Avian Tides of Change: Charting Wood Stork Bird Migrations on a Climate-Altered Coastline

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Contents

1. Executive Summary

Migratory birds are dying off across the Western Hemisphere, with about 3 billion bird deaths since the 1970s due to climate change alone [30]. Climate change is especially dangerous for migratory birds like the Wood Stork, which depends on specific wetlands in the southeastern U.S. and Latin America for its seasonal movement. These wetlands are essential for their breeding, nesting, and foraging activities, making them highly vulnerable to the effects of climate change. Two main environmental changes affecting these birds are shifts in rainfall patterns and rising surface air temperatures. These changes make the Wood Stork arrive earlier or later at its breeding grounds, causing a mismatch in food availability, such as fish and insects, essential to their survival. Without enough food at the right time, reproduction rates can drop, and populations can suffer. Over time, many bird species, including the Wood Stork, have shifted their migration routes in response to these environmental pressures.

According to the U.S. Environmental Protection Agency (EPA), 61% of North American bird species have shifted their ranges, with some moving more than 200 miles from their usual paths in the last 50 years [31]. The decline in Wood Stork populations can disrupt aquatic ecosystems, as these wading birds help regulate fish populations by preying on small fish in wetlands, preventing imbalances that could affect other species. Their foraging behavior also stirs up sediments, aiding nutrient recycling and maintaining wetland health. Additionally, Wood Storks consume insects, helping control pest populations that impact local farms. The loss of Wood Storks from certain regions may lead to higher pest-related crop damage, increasing farming costs. Ecotourism, which thrives on birdwatching and wildlife observation, also suffers when Wood Storks disappear from their usual habitats, reducing revenue for local communities that depend on nature-based tourism. To better understand how climate change affects the Wood Stork, migration patterns have been analyzed using climate data. Two primary sources for this research include the Climate Change Knowledge Portal and Movebank for Animal Tracking Data [25][24]. The Climate Change Knowledge Portal, created by the World Bank, provides data on temperature and rainfall trends in the southeastern U.S., where the Wood Stork resides. This data is essential for understanding how climate changes impact migratory species and for predicting where the Wood Stork might migrate in the future. Movebank provides real-time tracking data for birds, including time, location, species, and migration length, which helps in studying the Wood Stork's migration patterns.

By combining these data sources, a clearer picture emerges of how changing environmental conditions are affecting migration. Kernel Density Estimation was used to map out where the Wood Stork migrates based on past data. Additionally, a model called SARIMA was employed to predict future temperature and rainfall trends in areas like Florida, Georgia, South Carolina, and North Carolina, where the Wood Stork migrates. This model helps understand how future climate trends may affect migration in these key habitats. Lastly, a Random Forest Regressor Model was applied to predict how the Wood Stork's migration path might change by 2035, taking various climate variables into account. The model indicates that the Wood Stork's migration route, traditionally starting in Florida and moving into Georgia and South Carolina, is now shifting further north into North Carolina. This change is driven by the effects of climate change, including higher temperatures and changing rainfall patterns. These changes not only impact the birds but also affect the ecosystems they rely on, including wetlands and aquatic environments.

The risk analysis revealed that urbanization and climate change threaten wetlands and agriculture, increasing economic burdens on farming. The SARIMA model showed uncertainty in future temperature and rainfall trends, heightening risks to Wood Stork habitats. Farmers in regions where wetlands and agriculture are closely linked face the greatest challenges, as habitat loss and rising pesticide use drive up costs and disrupt ecological balance for other organisms.

To address these problems, a comprehensive approach is needed, focusing on habitat restoration, sustainable farming practices, and strong policies. Wetland restoration efforts should focus on creating and preserving wetlands that are crucial for the Wood Stork's foraging and nesting. Wetland conservation is not only vital for the Wood Stork but also for maintaining healthy ecosystems that support biodiversity. Programs like the Wetland Reserve Program (WRP) can assist landowners in restoring wetlands, especially in areas heavily impacted by climate change. Managing water levels in wetlands can improve foraging success, and practices like flooding rice fields can also provide support. Reducing pesticide use is essential, which can be achieved by establishing pesticide-free zones and using Integrated Pest Management (IPM) strategies. These methods help reduce reliance on harmful chemicals while promoting a healthier environment for both wildlife and humans.

Additionally, using cover crops and technology for more precise pesticide application can further reduce chemical use, benefiting both farmers and Wood Storks. Public awareness plays a key role in protecting migratory birds, and local conservation programs can encourage people to get involved in these efforts. Water management strategies, such as wetland restoration, controlled flooding, and stormwater retention ponds, can help protect the Wood Stork's habitat from the effects of changing weather patterns. State governments should pass laws to protect wetlands, limit development in crucial areas, and incorporate migratory bird protection into climate action plans. Financial incentives for wetland conservation and collaboration with local organizations can help protect migration routes. These actions—combining habitat restoration, sustainable farming, and effective policies—are essential for protecting the Wood Stork and its migration routes despite the challenges posed by climate change.

2. Introduction and Background Information

Bird migration, a critical ecological process where birds travel vast distances between breeding and wintering grounds, is under increasing threat due to climate change. In particular, the Wood Stork (*Mycteria americana*) faces significant disruptions to its migration patterns due to shifting environmental conditions [1]. Climate change is profoundly altering ecosystems worldwide, impacting bird migration patterns that have evolved over centuries. As key contributors to wetland ecosystems, Wood Storks play a crucial role in nutrient cycling, maintaining water quality, and regulating aquatic prey populations [2]. However, rising global temperatures and widespread forest cover loss are disrupting these key processes. According to the *National Audubon Society*, rising temperatures and shifting weather patterns are causing birds to arrive at their migratory destinations earlier or later than usual, disrupting their life cycles [3]. Additionally, research from the Financial Times, in collaboration with global studies, indicates that some migratory bird species are actually experiencing an expansion in their migratory ranges due to climate change. As temperatures rise, many species are shifting their habitats toward cooler areas, often moving northward or to higher altitudes. This shift has allowed certain species to explore new territories that were previously inaccessible.Over the past few decades, some North American bird populations have been observed migrating further than they traditionally did, with evidence suggesting that these changes may offer new opportunities for survival, despite the broader challenges posed by climate change [4].

While range shifts and altered migration timing are common among migratory birds, Wood Storks encounter additional ecological pressures that distinguish their response to climate change.Wood Storks rely heavily on stable wetland conditions and specific climate factors such as rainfall and water levels. These unique dependencies make them more vulnerable to climate change and environmental disruptions compared to other birds.

2.1 Ecological Role of Wood Storks

Wood Storks play a crucial role in the ecosystems of the Western Hemisphere, particularly within wetland environments. In order to fulfill their role, their cyclical migration pattern should remain relatively constant. Numerous agricultural groups depend on migratory birds for food security and income, and as temperatures rise, farmers may face higher risks of crop failure and financial instability. In regions where bird populations are declining, up to 100 million people could experience heightened vulnerability to climate impacts by 2050 [5]. At a wide economic scale, The *U.S. Fish and Wildlife Service* reports that insect-eating birds contribute \$3.2 billion annually to the economy in pest control services, which include reducing the need for pesticide applications in residential and agricultural settings [6]. In the U.S., agricultural industries that depend on migratory birds, such as cranberry and cherry farms, could face substantial economic losses due to changes in bird behavior. The *National Audubon Society* reports that birds contribute nearly \$107 billion annually to the U.S. economy through their roles in agriculture, tourism, and ecosystems [7].

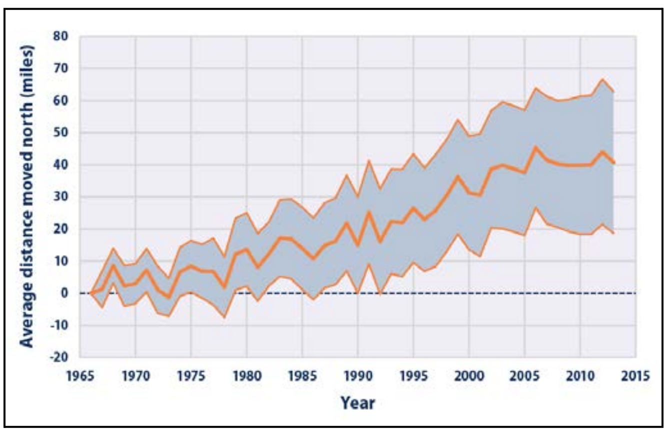


Figure 1: *This figure illustrates the annual shift in latitude of the center of abundance for 305 widespread bird species in North America from 1966 to 2013. It highlights how changing temperatures are affecting bird migration patterns, with species shifting their ranges over time. The shaded band represents the likely range for the average movement of these species. These shifts in migration are a clear indicator of the ecological impacts of climate change, potentially disrupting critical services like pest control, pollination, and seed dispersal, which are essential for agriculture and ecosystems (Courtesy of the National Audubon Society [8]).*

The Western Hemisphere contains some of the most crucial migratory routes for Wood Stork, yet these paths are increasingly threatened due to climate change and habitat destruction. Wood Storks primarily migrate within the Atlantic and Gulf Coastal regions, relying on wetland ecosystems in the southeastern United States, Central America, and South America for breeding and foraging [9]. Their migration is heavily influenced by seasonal rainfall and water levels, which regulate food availability and nesting success. This hemisphere is home to diverse ecosystems, ranging from Arctic tundras to tropical rainforests, making it a region full of biodiversity. However, Wood Storks are particularly vulnerable to climate-induced changes, as their survival depends on stable wetland conditions. Two key environmental shifts—precipitation patterns and surface temperature—directly impact their migration and breeding cycles. Wood Storks rely on drying wetlands to concentrate fish for efficient foraging, but unpredictable rainfall and prolonged droughts can disrupt this process, reducing their food supply and forcing them to alter migration timing or location.

A study by Carey et al. identified that birds that rely on specific climate conditions for breeding, feeding, and migration face increasing risk as their habitats undergo rapid changes [10]. In regions experiencing prolonged droughts or erratic precipitation patterns, food sources such as nectar, insects, and seeds, become less abundant, leading to malnutrition and decreased survival rates [11].

2.2 Economic and Agricultural Implications of Migratory Disruptions

The impact of Wood Stork migration disruptions goes beyond ecosystems and can alter the lives of individuals in everyday households. Wood Storks play a crucial role in maintaining the health of wetland ecosystems, which benefits human communities by naturally regulating pest populations. Their foraging activities help control fish and invertebrate populations, contributing to the balance of aquatic ecosystems [13]**.** However, declines due to climate change can lead to imbalances, resulting in increased pest populations in nearby communities. The disruption of nutrient cycling in wetlands can change vegetation and aquatic life, increasing populations of pests such as mosquitoes, which carry diseases like West Nile virus, Zika virus, and malaria [14]. The absence of natural predators, in this case, Wood Storks, raises the probability of mosquito swarms and disease risk. Termites are a significant concern for homeowners, as they cause severe structural damage and can drastically alter an individual's quality of life if left unchecked [15].

