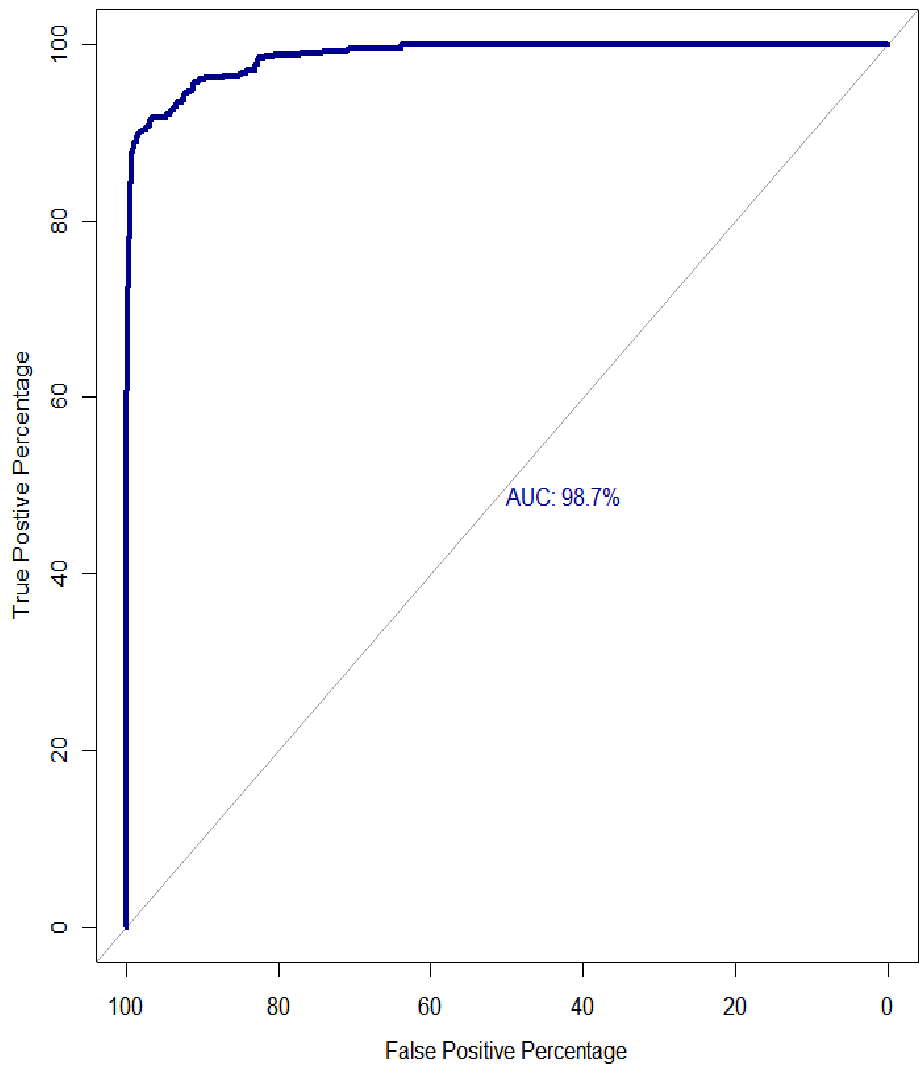
Appendix Figure B.11 Prediction map for the study area using all variables in the model.



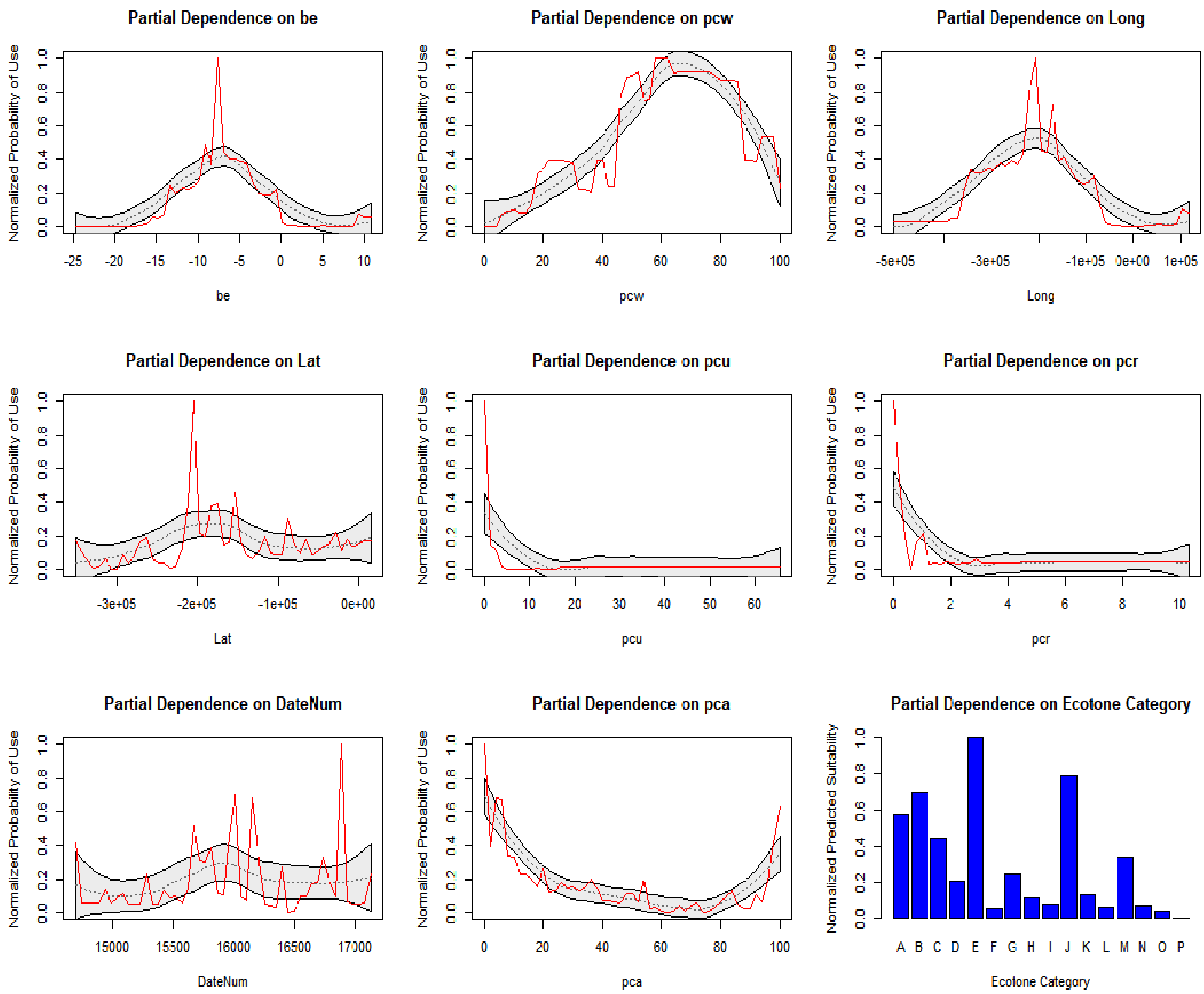
Appendix Figure B.12 Binary map of occurrence threshold for the study area.



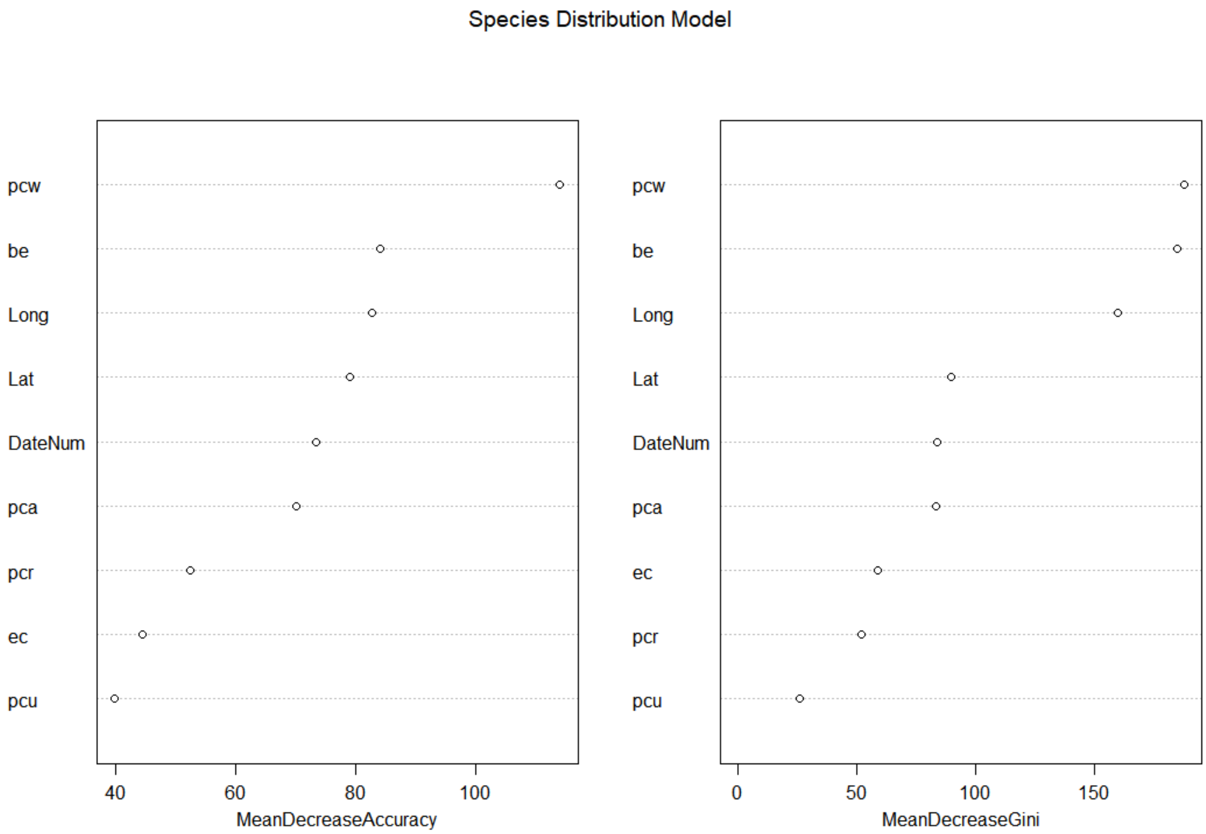
Appendix Figure B.13 Area Under the receiver Curve Plot.



Appendix Figure B.14 Partial Dependence Plot arranged in decreasing order of importance.



Appendix Figure B.15 Variable Importance plots.

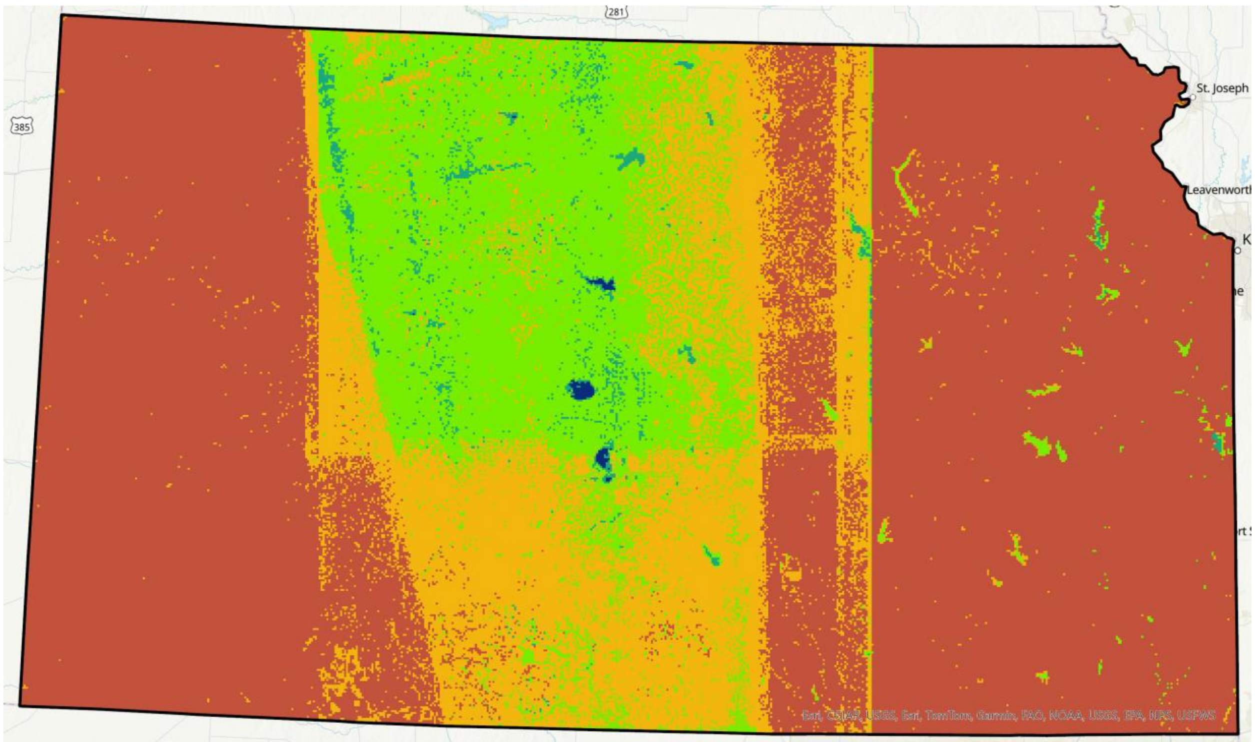


Appendix C - Time-series Maps

Individual time-series maps from spring 2010 to fall 2016.

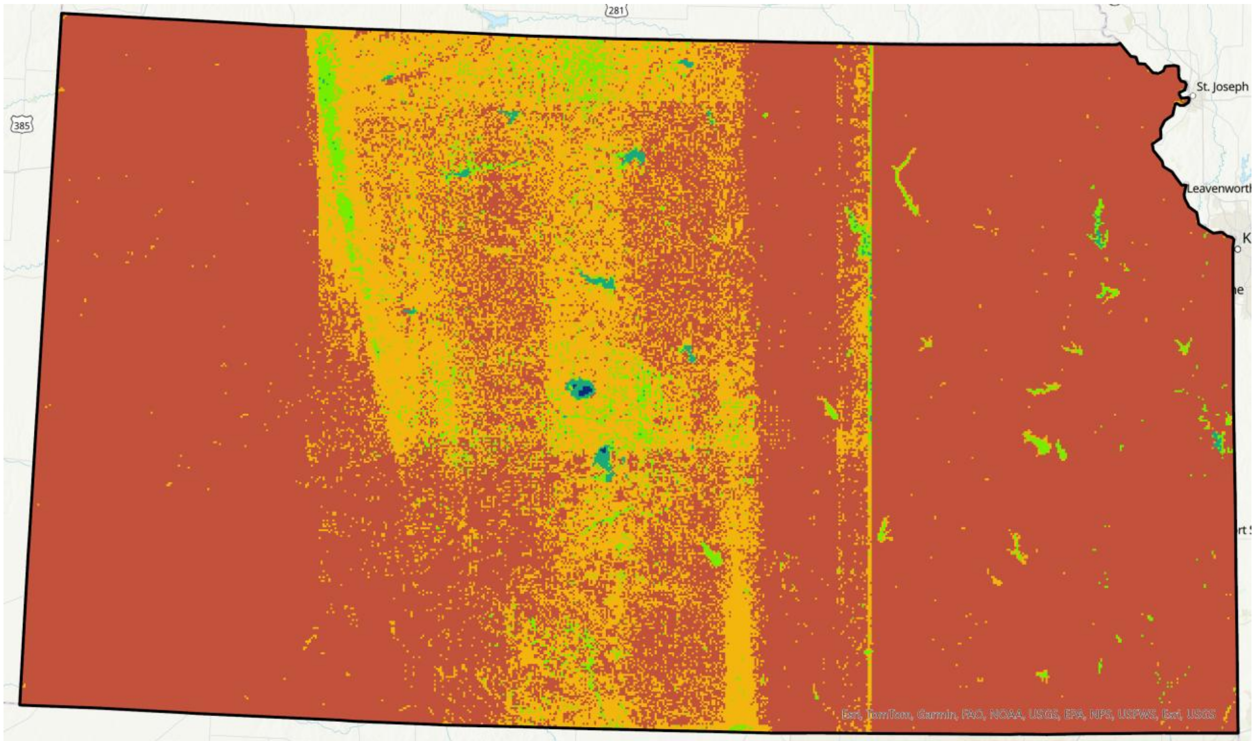
Appendix Figure C.1. Time-series Map Key

Appendix Figure C.2. Prediction map for Spring 03-23-2010.