Public health expenses may rise due to an increase in disease-carrying insects, as well as zoonotic diseases sea life carry, which Wood Storks help control. The Centers for Disease Control and Prevention (CDC) reports that tick-borne illnesses, including Lyme disease, cost the U.S. healthcare system between $345 million and $968 million annually [21]. Additionally, a study by Ralston et al. estimated that marine-borne pathogens in the United States result in annual health costs of approximately $900 million [63]. With fewer Wood Storks controlling these populations, vector-borne diseases could worsen, increasing public health expenditures and economic strain. The decline in migratory Wood Storks has consequences for businesses dependent on natural pest control. In the U.S., pest-related crop damage costs farmers around $30 billion annually [14]. The birds help manage large insects, like grasshoppers, locusts, and dragonflies, which damage crops such as tomatoes, strawberries, cabbage, and other brassicas. Historically, farmers relied on birds to reduce pesticide use, but as Wood Stork populations decline, many are turning to chemical pest control, increasing both production costs and produce prices. The U.S. pest control market was valued at $17.6 billion in 2022 and is expected to continue growing [16].

Wood Storks also regulate sea life by feeding on small fish, crustaceans, and frogs [61], which has long-term environmental impacts on soil health, water quality, and biodiversity. Pesticides used in agriculture contribute to 70% of insecticide runoff into water bodies, harming ecosystems [15]. In the Florida Everglades, restaurants and tourist spots benefit from Wood Storks and other wetland birds that help control insect populations naturally. Open-air dining areas, eco-lodges, and nature-based attractions rely on a balanced ecosystem to keep pests in check. However, as Wood Stork populations decline due to habitat loss and climate change, businesses face increased insect problems and higher pest control costs. The Everglades spends tens of billions of dollars to manage invasive species such as tree frogs, snakes, and fish, an issue worsened by the decline of Wood Storks [62]. These additional expenses increase operating costs and affect customer satisfaction. A study by Cornell Hospitality Research found that 87% of hospitality customers consider cleanliness, including pest control, a critical factor in their experience [17].

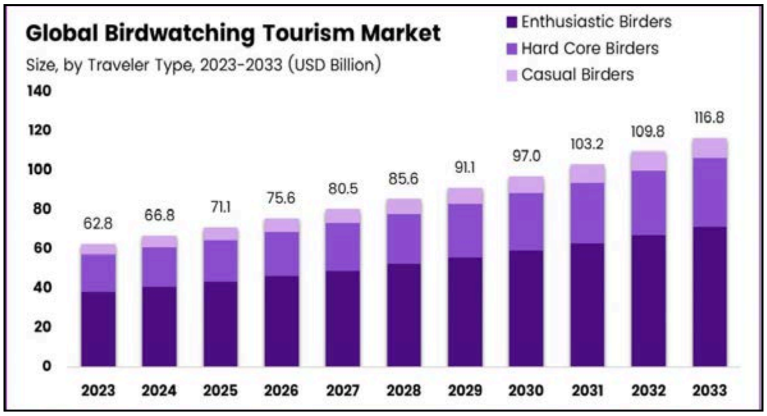


Figure 2: *The bar chart illustrates the projected growth of the Global Birdwatching Tourism Market from 2023 to 2033, segmented by traveler type: Enthusiastic Birders, Hard Core Birders, and Casual Birders. The market size is measured in USD billion, with an expected increase from $62.8 billion in 2023 to $116.8 billion in 2033, growing at a compound annual growth rate (CAGR) of 6.4%. Each bar represents the total market size for a given year, with different shades of purple indicating the contribution of each traveler type. The data suggests steady growth, with significant contributions from enthusiastic and hard-core birders (Courtesy of Market.us [19]).*

Businesses reliant on tourism, especially in regions known for their natural beauty and wildlife, could see a decline in visitors. For example, birdwatching contributes approximately $41 billion annually to the U.S. economy [18]. Iconic destinations like the Everglades in Florida or Eufaula National Wildlife Refuge on the Alabama-Georgia Border could experience reduced visitor numbers if bird populations continue to decline. This could negatively impact eco-lodges, nature reserves, and wildlife parks that depend on birdwatching tourism. As bird populations dwindle, businesses in these sectors could face a loss of revenue from ecotourism activities.

The economic impact due to declining Wood Stork populations is substantial in the Western Hemisphere. Eco-tourism that relies on bird-watching could face a major loss of revenue, as an estimated 96 million people (or 3 in 10 individuals) in the U.S. participate in bird-watching, contributing around $279 billion in 2022 [20]. Many bird watching destinations across the Western Hemisphere, such as the Galápagos Archipelago of the Republic of Ecuador, rely on consistent bird populations to attract visitors. A decline in bird numbers could lead to decreased ecotourism revenue, affecting local economies that depend on nature-based tourism. This leads to a chain of events, which spreads to neighboring hotels, restaurants, and tour operators that cater to this crowd of individuals, leading to financial and job losses. Data from the U.S. Fish and Wildlife Service found that birding activity helped support the jobs of 1.4 million jobs and generated 90.2 billion in labor income [20].

The Wood Stork population in the coastal southeastern U.S. faces increasing risks due to climate change and human-driven habitat loss. These long-legged wading birds, historically concentrated in Florida and Georgia, are now shifting their migratory patterns northward into the Carolinas. This study examines how key climate factors—precipitation and surface air temperature—are altering their traditional migration routes, nesting behaviors, and food availability. Habitat destruction from agricultural expansion, urbanization, and wetland degradation further exacerbates these challenges, pushing the species toward potential population declines. Wood Storks are also dying due to extra energy expenditures because they have to travel further in migration for resources for breeding and nesting. Without intervention, Wood Storks may experience reduced breeding success, decreased foraging efficiency, and habitat fragmentation, ultimately threatening their survival. These changes not only disrupt ecological balance but also have broader implications for wetland health, pest control, nutrient cycling, and the well-being of human systems. The risks associated with wetland loss and urbanization are analyzed, along with an expected loss to agricultural systems due to the shifts of Wood Storks, and uncertainty in factor trends is identified. To mitigate these risks, this research explores conservation strategies, including habitat restoration, sustainable water management, and policy-driven land protection efforts.

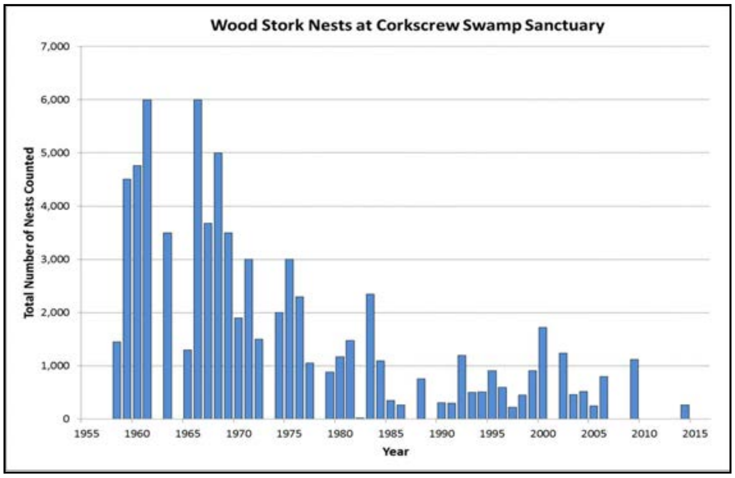


Figure 3: *Historical trends in Wood Stork nest counts at Corkscrew Swamp Sanctuary from 1955 to 2015. The data illustrate a peak in nesting activity during the 1960s, followed by a significant decline in later decades. This decline may be attributed to climate change impacts, habitat loss, and altered hydrological conditions affecting food availability and breeding success. (Courtesy of the Audubon Corkscrew Swamp Sanctuary)* [64].

Specific recommendations focus on restoring key wetlands like Florida's Corkscrew Swamp Sanctuary, implementing fish stocking programs to support foraging, and incentivizing agricultural practices that sustain wetland conditions. By understanding and addressing these risks, this study aims to preserve Wood Stork populations and the ecosystems they support, ensuring their long-term viability in a rapidly changing environment.

3. Data Methodology

3.1 Data Collection

Due to the absence of data for the period from 2020 to 2024, predictive modeling was used to estimate the data for these years. This approach allowed for a more complete analysis, and the limitations of this method are discussed in **Section 4.6.** The data sets below correspond to the years 2004-2019.

Climate Change Knowledge Portal Data [25]

- ❖ **Data Type:** Average Surface Air Temperature and Average Precipitation Trends From Historical Records for Every State and Country.
- ❖ **Source:** World Bank Group
- ❖ **Variables:** Annual average surface temperature, monthly temperature variation, Annual total precipitation, monthly precipitation trends for each state and country in both continents.
- ❖ **Use:** This dataset from World Bank Group provided historical temperature and precipitation trends, which were used to analyze long-term climate patterns affecting bird migration. SARIMA (Seasonal Autoregressive Integrated Moving Average) was applied to project future temperature and precipitation trends, which were then fed into Random Forest Regressor to simulate how climate change could impact migration patterns.

The Movebank for Animal Tracking Data contained individual bird data recorded at hourly intervals over multiple days. In order to refine this for analysis, we extracted the first recorded location of each bird for each month and inputted it into the Kernel Density Model (KDE). There was not any available data on the overall population of Wood Stork birds, and the limitations of this data are discussed in **Section 4.6.**

Movebank For Animal Tracking Data [24]

- ❖ **Data Type:** Migration Patterns for Bird Species Over a Period of Time.
- ❖ **Source:** Movebank
- ❖ **Variables:** Timestamp, Longitude, Latitude, Species Type, Migration Duration, and Local Tag Identifier.
- ❖ **Use:** The migration data from Movebank was processed using Kernel Density Estimation (KDE) to create heatmaps of bird movement patterns, identifying key migration corridors and stopover sites. This information was then used to train the Random Forest Regressor model, which incorporated climate projections from SARIMA to predict how

bird migration routes may shift due to changing temperature and precipitation trends. By integrating these methods, the model was able to estimate potential future pathways for the Wood Storks under varying climate settings.

U.S. Fish & Wildlife Service [89]

- **Data Type:** Wetland Data for each State
- **Source:** U.S. Fish & Wildlife Service
- **Variables:** Wetland Type, geometry
- **Use:** The Wetland Data was overlaid for selected states to visualize the wetlands over the state in the risk analysis

ArcGIS Online [86]

- **Data Type:** Urban Area Data for South Carolina
- **Source:** ArcGIS Online
- **Use:** The Map of Urbanization of South Carolina in 2000 and 2010 was overlaid to visualize the change in urbanization. This map was also used to view against the wetlands

ArcGIS Storymaps [87]

- **Data Type:** Urban Area Data for North Carolina
- **Source:** ArcGIS Storymaps
- **Use:** The Map of Urbanization of North Carolina in 2000 and 2020 was overlaid to visualize the change in urbanization. This map was also used to view against the wetlands

Florida Department of Environmental Protection - MapDirect Data [88]

- **Data Type:** Urban Area Data for North Carolina
- **Source:** MapDirect Data
- **Use:** The Map of Urbanization of Florida was created to visualize urbanization. This map was also used to view against the wetlands

3.2 Data Cleaning

The migration dataset [24] consisted of longitude and latitude coordinates corresponding to recorded locations of migratory birds over time. To facilitate analysis, these coordinates were converted into identifiable geographic regions—specifically, state and country designations—to align them with corresponding climate data. This was achieved using a geopackage (GPKG) file, which contained global boundary information at the state level, labeled as NAME_1 in the GPKG. By inputting the longitude and latitude of each recorded bird location, the geopackage file provided the corresponding state and country. This process was repeated for each timestamp in the dataset, ensuring accurate geographical classification of bird migration data. Once the state and country of each bird observation were identified, the next step was to integrate this information with climate data, specifically temperature and precipitation records. The climate dataset [25] contained historical temperature and precipitation values organized by state and country from 1951 to 2020 on a monthly basis. The average values for all southeastern states (from Florida to Virginia) were calculated for each month and year. For example, all target states' January 2000 values for both temperature and precipitation were averaged to determine the overall temperature and precipitation for that month. By matching each bird's location and timestamp to the corresponding climate data based on month and year, it became possible to analyze temperature and precipitation conditions along migration routes.After completing the geographic conversion and climate data matching, all processed data were compiled into a structured CSV file. Each row contained the bird's recorded location, the corresponding state and country, the timestamp, and the temperature and precipitation values for that location and time. This compiled dataset formed the foundation for subsequent analyses of how climate variability influences migratory patterns.

4. Mathematics Methodology

4.1 Assumptions

Two key assumptions were formed about the expected results of mathematical modeling related to migratory Wood Stork populations. For each environmental factor, a prediction is made on whether bird migration routes are expected to shift or remain stable in response to the variable. Mathematical analysis is performed in **Sections 4.3-4.5**. Variables that are referenced appear in **Section 4.2** with further explanation.

Assumption: Increased variability in precipitation (C_{precip}) patterns leads to shifts in migration routes, as Wood Storks alter their stopover sites and timing to find suitable habitats.

Explanation: Changes in precipitation patterns affect the availability of food and water resources along migration routes. Prolonged droughts can reduce insect populations, decreasing vegetation cover, and dry wetlands that serve as important stopover sites for Wood Storks. The birds migrate short or long distances based on food availability and climate conditions associated with their annual life cycles, in which above-average temperatures are causing birds to migrate earlier in the spring [27]. On the other hand, extensive rainfall can lead to flooding, which may destroy nesting areas and reduce foraging efficiency. According to a study by Georgetown University, conditions in the Caribbean, for example, have been getting progressively drier, leading to migrating birds, including Wood Storks, to have a disadvantage, causing a shift in their current breeding origin to shift more than 500 km south of their origins in 1990 [26]. As precipitation variability increases, Wood Storks may be forced to take longer, less direct routes, potentially leading to increased energy expenditure and reduced survival rates.

Assumption: Rising surface temperatures (C_{Temp}) disrupt migratory Wood Stork patterns by forcing the birds to shift their migration timing, leading to mismatches between their arrival and food availability.

Explanation: Warmer temperatures can cause Wood Storks to migrate earlier or later than usual, affecting their access to critical food sources upon arrival. If the birds arrive too soon, insects and plants they depend on may not be readily present, which in fact, has led to a decline of 53% in populations of birds that feed in grassland areas of the U.S. and Canada [28]. This starvation further leads to a decrease in breeding opportunities, which leads to a reduction in bird populations. Excessive heat increases metabolic stress on Wood Storks, reducing survival rates during migration due to adaptations they make in their path along with timings of travel. A study published by researchers with *Global Change Biology* found that migratory birds in North America, including Wood Storks, have shifted their spring migration earlier by an average of 1.5 days per decade in response to rising temperatures [29]. As temperatures continue to rise, Wood Storks will be forced to change the patterns and timings of travel, which not only has detrimental effects on them, but the ecosystems that depend on them for ecological balance.

4.2 Variables

To ensure the coherence of our data analysis, it's imperative to define the variables used based on the collected data, as outlined in **Section 3.1**. The data collected can be split into two types, as stated below. Variables for unpredicted and predicted migration paths are also established.

i) Environmental Factors

Variable Name	**Representation**	**Measurement Explanation**
C_{Temp}	Surface Air Temperature Change	The difference in average monthly temperature compared to historical norms for a given time period (monthly temperature change from 1951-2020). Data is presented by year, with specific attention to current climatology trends.
C_{Precip}	Precipitation Change	The difference in average monthly precipitation compared to historical norms for a given time period (monthly precipitation change from 1951-2020). This variable tracks shifts in rainfall amounts during migration periods.
MigrationStartDate	Migration Start Data	The average date on which Wood Storks begin their migration. Changes in the timing of migration due to temperature and precipitation shifts are tracked.
MigrationRoute	Migration Route	The path migratory Wood Storks follow between breeding and wintering grounds, influenced by temperature and precipitation changes. This includes longitudinal and latitudinal coordinates of key stopover points.

ii) Bird Data Variables

Variable Name	Representation	Measurement Explanation
Timestamp	Time in Year, Month, Day, Hour, and Second bird is at specific location	The specific date and time when Wood Stork migration data is recorded. This will allow for tracking seasonal shifts and migration patterns in response to changing climatic conditions.
Location-Lon	Longitude	The longitudinal coordinate of Wood Stork migration points or stopover sites. Tracks the birds' movement across geographical locations over time.
Location-Lat	Latitude	The latitudinal coordinate of Wood Stork migration points or stopover sites. Tracks the birds' movement across geographical locations over time.
Species	Species of Bird	The specific species of birds being tracked for migration and behavioral data. For the purpose of this study, Wood Storks are analyzed.
Migration Duration	Length of time bird takes to migrate from start to end of route	The total length of time taken for Wood Storks to complete their migration route, from departure to arrival, measured in months. This may vary as a result of precipitation and temperature variations.
Tag_Local_Identifier	Number Tag for each individual Wood Stork	Each bird in the dataset has their own respective tag number.

iii) Wetland Data Variables

Variable Name	Representation	Measurement Explanation
WetlandType	Type of Wetland	General description of the wetland based on the Cowardin wetland classification
Geometry	Location	Coordinates defining the features

4.3 Kernel Density Estimation

To accurately represent the spatial distribution of migratory birds over time, a Kernel Density Estimation (KDE) was applied to transform discrete bird location data into a continuous density surface. Each purple dot in the dataset represents the latitude and longitude of an individual bird at a specific time. However, using individual points alone can make it difficult to identify broader migration patterns. To address this, KDE to estimate regions where birds are most densely concentrated, allowing the representative migration areas to be defined while filtering out outliers.

Kernel Density Estimation works by smoothing bird locations over a given area to create a probability density function. Mathematically, this is expressed as:

$$f(x) = \frac{1}{nh^d}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right)$$

where f(x) represents the estimated density at location x, n is the number of bird observations, h is the bandwidth (determining the level of smoothing), d is the dimensionality of the data, and x_i represents the observed locations, and K is the kernel function, where:

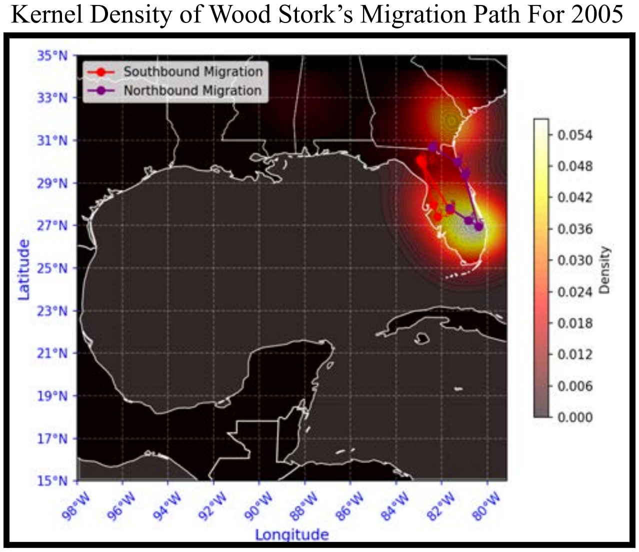
$$K(u) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}u^2}$$

Specifically, K(u) is the Kernel function value at u, e is Euler's number, and u^2 is squared standardized distance.

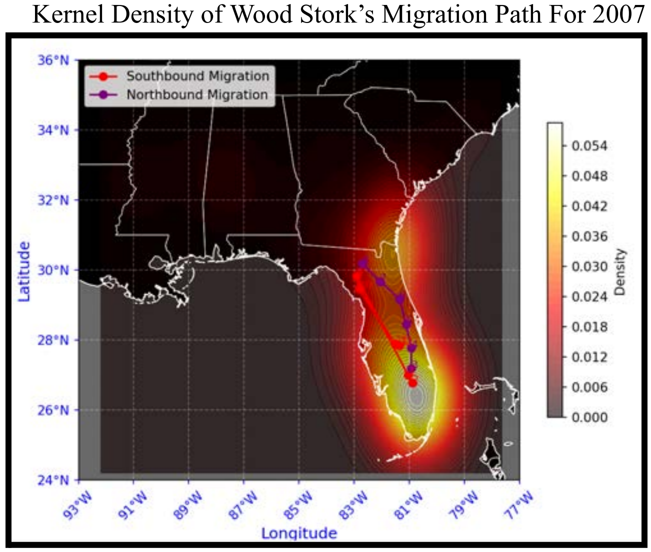
By applying KDE, migration heatmaps were generated, with high-density areas corresponding to primary migration routes and stopover sites, while low-density areas represent regions with fewer recorded birds. This allows for a more precise visualization of the migration corridors and reduces the impact of outliers that may not reflect actual migratory behavior. To further enhance the analysis, seasonal migration paths were overlaid on the KDE-generated density maps. These paths, shown in red for southward migration and purple for northward migration, were constructed by connecting sequential bird locations over time. This visualization technique provides a clear depiction of how birds transition between breeding and wintering grounds throughout the year. By analyzing KDE density maps across multiple years, we can track shifts in migratory behavior over time, assess the impact of environmental changes on migration routes, and identify emerging trends in bird movement. This method serves as an important tool for understanding how external factors, such as climate change or habitat loss, influence migration patterns and population distribution. The code for this algorithm can be found in **Appendix 1**.

In this study, KDE was utilized to map trends in migration paths for two bird species: Below is a 15 year succession of the migratory paths in relation to location on the map.