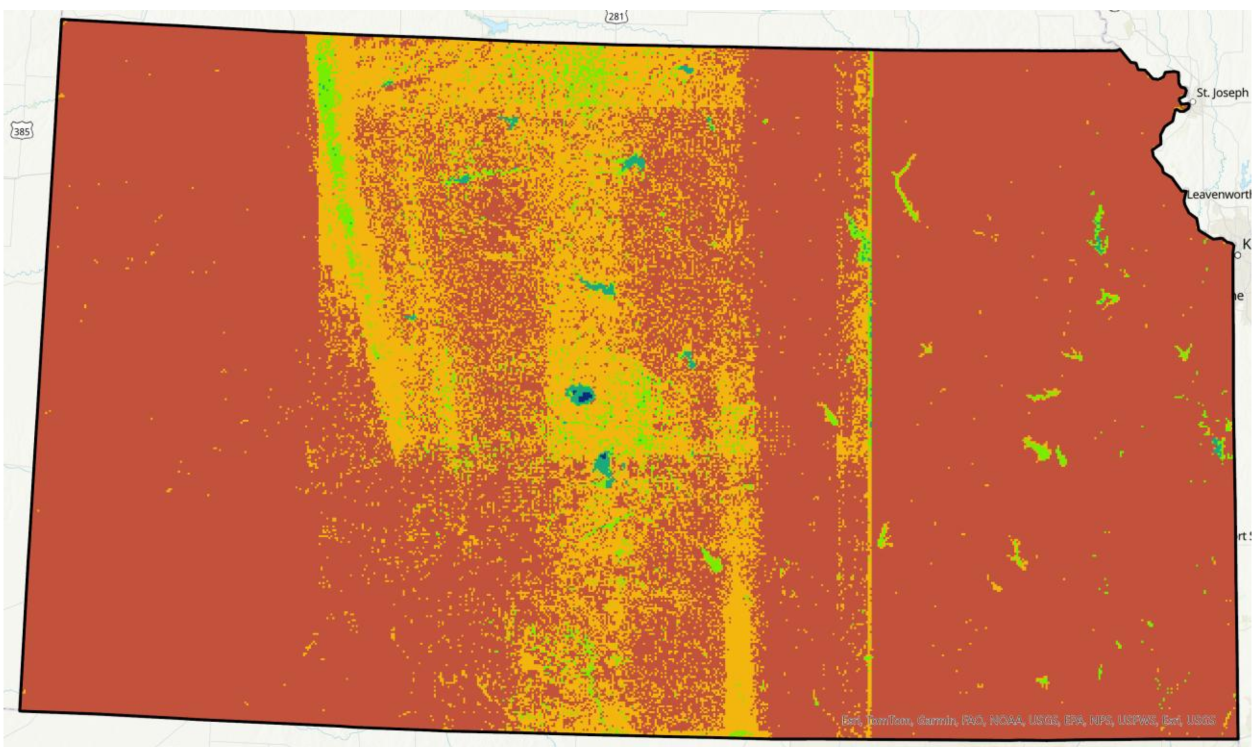
Spring: 03-23-2010

Appendix Figure C.3 Prediction map for Spring 04-15-2010.



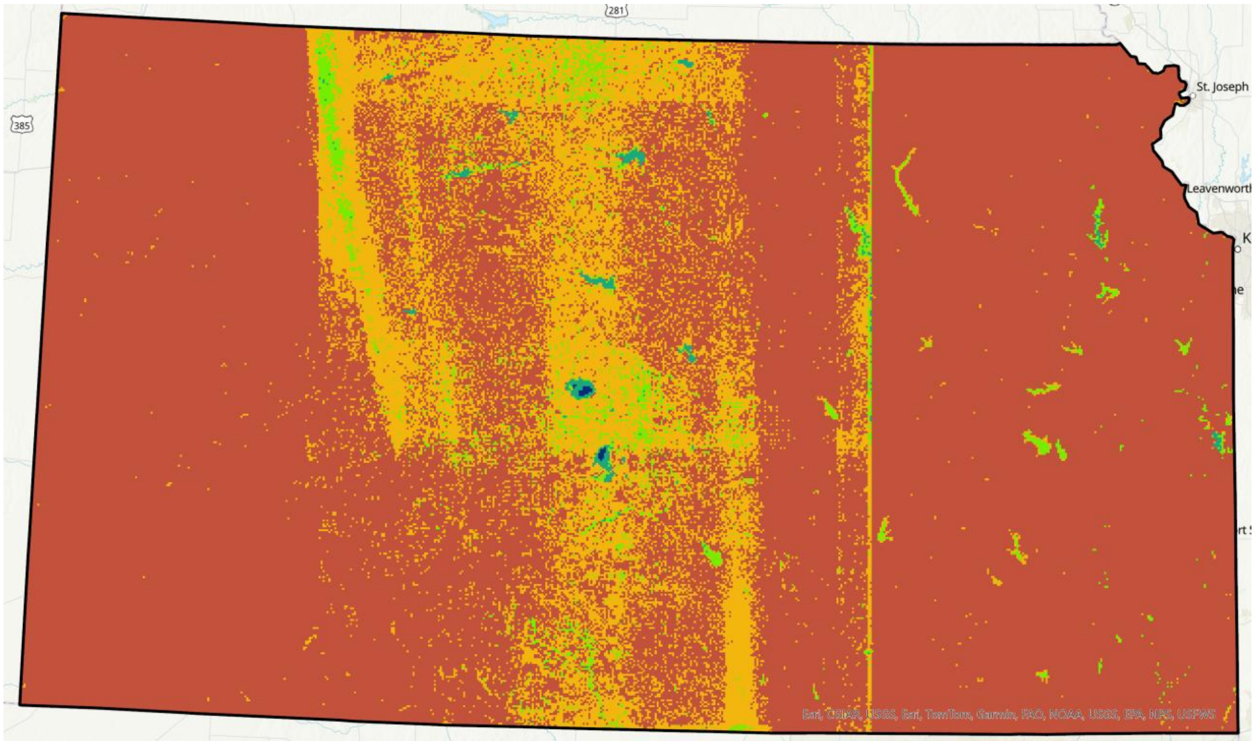
Spring: 04-15-2010

Appendix Figure C.4 Prediction map for Spring 05-10-2010.



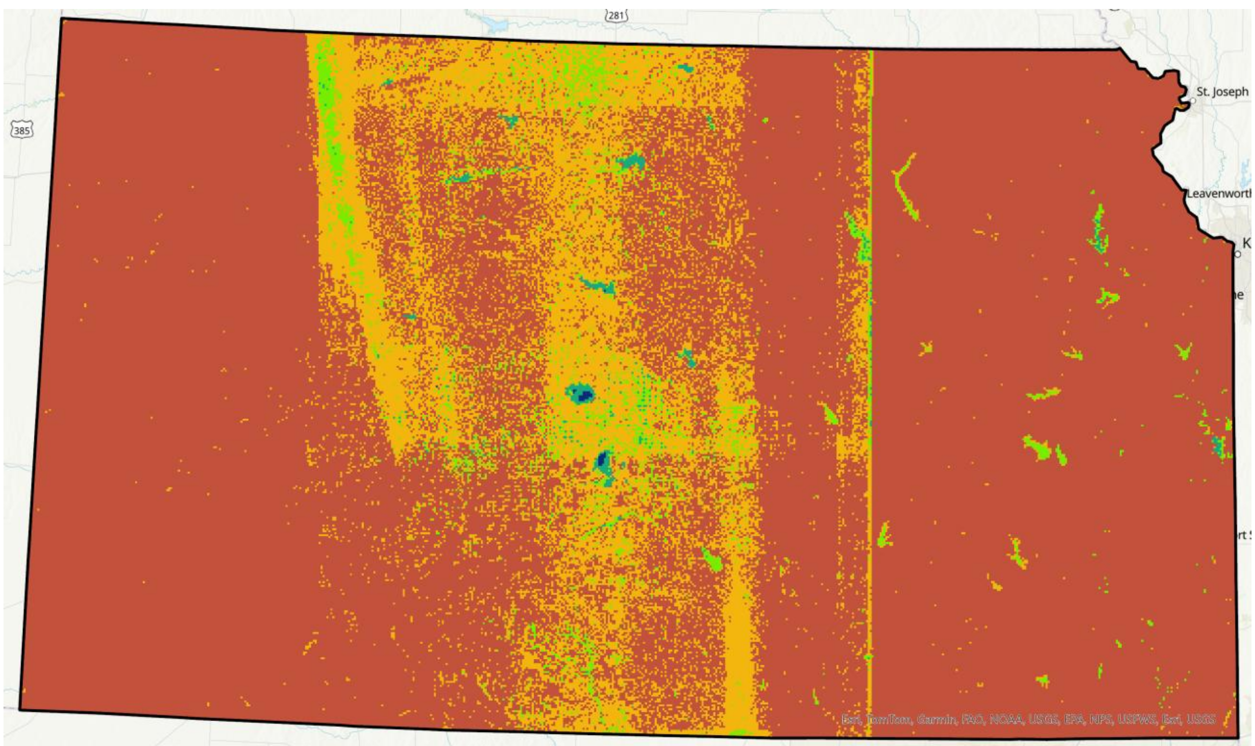
Spring: 05-10-2010

Appendix Figure C.5 Prediction map for Fall 09-15-2010.



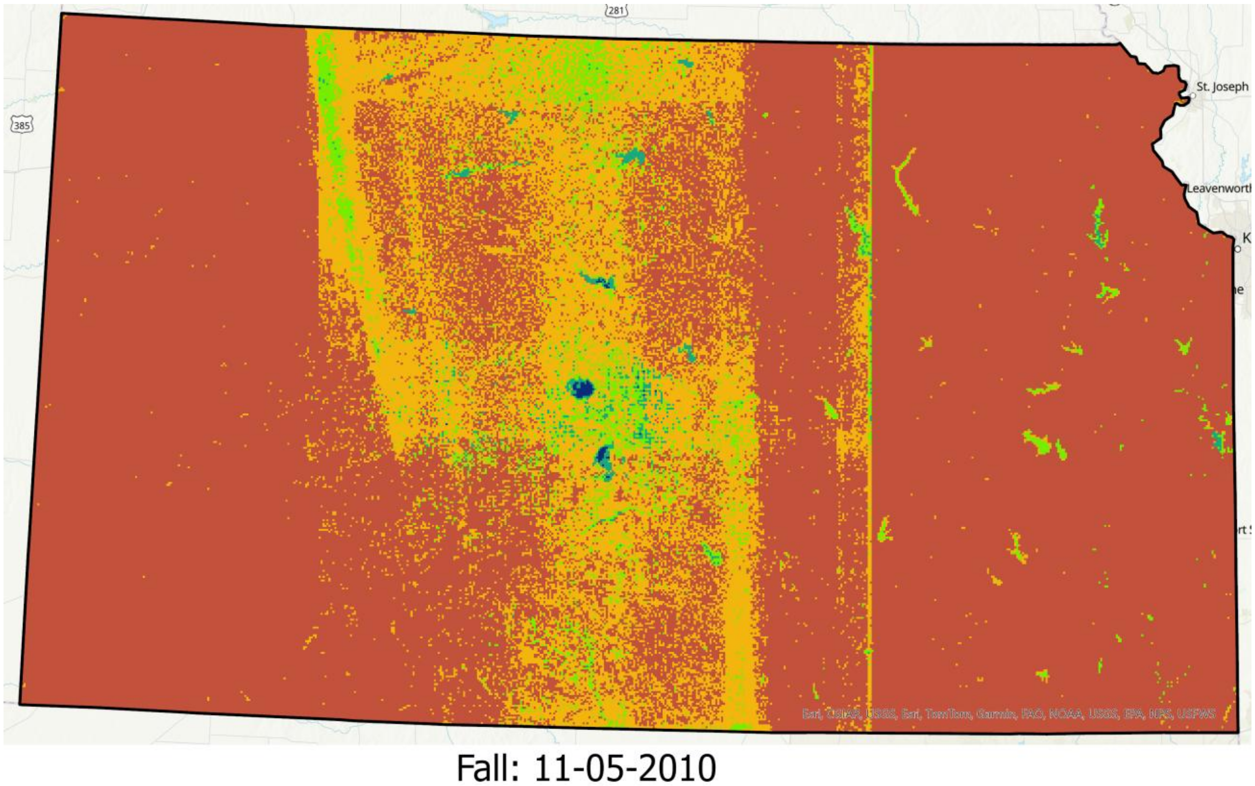
Fall: 09-15-2010

Appendix Figure C.6 Prediction map for Fall 10-10-2010.