Kernel Density of Wood Stork's Migration Path For 2005

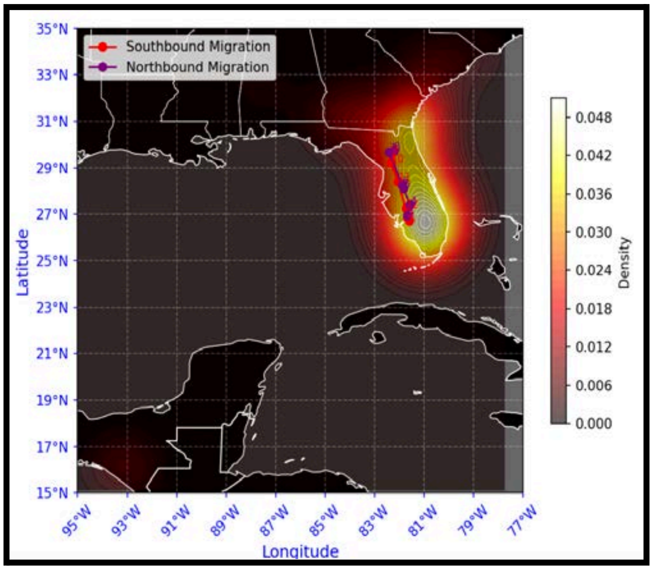


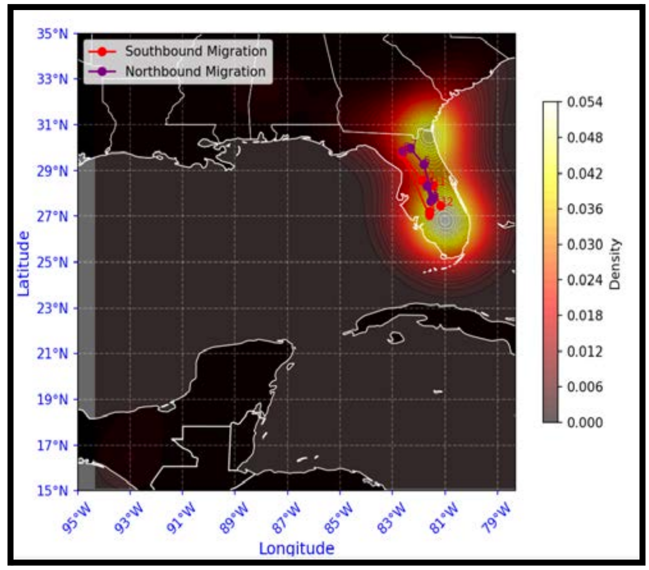
Kernel Density of Wood Stork's Migration Path For 2007



Kernel Density of Wood Stork's Migration Path For 2009

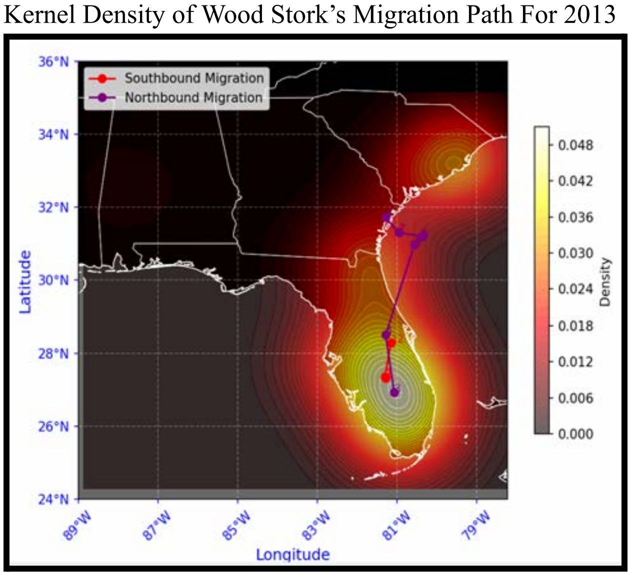
Kernel Density of Wood Stork's Migration Path For 2011

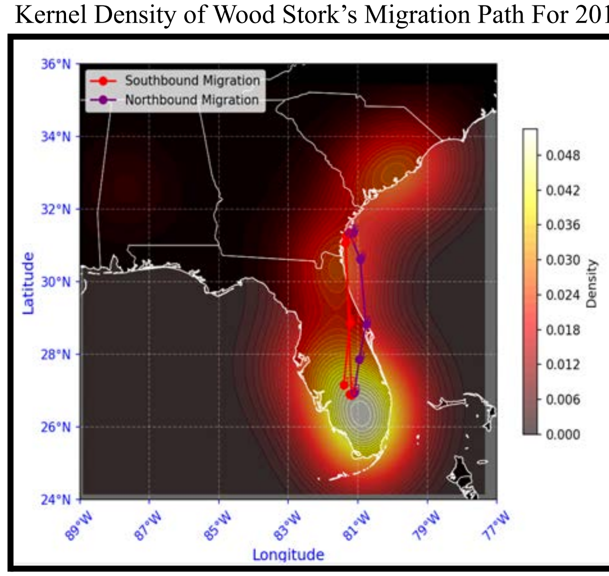




Kernel Density of Wood Stork's Migration Path For 2013

Kernel Density of Wood Stork's Migration Path For 2015





Kernel Density of Wood Stork's Migration Path For 2017

Kernel Density of Wood Stork's Migration Path For 2019

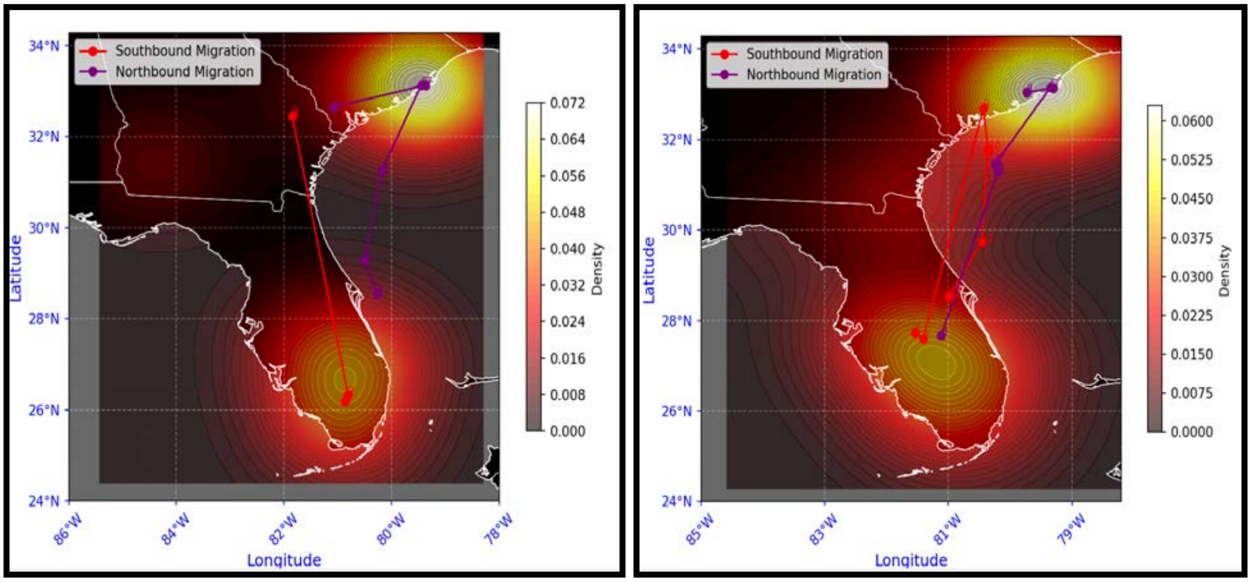


Figure 4: *Kernel Density Spatial Diagrams illustrating the migration patterns of the Wood Stork from 2005 to 2019 in two-year increments. The heat maps represent the density of Wood Stork flocks, with warmer colors indicating areas of higher concentration. The red and purple lines depict southbound and northbound migration paths, respectively. These diagrams help visualize shifts in the bird's migration routes over time, showing how the general curve of movement is based on density patterns observed across different years.*

The density maps show that in 2005, Wood Stork populations were mainly concentrated in southern Florida, making it a key migration stop. Over time, Florida remains an important area, but the way the birds are spread out has changed slightly. In later years, like 2017 and 2019, the maps show that stork populations were more spread out, with some movement shifting northward and westward. This could be due to changes in habitat conditions, food availability, or environmental factors affecting where the birds stop during migration. For example, in 2005, the highest density of storks was seen around 26°N latitude and 81°W longitude in southern Florida. By 2011, there was still a strong concentration in that region, but the density of birds increased slightly further north, around 29°N latitude and 82°W longitude near northern Florida and southern Georgia. By 2017 and 2019, the migration path extended even more, with noticeable movement westward toward 30°N latitude and 85°W longitude, indicating a possible expansion in their stopover sites. While the general migration path remains the same, these shifts suggest that storks may be adapting to changing environmental conditions, possibly due to climate changes or wetland changes affecting food sources. Some years, like 2009 and 2013, show a higher concentration in specific areas, while in other years, such as 2015 and 2019, the birds are more spread out. These changes point to a broader redistribution of migration stopovers, signaling how Wood Storks are adjusting to a transforming ecological landscape.

4.4 Seasonal Auto-Regressive Integrated Moving Average Time Series

The Seasonal Auto-Regressive Integrated Moving Average (SARIMA) Time Series Program Model is a method used to analyze and predict data that follows a pattern over time, especially when the data has repeated seasonal trends [60]. It builds on the ARIMA model by adding seasonal components, making it useful for studying climate factors like temperature and rainfall. SARIMA is represented by the parameters (p,d,q)(P,D,Q,s) where (p,d,q) define the non-seasonal parts of this model, and (P, D, Q, s) capture the seasonal patterns with 's' representing the seasonal length. The model works by using past values and their seasonal changes to estimate future trends. The equation that models this time series is shown below:

$$y_t = c + \sum_{n=1}^{p} \alpha_n y_{t-n} + \sum_{n=1}^{q} \theta_n \epsilon_{t-n} + \sum_{n=1}^{P} \phi_n y_{t-sn} + \sum_{n=1}^{Q} \eta_n \epsilon_{t-sn} + \epsilon_t$$

Where the equation utilized in the SARIMA analysis is depicted above, where y_t is the data at time t, c is the constant term of the data, α_n, and ϕ_n, are the autoregressive (past values) terms, θ_n and η_n are the moving average (error correction) terms, and ε_t is random error [59].

The SARIMA algorithm follows a structured process to generate forecasts. It begins by testing for stationarity, which means checking whether statistical properties like mean and variance remain constant over time. The Augmented Dickey-Fuller (ADF) test is used for this purpose. If the data is not stationary, differencing is applied by subtracting consecutive values until stationarity is achieved. Next is parameter selection, which involves determining the values of (p,d,q) and (P,D,Q,s). This is done by analyzing autocorrelation (ACF) and partial autocorrelation (PACF) plots, which reveal relationships between past and current values. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) help select the best model by balancing complexity and accuracy.