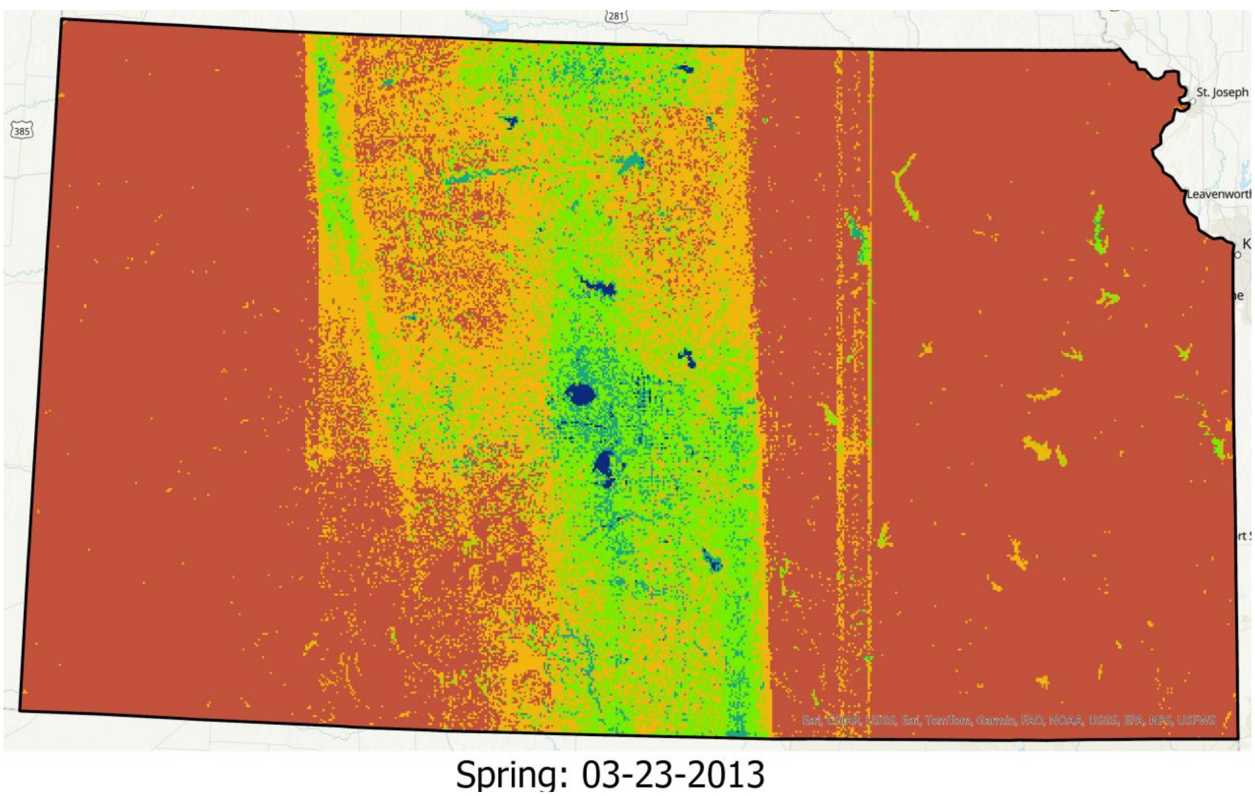


Fall: 10-10-2010

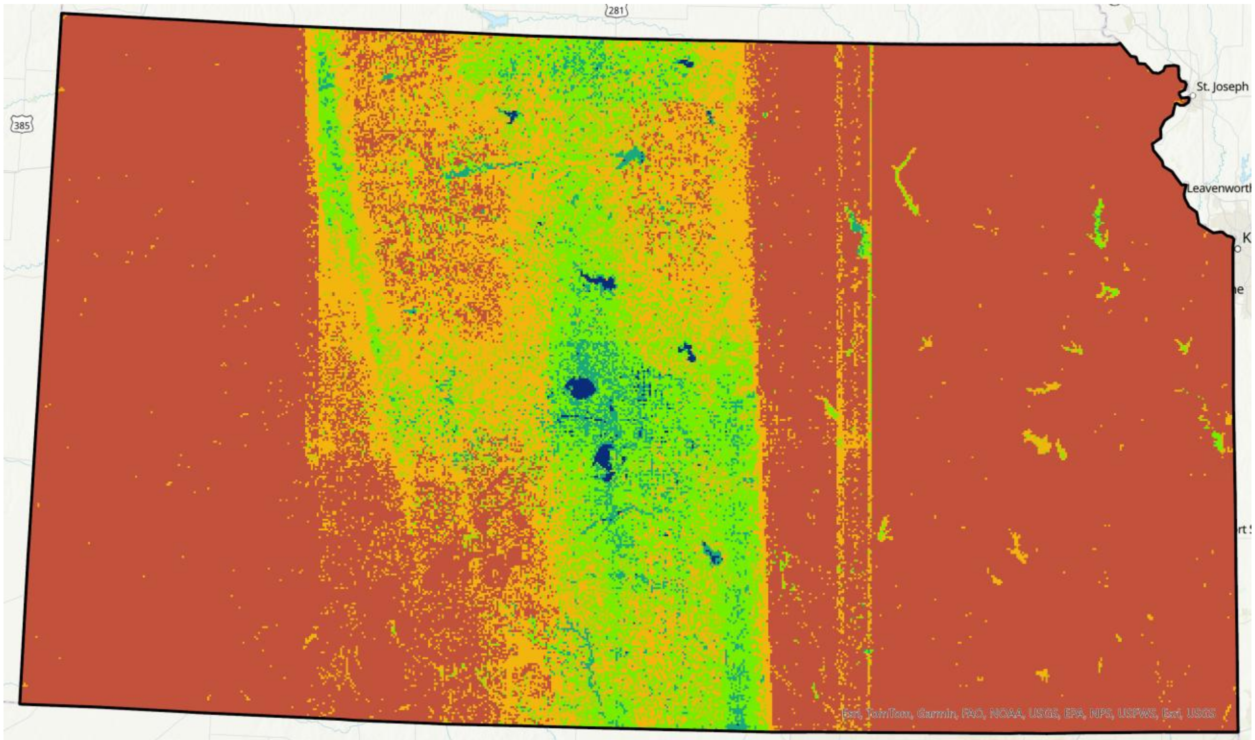
Appendix Figure C.7 Prediction map for Fall 11-05-2010.



Appendix Figure C.8 Prediction map for Spring 03-23-2013.

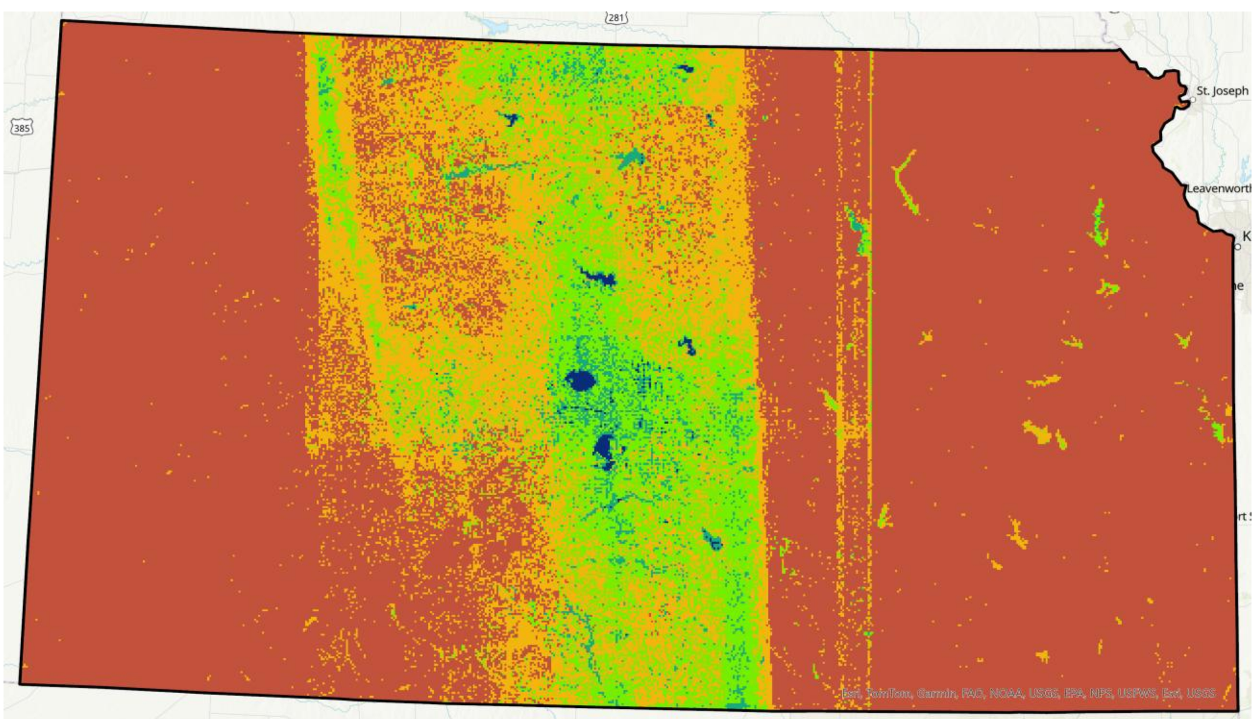


Appendix Figure C.9 Prediction map for Spring 04-15-2013.



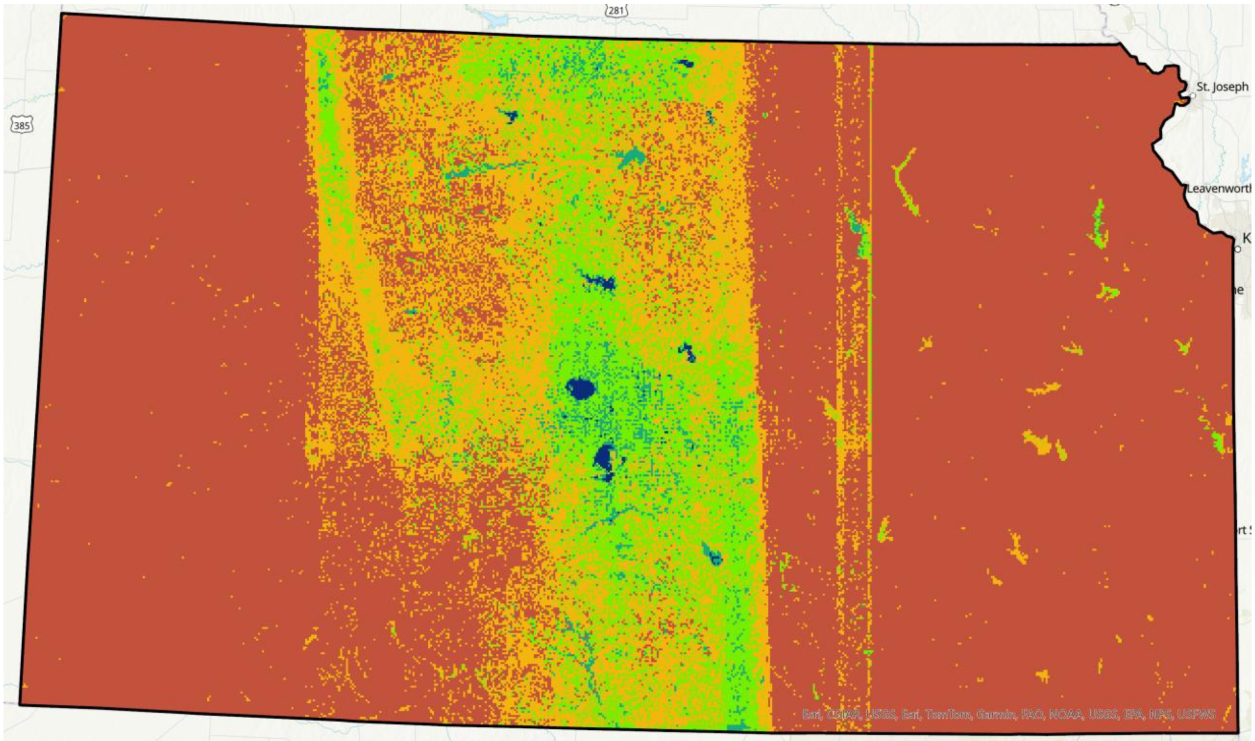
Spring: 04-15-2013

Appendix Figure C.10 Prediction map for Spring 05-10-2013.



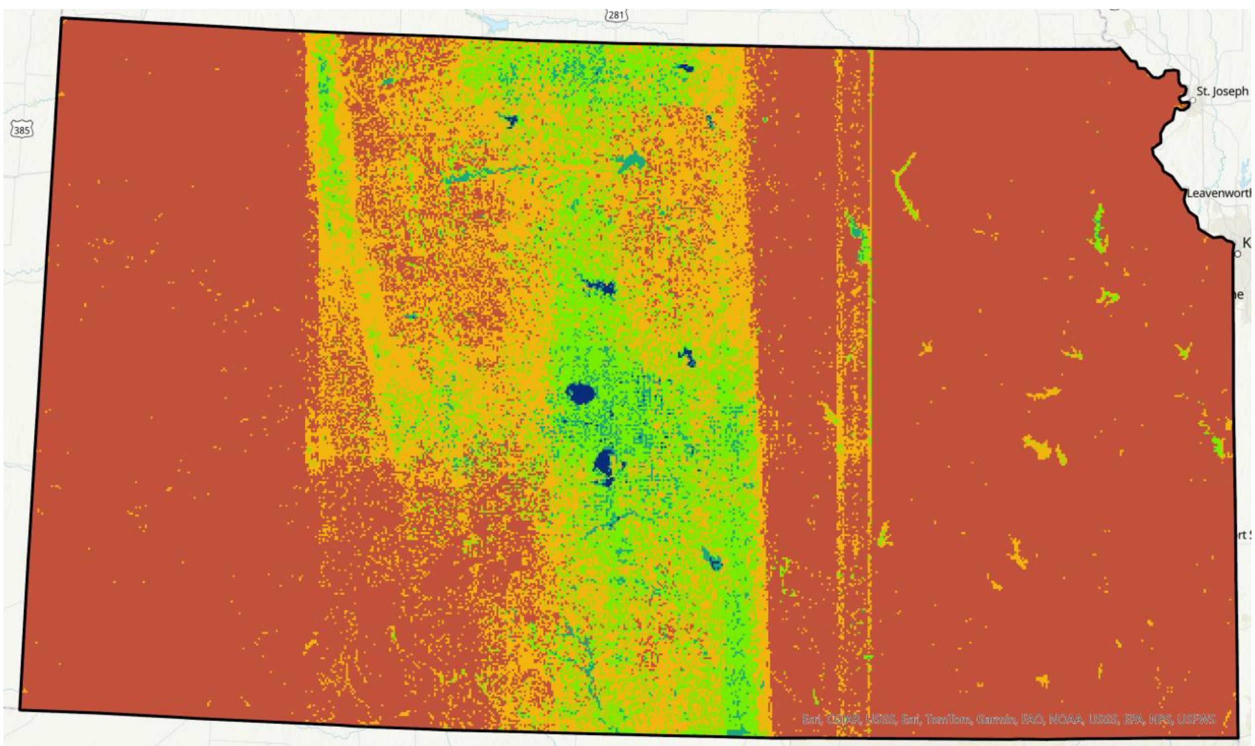
Spring: 05-10-2013

Appendix Figure C.11 Prediction map for Fall 09-15-2013.



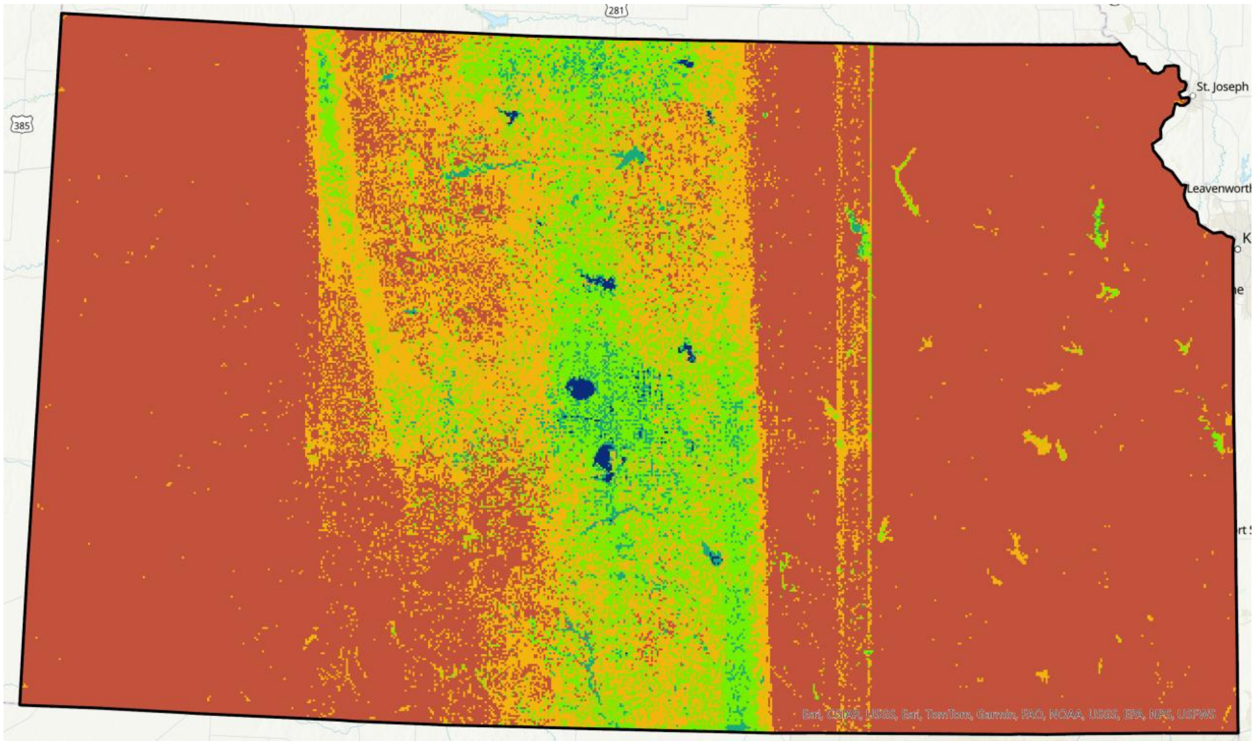
Fall: 09-15-2013

Appendix Figure C.12 Prediction map for Fall 10-10-2013.



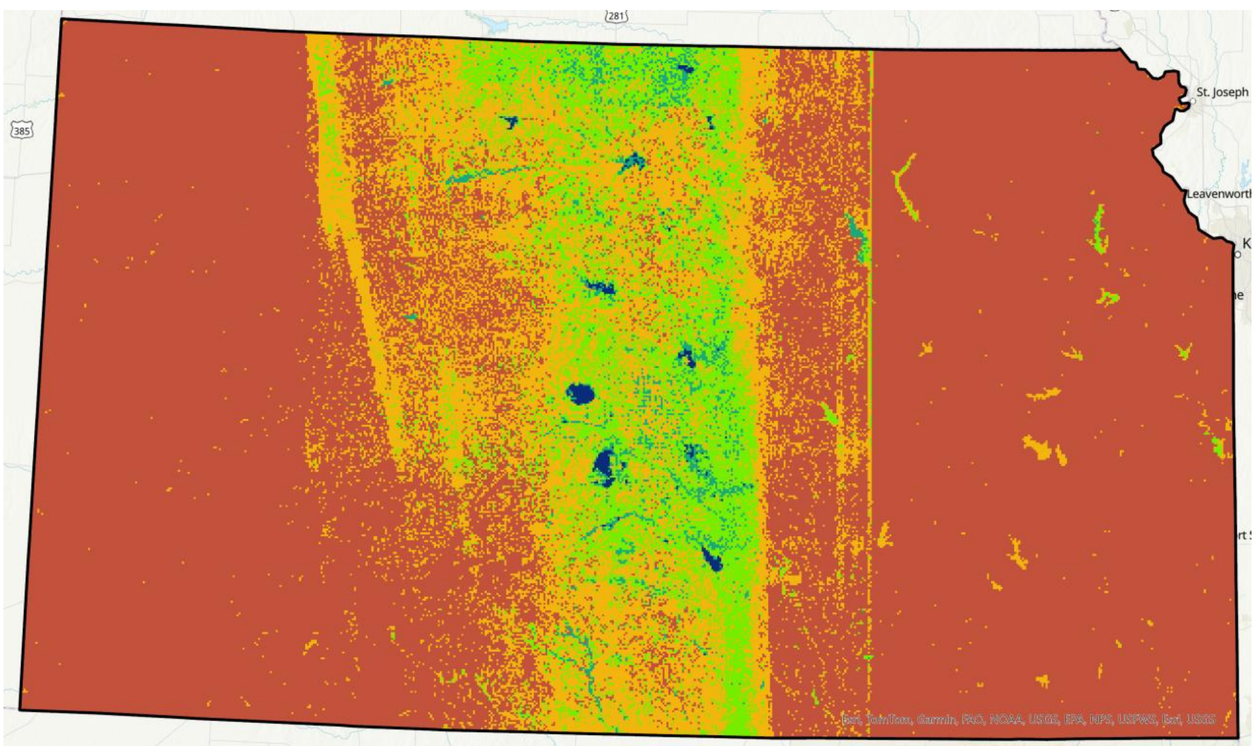
Fall: 10-10-2013

Appendix Figure C.13 Prediction map for Fall 11-05-2013.