After choosing the parameters, the SARIMA model is trained using historical data. It estimates coefficients for autoregressive and moving average terms through maximum likelihood estimation, identifying the best-fitting values for the data. With the trained model, forecasts are generated by applying learned patterns to predict future values. SARIMA accounts for both short-term fluctuations and long-term seasonal trends. Finally, the model's reliability is evaluated by comparing predictions to actual data and analyzing residuals to ensure the errors follow a random pattern, confirming that the model captures the underlying structure.

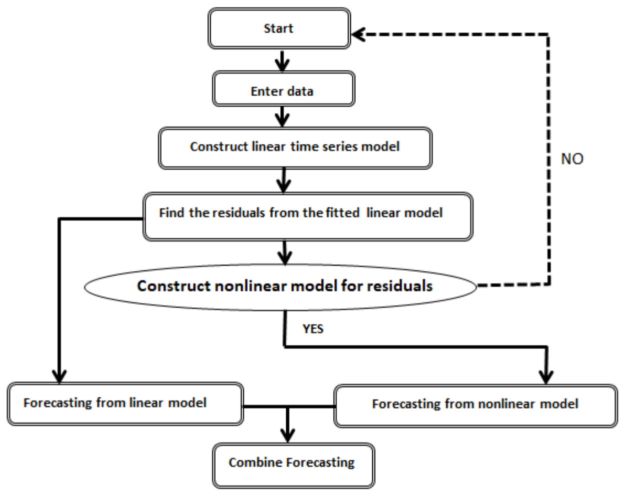


Figure 5: *This schematic outlines the SARIMA model development process for forecasting temperature and precipitation. It begins with data entry, followed by construction of an initial linear time series model. Residuals are then analyzed to assess model adequacy. If a nonlinear pattern is detected, a separate nonlinear model is built; otherwise, the model proceeds to forecasting. In this study, residuals showed no pattern, confirming the data's linearity. Therefore, only the linear model was used for forecasting. This process, detailed further in* ***Section 5.4****, illustrates how data characteristics inform model selection and refinement.*

In this study, SARIMA was used to predict temperature and precipitation patterns through 2035. Stationarity was evaluated using the ADF test, and differencing was applied where necessary. Each time series was decomposed into trend, seasonal, and residual components to better understand its structure. Optimal SARIMA parameters were selected using AIC and BIC to balance model fit and parsimony. Because the final model could not accommodate three-dimensional complexity—capturing space, time, and multiple climate features across space and time—future temperature and precipitation predictions were averaged across states to remove the spatial dimension of the analysis. The trained SARIMA models successfully captured long-term warming trends and seasonal shifts in precipitation. These projected changes may affect Wood Stork migration by altering wetland water levels and the availability of food. The corresponding code is provided in **Appendix 3**.
Below are the historical trends along with the SARIMA projections for precipitation and surface air temperature for Florida, Georgia, and South Carolina:

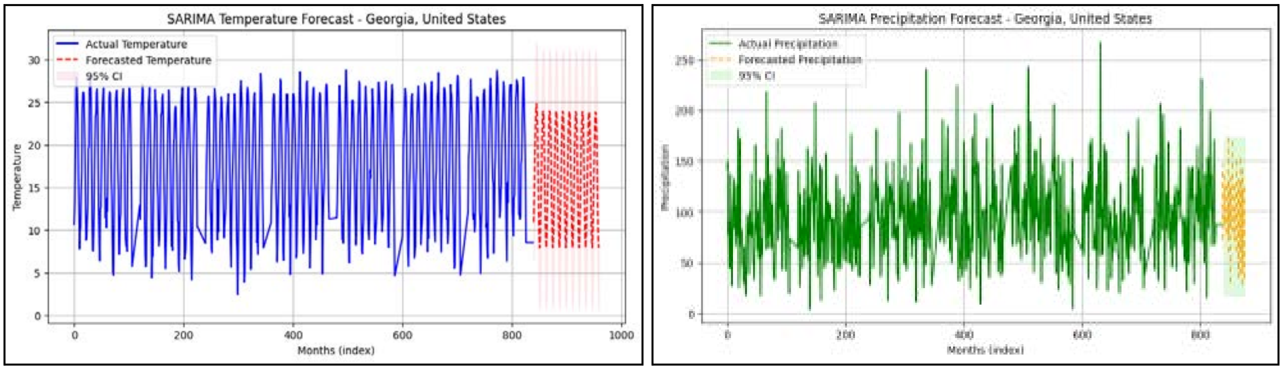


Figure 6: *Above are the graphs for historical and predicted trends of Georgia for Temperature and Precipitation. The red dashed line indicates the start of forecasting of the SARIMA algorithm.*

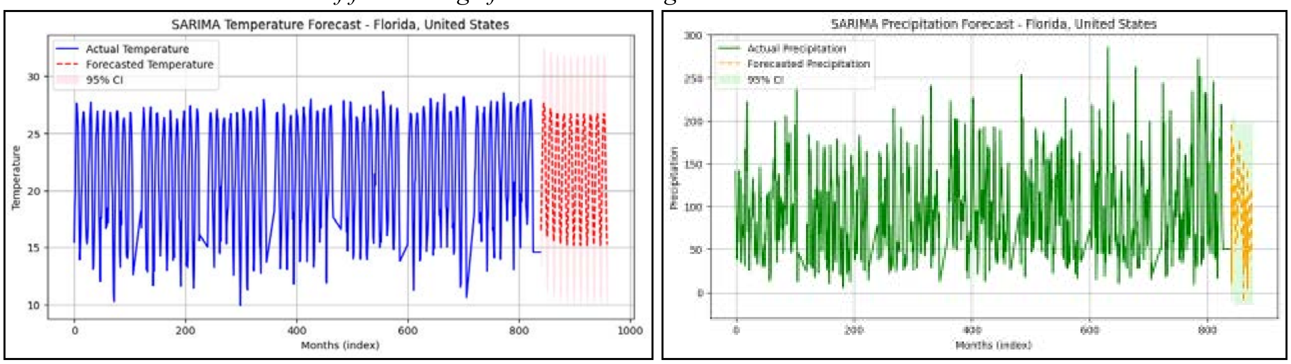


Figure 7: *Above are the graphs for historical and predicted trends of Florida for Temperature and Precipitation. The red dashed line indicates the start of forecasting of the SARIMA algorithm.*

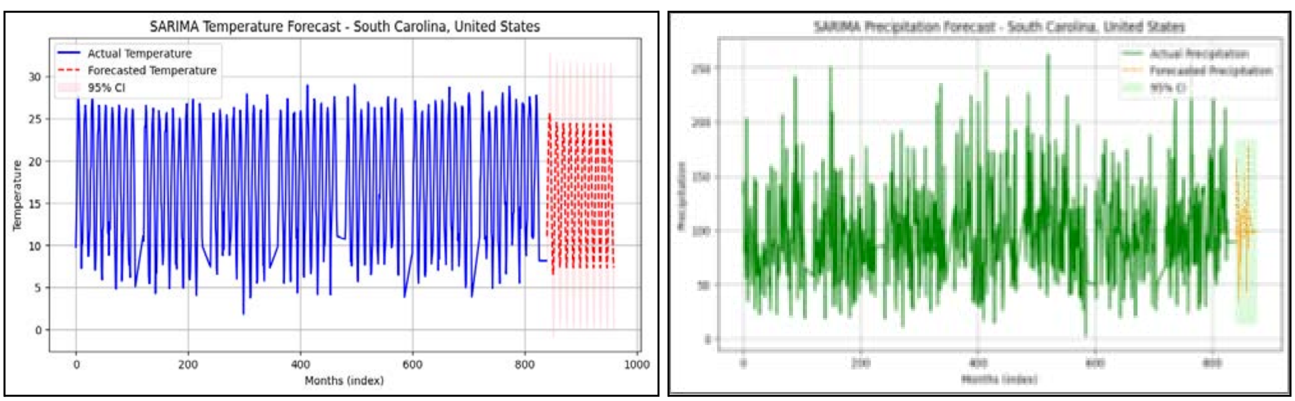


Figure 8: *Above are the graphs for historical and predicted trends of South Carolina for Temperature and Precipitation. The red dashed line indicates the start of forecasting of the SARIMA algorithm.*

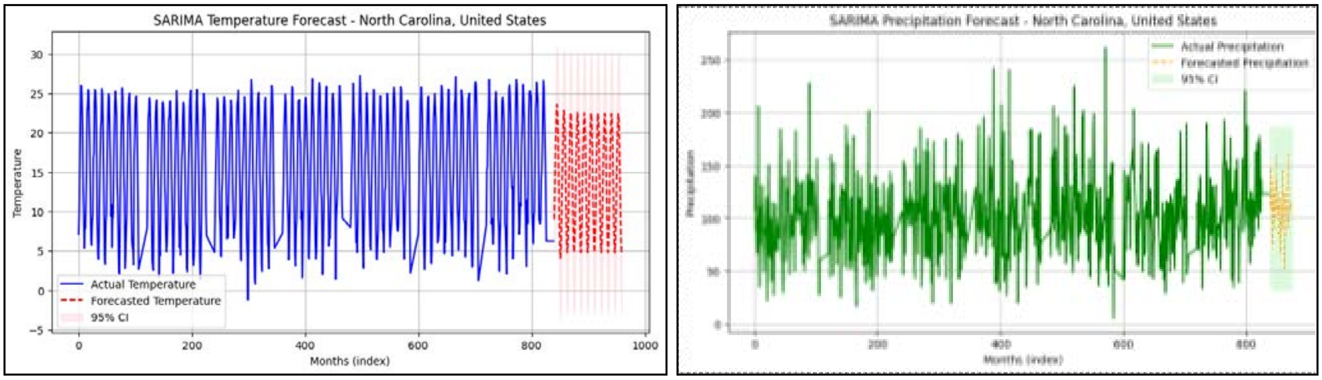


Figure 9*: Above are the graphs for historical and predicted trends of North Carolina for Temperature and Precipitation. The red dashed line indicates the start of forecasting of the SARIMA algorithm.*

These trends are further used in **Section 4.5** to project Wood Stork migratory paths into the future.

4.5 Random Forest Regressor Prediction Model

To accurately model and predict the future migration patterns of birds in response to environmental changes, a Random Forest Regressor Prediction Model was implemented. This Random Forest Regressor is designed for regression tasks, making it well-suited for analyzing bird migration trends using historical temperature and precipitation data. Unlike traditional statistical models, which may struggle with complex, nonlinear relationships, the Random Forest Regressor can capture both variable interactions and complex patterns, which improves predictive accuracy for migration shifts.

A Random Forest Regressor is an ensemble learning method that builds multiple decision trees and combines their predictions to generate a final output. While standard decision trees are powerful for regression tasks, they may overfit or fail to capture complex relationships in the data. By combining many trees, the Random Forest Regressor reduces the risk of overfitting and improves model robustness. Mathematically, the Random Forest Regressor aggregates the predictions from all individual trees, where each tree makes a prediction based on a subset of the data features, providing a more accurate and stable prediction overall. Below is a standard equation and defined variables for the model:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (fi - yi)^2$$

Where:
- MSE is Mean Squared Error
- N is the number of data points.
- f_i is the value returned by the model.
- y_i is the actual value for data point i.

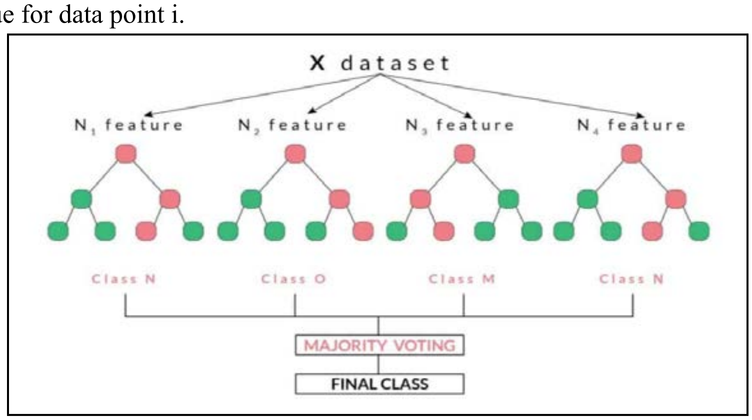


Figure 10*: This figure illustrates the structure of the Random Forest model used to predict the migratory paths of wood storks. The model is built on multiple decision trees, each trained on different features of the dataset. Each tree makes an independent classification decision, and the final prediction is determined through majority voting, ensuring robustness and reducing overfitting. This ensemble learning approach enhances the accuracy and reliability of migration forecasts by considering multiple predictive pathways. The model's ability to generalize trends over time makes it a valuable tool for analyzing shifts in migratory behavior due to environmental changes.*

Before making projections, the team used a package for random forest regression called RandomForestRegressor from sklearn.ensemble. This package handles all the complex mathematical computations in the background, allowing us to implement the regression model efficiently and generate the final graphs. The code for this algorithm can be found in **Appendix 4**. The projection to 2035 is depicted below for the Wood Stork Bird Flock.

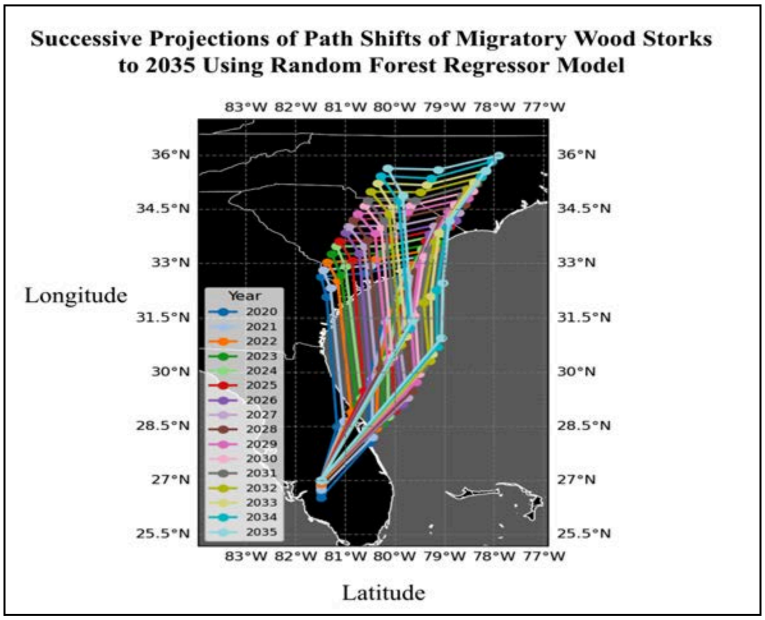


Figure 11: *This figure presents the predicted annual shifts in the migratory paths of wood storks from 2020 to 2035, modeled using a Random Forest Regressor. The visualization highlights a consistent northward movement over time, with migration patterns progressively shifting from Florida toward the Carolinas. This trend suggests significant ecological changes, potentially driven by climate change, habitat loss, and alterations in food availability. Understanding these successive shifts is crucial for conservation planning, as it enables the identification of future critical habitats and informs strategies for mitigating the impact of environmental changes on migratory bird populations.*

It is also essential to analyze the centroid shift of the Wood Stork's path to quantify distance changes. This projection is shown below, comparing historical and projected shifts.

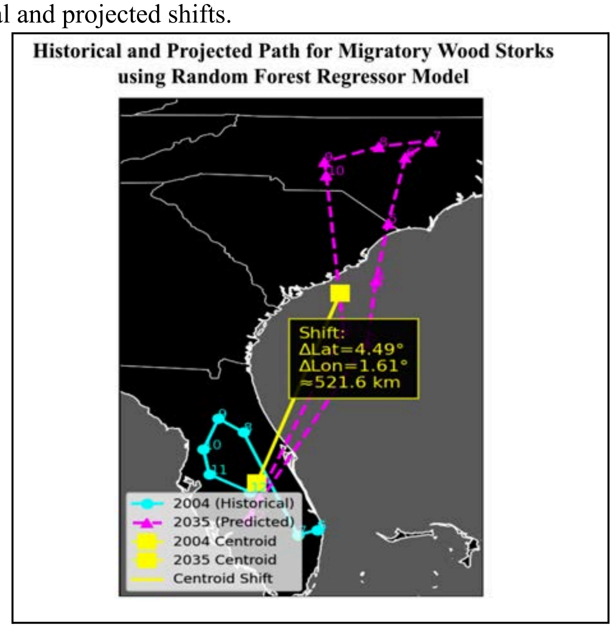


Figure 12: *This figure illustrates the historical (2004) and projected (2035) migration paths of wood storks based on a*

Random Forest Regressor model. The centroid shift indicates a northward migration trend, with a latitude shift of +4.49°, a longitude shift of +1.61°, and a total displacement of 521.6 km. The analysis provides insights into potential habitat changes due to environmental and climatic factors.

Throughout the decades there is an apparent shift, as noted in *Figure 11* above. The previous path which resided in Florida gradually moved upward into the Carolina's, and by 2035 is expected to be in North Carolina.

4.6 Limitations

The study encountered several limitations that affected both the scope and accuracy of its findings. First, the availability of migration data was limited, as most datasets tracked only a small number of birds, restricting the ability to generalize results across broader populations. Additionally, monthly data were available only for precipitation and surface air temperature. Other critical variables—such as wind currents, food availability, habitat loss, and light pollution—were available only on a yearly basis, limiting the potential for seasonal or monthly analysis. The absence of these variables constrained the ability to assess how non-climatic environmental factors may influence migratory behavior. Furthermore, the analysis relied on state-level weather data rather than more granular, county-level data, potentially overlooking important regional variations. Another significant limitation involved the temporal scope of the data; predicting migration trends beyond 10–20 years proved challenging due to uncertainties in long-term environmental patterns. Addressing these limitations in future research through more comprehensive data collection and the inclusion of additional environmental variables would offer a deeper and more accurate understanding of bird migratory dynamics.

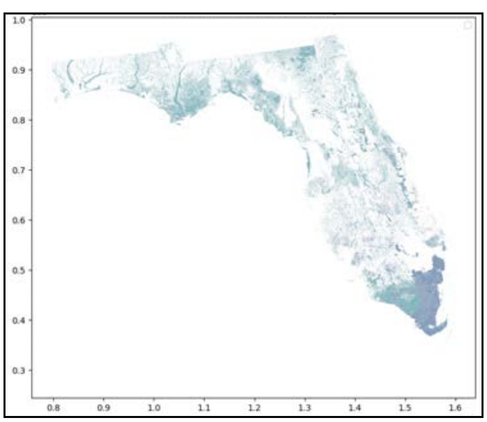
5. Risk Analysis

5.1 Risk Overview: Assessing Climate Change Impacts on Bird Migration

Climate change is reshaping bird migration in ways that carry significant ecological and economic consequences. This analysis focuses on Wood Storks as an indicator species to assess the broader risks posed by shifting climate conditions. Key areas of concern include changes in migratory timing and route, loss of critical wetland stopover habitats due to urbanization, and the resulting strain on both species survival and agricultural systems. **Section 5.2** models habitat loss across Florida, South Carolina, and North Carolina, highlighting how urban expansion reduces available nesting and feeding grounds. **Section 5.3** quantifies the economic consequences of these ecological changes, demonstrating how disrupted Wood Stork migration increases reliance on pesticides and contributes to rising agricultural costs. **Section 5.4** evaluates the reliability of the climate projections used to anticipate these risks. Collectively, these findings underscore the urgent need for targeted conservation efforts and land-use planning. Potential strategies to mitigate these risks are explored in **Section 6: Recommendations**.

5.2 Habitat Loss Simulation: Modeling the Effects of Urbanization on Bird Habitats

Urbanization is rapidly transforming landscapes across South Carolina, North Carolina, and Florida, leading to the loss of crucial bird habitats, such as in the wetland. This study aims to simulate and forecast the potential loss of bird habitats due to increasing urban expansion in these states, with a focus on identifying the species most at risk, particularly in key migration corridors. The code for this analysis can be found in **Appendix 5**.



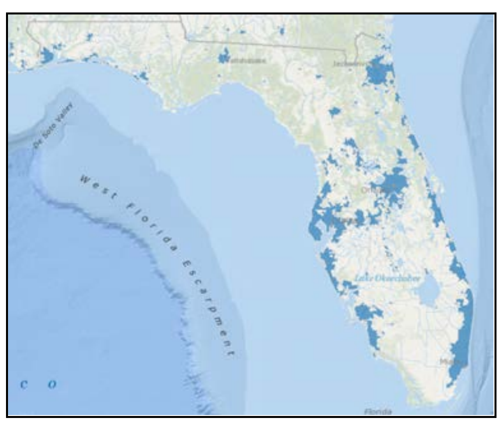


Figure 13: *The first map is a map of Florida and shows where the Freshwater Emergent Wetland and Freshwater Forested/Shrub Wetland are located in the state. The second map shows the urbanization of Florida (Data courtesy of U.S. Fish & Wildlife Service and Urbanization Graph courtesy of Florida Department of Environmental Protection - MapDirect Data)* **[88][89]**.

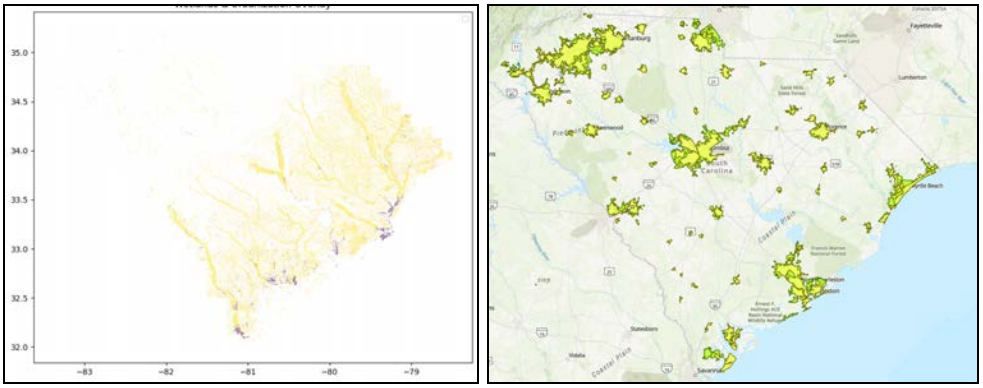


Figure 14: *The first map is a map of South Carolina and shows where the Freshwater Emergent Wetland and Freshwater Forested/Shrub Wetland are located in the state. The second map shows the urbanization of South Carolina where the yellow regions are from 2000 and the green regions show how much urbanization increased in 2020 (Data courtesy of U.S. Fish & Wildlife Service and Urbanization Graph courtesy of ArcGIS Online)* **[86][89]**.