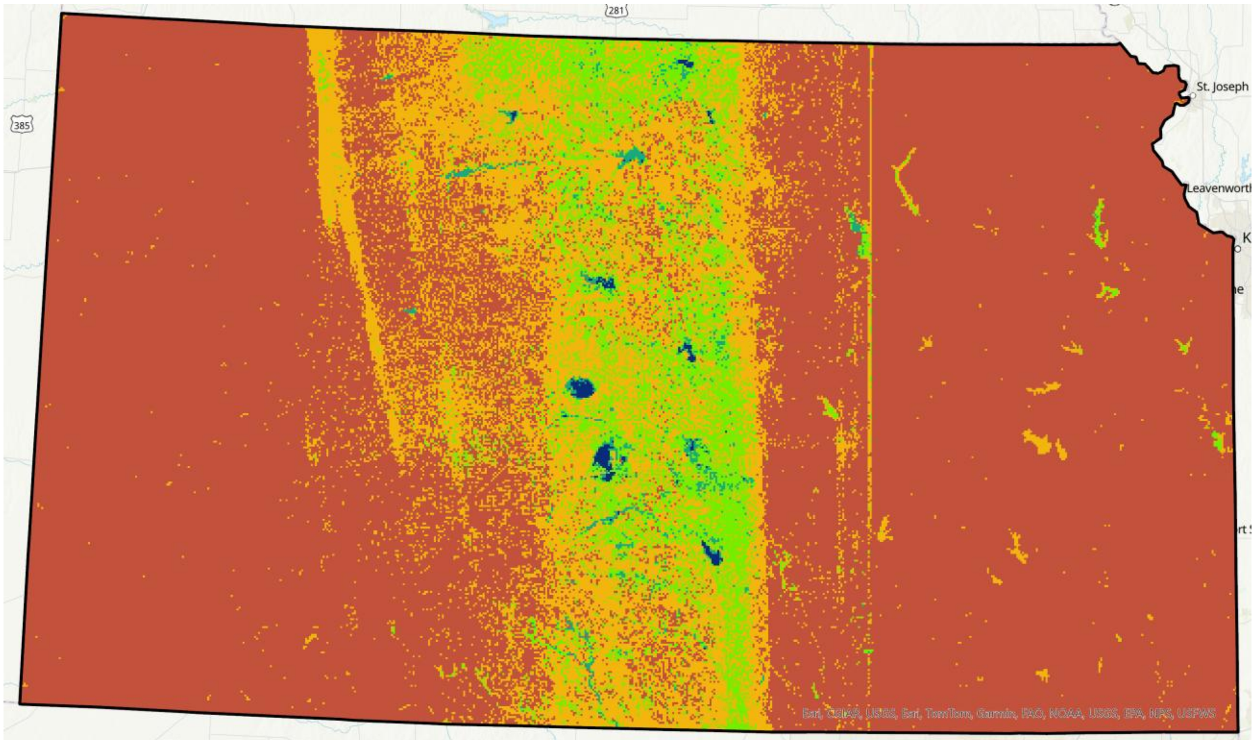
Fall: 11-05-2013

Appendix Figure C.14 Prediction map for Spring 03-23-2016.



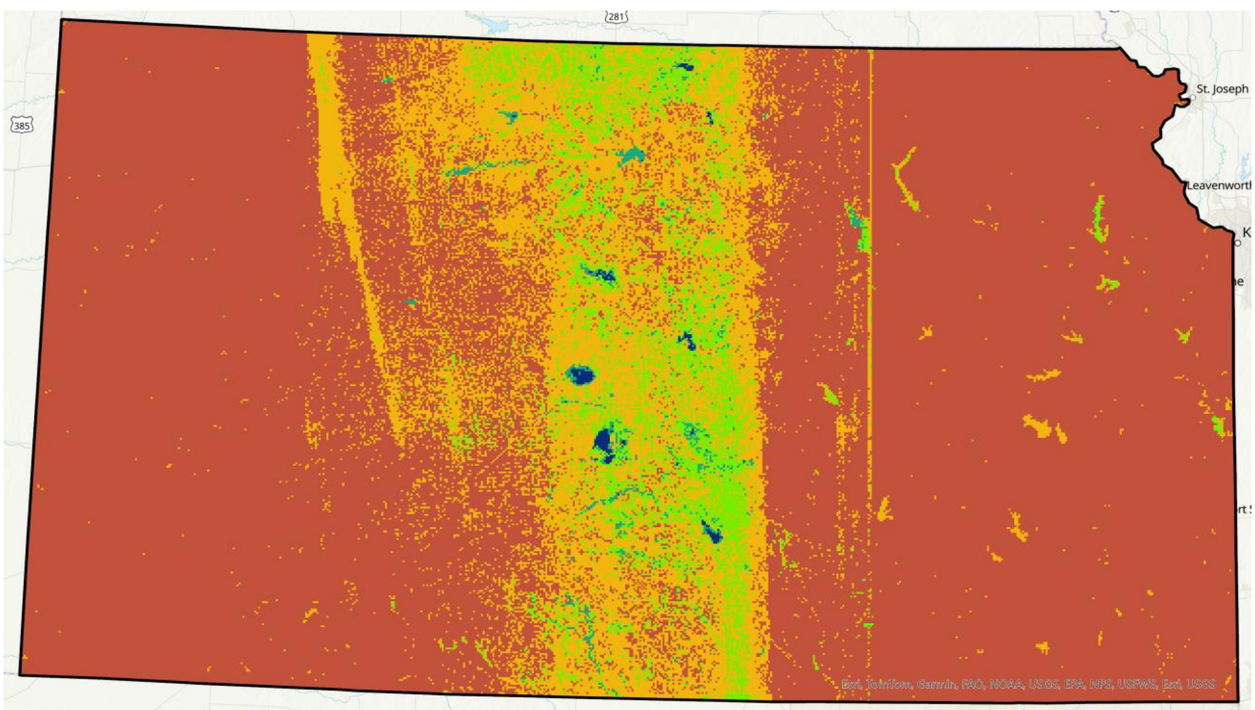
Spring: 03-23-2016

Appendix Figure C.15 Prediction map for Spring 04-15-2016.