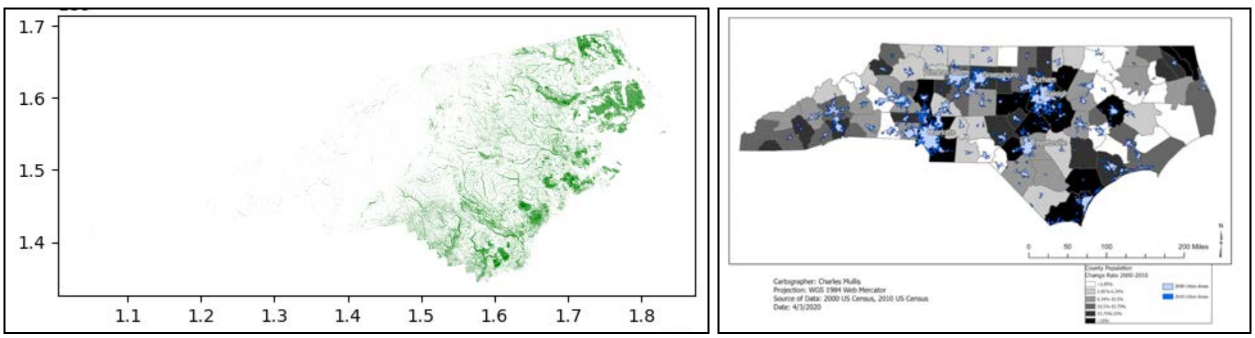


Figure 15: *The first map is a map of North Carolina and shows where the Freshwater Emergent Wetland andFreshwater Forested/Shrub Wetland are located in the state. The second map shows the urbanization of North Carolina where the light blue regions are from 2000 and the dark blue regions show how much urbanization increased in 2010 (Data courtesy of U.S. Fish & Wildlife Service and Urbanization Graph courtesy of ArcGIS StoryMaps)* **[87][89]**.

Urbanization in the southeastern United States is rapidly reshaping the landscape, posing significant challenges for migratory bird species. Based on the migration model, birds have been observed gradually shifting their final destinations to South Carolina, with projections indicating continued movement toward North Carolina. This transition raises concerns about habitat availability and the overall space available for these species as they relocate.

The provided maps (*Figures 13, 14, and 15*) illustrate the extent of wetland distribution and urbanization in South Carolina, North Carolina, and Florida. Florida (*Figure 13*) historically provided a relatively larger and more connected space for bird populations, as seen in the first map. Compared to Florida's extensive wetland reserves, both South Carolina and North Carolina offer less continuous wetland coverage, further restricting habitat space for migrating wood storks.

In South Carolina (*Figure 14*), urban development has steadily increased between 2000 and 2020, as shown in the second map. The expansion of urban areas, represented in green, indicates a reduction in natural habitats, including freshwater wetlands and forested shrublands that are crucial for wood stork populations. Wood storks arriving in South Carolina will find a landscape that has already undergone significant development, reducing available nesting and feeding areas.

As the birds continue their movement northward to North Carolina (*Figure 15*) per prediction, they will encounter an even more urbanized environment. The urbanization data from 2000 to 2010, shown in the second map, suggests that major population centers in North Carolina have expanded, with dark blue regions marking areas of increased development. Compared to South Carolina, North Carolina's urbanization may present an even greater challenge, as critical wetland spaces are fragmented by human expansion.

The loss of wetland availability directly impacts wood storks populations by reducing available feeding grounds, increasing habitat fragmentation, and creating competition for limited resources. Many bird species rely on freshwater wetlands for food, and increased urbanization limits these resources. Urban sprawl also breaks natural habitats into smaller, isolated patches, making it difficult for species to establish stable populations. With fewer nesting sites available, wood storks populations may experience increased competition for resources, leading to declines in species diversity [42].

5.3 Quantifying Loss: The Impact of Climate-Driven Wood Stork Migration on Rising Agricultural Costs

Migratory birds like the Wood Stork play an essential role in agriculture by providing natural pest control. As climate change alters their migration patterns, Wood Stork populations are arriving too early, too late, or not at all in traditional habitats. This shift disrupts the ecological balance, forcing farmers to rely more heavily on pesticides, increasing production costs and crop vulnerability. This section examines the financial impact of these changes using USDA data from 1987 to 2017. Costs are grouped into three categories: Land Conversion, Pesticide Usage, and Crop Yield Loss. Over the 30-year period, the **total cost to agriculture** rose from **$5.07 billion in 1987 to $16.28 billion in 2017**, driven in large part by the ecological services lost as Wood Storks and similar birds decline or shift routes.

Year	Land Conversion ($) [34][38][39][40]	Pesticide Use ($) [42]	Crop Yield Loss ($) [33][35][36][37][41]	Total Cost ($)
1987	421,381,250	4,512,190,000	135,747,492	5,069,318,742
1992	420,555,000	6,470,510,000	177,053,936	7,068,118,936
1997	410,491,250	9,017,440,000	294,639,218	9,722,570,468
2002	405,837,500	8,316,340,000	361,106,860	9,083,284,360
2007	377,975,000	10,517,530,000	657,459,360	11,552,964,360
2012	363,523,750	12,629,550,000	811,145,750	13,804,219,500
2017	364,111,250	14,988,990,000	929,470,920	16,282,572,170

***Figure 16**: USDA data on agricultural costs from 1987 to 2017, showing increases in all three categories, with the total cost rising from $5.07 billion to $16.28 billion over 30 years.*

To evaluate the economic burden, the **Expected Value Formula** was used to model costs over time. As seen below, expected economic losses climbed **from $4.05 billion in 1987 to nearly $15 billion in 2017**.

$$E[X] = \sum_{i=1}^{n} x_i \cdot p_i$$

Where:

- **E[X]** = Expected economic loss
- x_i = Economic loss from each category (Land Conversion, Pesticide Use, Crop Yield Impacts)
- p_i = Proportion of total cost for each category

For each of the year increments, the three categories of cost for land conversion, pesticide use, and crop yield loss were utilized to calculate the Expected Economic Loss for the United States. As seen below, expected economic losses climbed **from $4.05 billion in 1987 to nearly $15 billion in 2017**.

Year	Expected Economic Loss ($)
1987	4,054,640,000
1992	6,473,000,000
1997	9,005,000,000
2002	8,316,000,000
2007	10,517,000,000
2012	12,629,000,000
2017	14,989,000,000

Figure 17*: This figure shows the Expected Economic Loss in the United States from 1987 to 2017, based on the costs of land conversion, pesticide use, and crop yield loss. The values are given in US dollars for each year.*

It appears that over the years, expected economic loss is increasing, with a 369.7% jump in costs from 1987 to 2017. Using an **ARIMA model**, projections suggest this trend will continue, reaching **$18.62 billion by 2027** and **$20.44 billion by 2032**.

The Autoregressive Integrated Moving Average (ARIMA) was utilized to project the Expected Economic Loss for Agriculture to 2032:

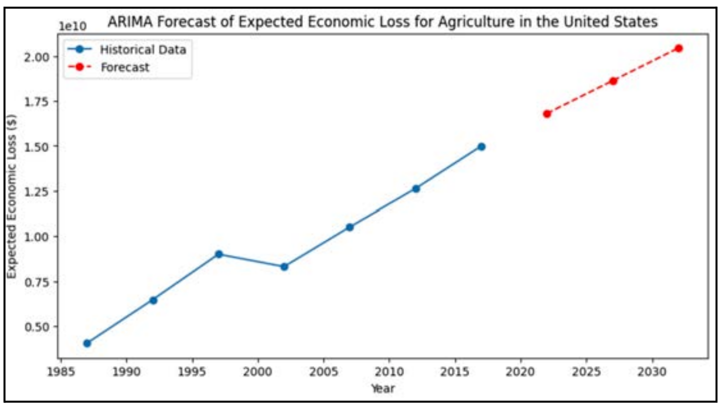


Figure 18: *ARIMA forecast of expected economic loss for agriculture in the United States. The graph displays historical data (blue) from 1985 to 2017, showing a steady increase in economic losses over time. The ARIMA model projects future losses (red) beginning in 2022 and extending through 2032. The apparent gap between 2017 and 2022 is due to the dataset being recorded in five-year increments, meaning no data point was available for the intervening years. As a result, the forecast begins with the next expected interval. The y-axis represents expected economic loss in U.S. dollars, while the x-axis represents the year. The model predicts that agricultural losses will continue rising significantly in the coming years.*

The connection is clear: as Wood Storks shift migration in response to changing precipitation and temperature (as shown in **Section 4.5: Random Forest Regressor Prediction Model**), their pest-regulating services are disrupted. With fewer Wood Storks present during peak pest seasons, farmers turn to chemical solutions. This has led pesticide costs to triple from 1987 to 2017, and crop yield losses to rise by over 585%. This cycle, driven by the climate's effect on bird behavior, is unsustainable. Smaller farms are especially at risk, facing rising operational costs, and some may be forced to shut down. Moreover, heavy pesticide use causes long-term soil and water degradation, worsening the problem. As the Wood Stork continues to be impacted by climate change, its absence adds hidden costs to agriculture. Addressing this issue will require farmers to adopt adaptive, sustainable practices. **Section 6: Recommendations** outline strategies to mitigate these growing challenges.