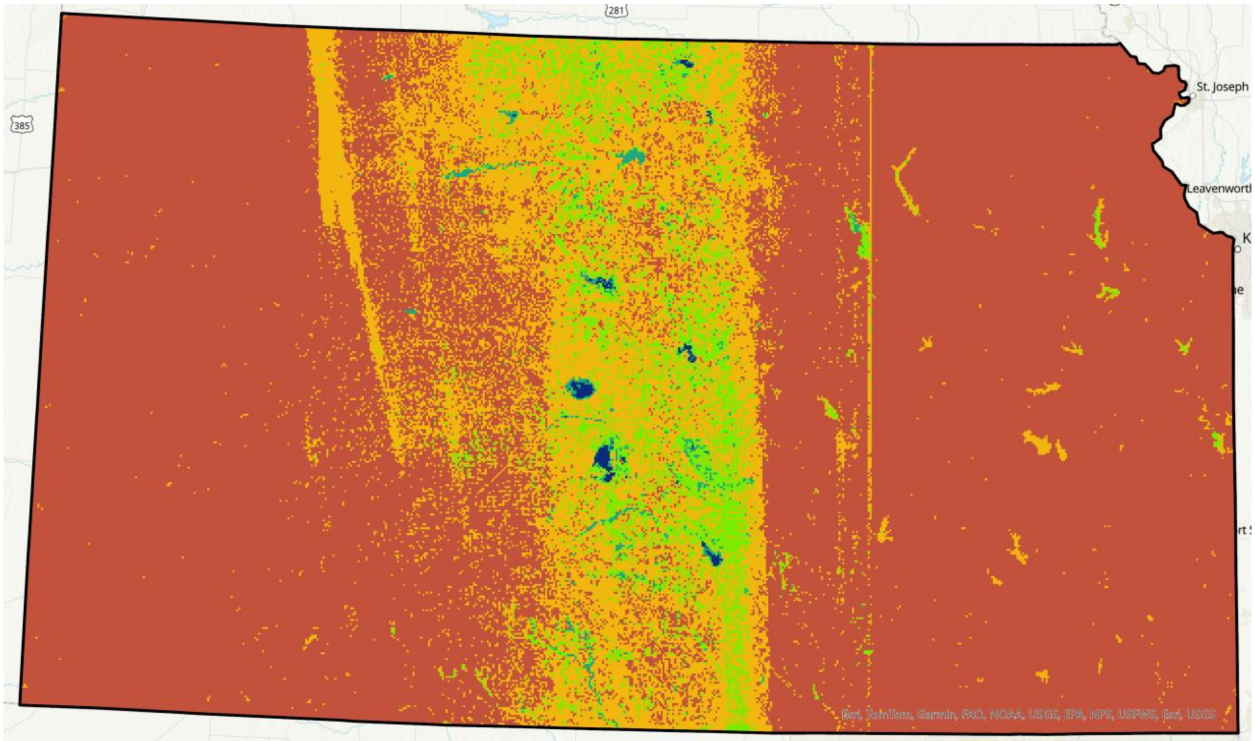
Spring: 04-15-2016

Appendix Figure C.16 Prediction map for Spring 05-10-2016.



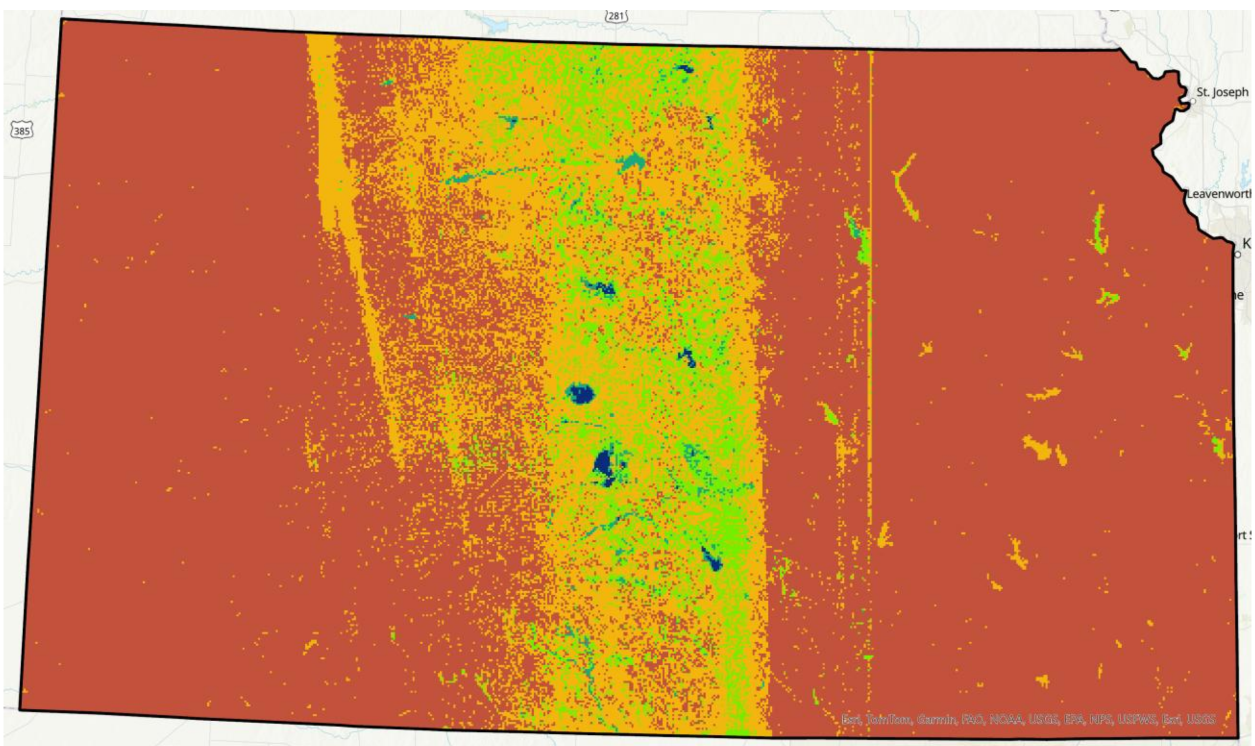
Spring: 05-10-2016

Appendix Figure C.17 Prediction map for Fall 09-15-2016.



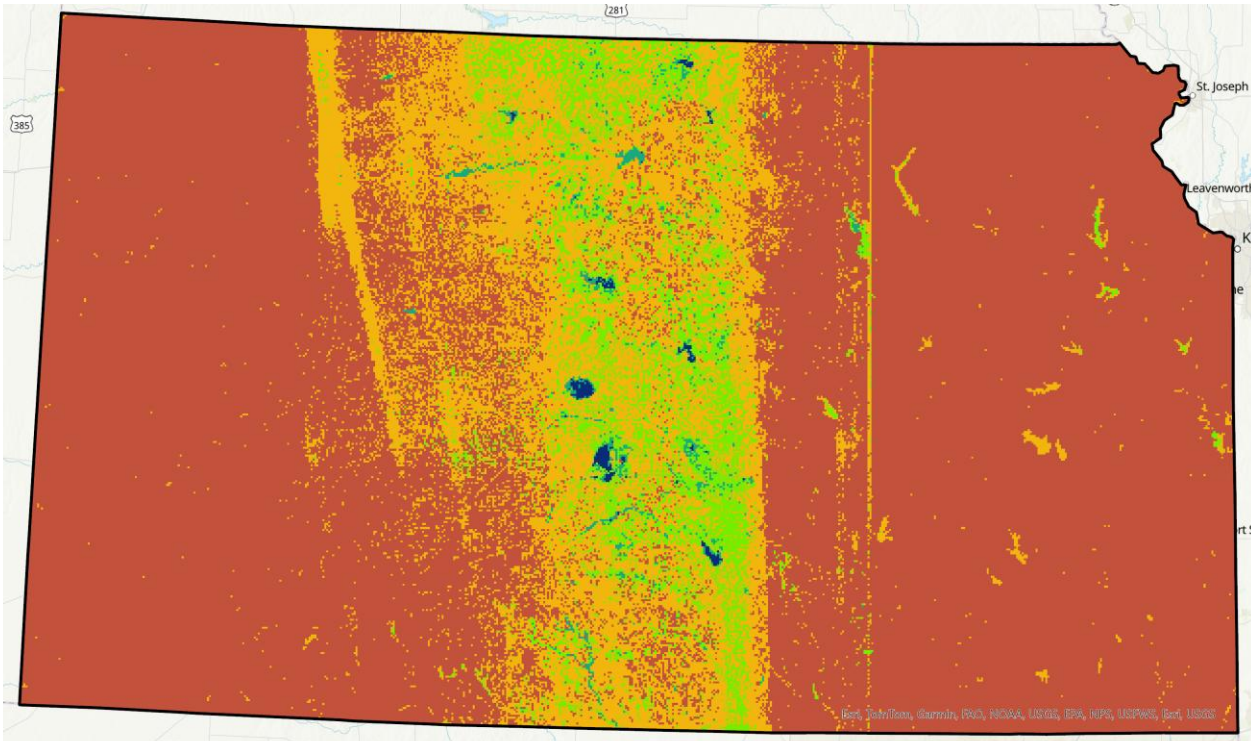
Fall: 09-15-2016

Appendix Figure C.18 Prediction map for Fall 10-10-2016.



Fall: 10-10-2016

Appendix Figure C.19 Prediction map for Fall 11-05-2016**.**



Fall: 11-05-2016

Appendix D - Whooping Crane Images

Appendix Figure D.1 Sketch of adult whooping cranes.

Appendix Figure D.2 Image of a baby crane.

Appendix Figure D.3 Image of two adult cranes.

Appendix Figure D.4 Image of rare twin juvenile cranes.