5.4 Evaluating Uncertainty in Data Trends

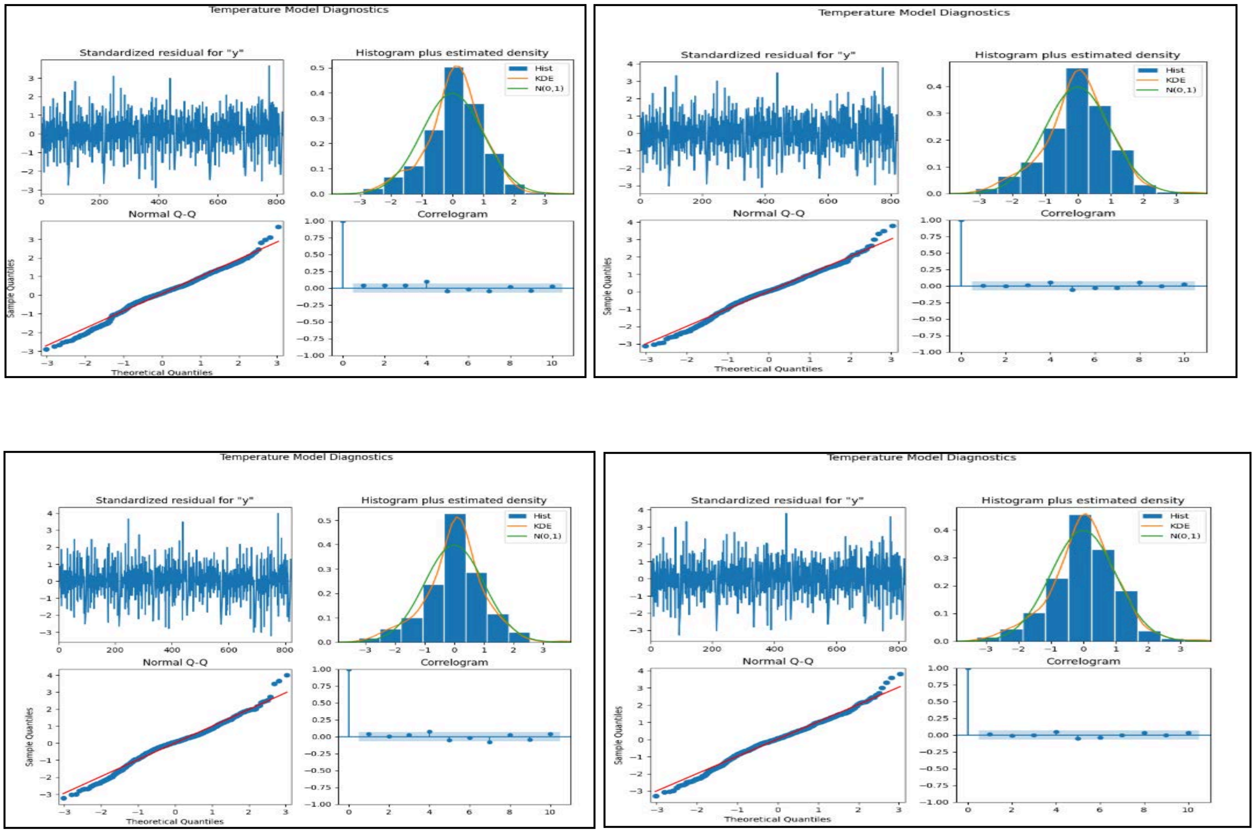


Figure 19: This figure presents diagnostic plots for the SARIMA model fitted to temperature data in Florida, Georgia, South Carolina, and North Carolina respectively. The top-left panel displays the standardized residuals, which should ideally resemble white noise with no visible patterns. The top-right panel shows the histogram of residuals alongside a kernel density estimate (KDE) and a normal distribution curve (N(0,1)), assessing whether the residuals follow a normal distribution. The bottom-left panel features a Q-Q plot, comparing residual quantiles to a theoretical normal distribution to check for normality. The bottom-right panel contains the correlogram (ACF plot), which measures autocorrelation in the residuals, helping determine if any patterns remain unexplained. These diagnostics help assess whether the SARIMA model is well-fitted to the temperature data.

State	**Model Fit Insight**	**Residual Pattern**	**Distribution (Histogram and KDE)**	**Q-Q Plot**	**Autocorrelation (ACF)**
Florida	SARIMA accurately reflects temperature trends with no major bias.	Residuals vary randomly with no visible patterns.	Roughly normal with slight tail deviations.	Closely follows normal distribution; minor extremes indicate rare anomalies.	Minimal autocorrelation; model is well-tuned.
Georgia	Model fits well overall, with slight signs of seasonality remaining.	Mostly random, with some clusters indicating short-term dependencies.	Near-normal distribution with slight skew.	Matches normal distribution closely.	Minor lag correlations suggest residual seasonality.
South Carolina	SARIMA fits data effectively with	Residuals are evenly spread	Centered near zero; close to	Strong alignment with normal	Very low autocorrelation;

	no major issues.	without pattern.	normal shape.	curve; slight deviations at upper end.	strong model performance.
North Carolina	Generally good fit, though some variation remains unexplained.	Random with occasional high-variance clusters.	Nearly normal, but with heavier tails.	Mostly normal fit; outliers suggest extreme temperatures.	Minimal autocorrelation; most patterns removed.

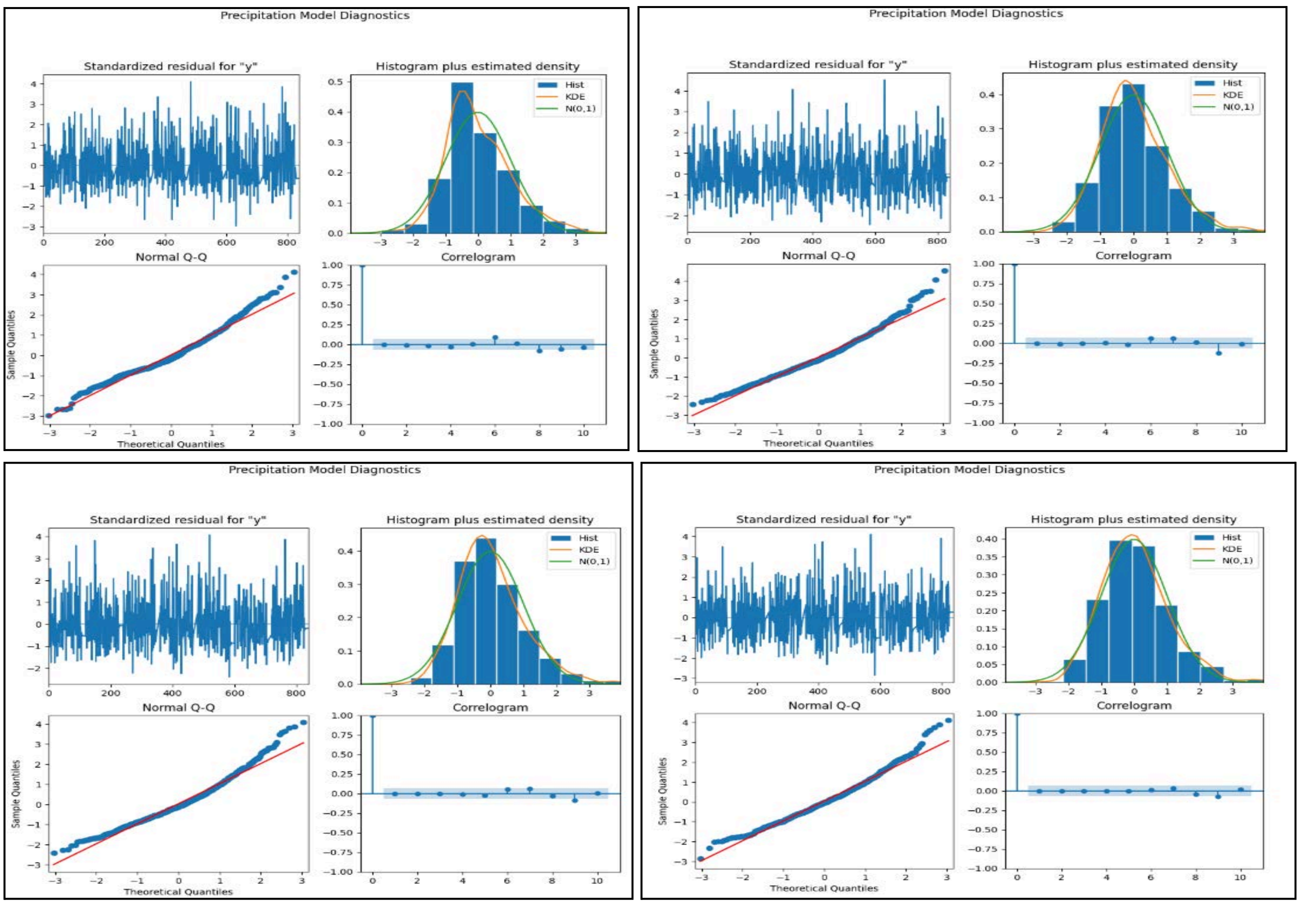


Figure 20: This figure presents diagnostic plots for the SARIMA model fitted to precipitation data in Florida, Georgia, South Carolina, and North Carolina respectively. The top-left panel displays the standardized residuals, which should ideally resemble white noise with no visible patterns. The top-right panel shows the histogram of residuals alongside a kernel density estimate (KDE) and a normal distribution curve (N(0,1)), assessing whether the residuals follow a normal distribution. The bottom-left panel features a Q-Q plot, comparing residual quantiles to a theoretical normal distribution to check for normality. The bottom-right panel contains the correlogram (ACF plot), which measures autocorrelation in the residuals, helping determine if any patterns remain unexplained. These diagnostics help assess whether the SARIMA model is well-fitted to the precipitation data.

State	**Model Fit Summary**	**Residual Pattern**	**Histogram and KDE**	**Q-Q Plot**	**Autocorrelation (ACF)**
Florida	SARIMA is well-fitted with only minor	Residuals are randomly distributed with	Roughly normal, with slight tail deviations due to	Closely matches normal curve; minor extreme	Low autocorrelation; model captures

	deviations at extremes.	no clear structure.	rare heavy events.	deviations observed.	time-dependent patterns effectively.
Georgia	Reasonably good fit; some signs of short-term seasonality remain.	Mostly random, but higher-variance clusters suggest possible missed seasonal effects.	Approximately normal with slight skewness.	Follows normal distribution; some outliers reflect extreme precipitation.	Minor short-lag autocorrelation indicates possible seasonal effects.
South Carolina	Model captures precipitation trends well.	Residuals are well-distributed without patterns.	Centered around zero with a near-normal distribution.	Strong alignment with normal curve; minor deviations in upper quantiles.	Very low autocorrelation; time-based patterns largely removed.
North Carolina	Generally strong fit; some residual variation remains.	Slightly increased variance in parts of the residuals.	Near-normal with heavier tails indicating rare extremes.	Mostly normal fit; tail deviations reflect heavy precipitation events.	Very little autocorrelation; most dependencies are accounted for.

6. Recommendations

6.1 Recommendations Overview

Wood Storks are facing significant challenges due to habitat loss, urban expansion, agricultural development, and changing climate conditions across Florida, Georgia, and the Carolinas. To protect their populations and reduce the impacts of disrupted migration, several key actions are recommended. **Section 6.2** focuses on restoring habitats in the Everglades by replanting native trees, improving wetland water flow, and stocking fish in key feeding areas to ensure food availability during the nesting season. **Section 6.3** outlines how farmers can contribute by setting aside wetlands, managing water levels in agricultural fields, and reducing pesticide use. These practices would support Wood Stork foraging while also lowering farming costs over time. **Section 6.4** emphasizes the importance of increasing public awareness and community engagement, particularly in areas near wetlands, to help people understand how Wood Stork migration affects both the environment and public health. **Section 6.5** presents strategies for improving water management, such as building stormwater retention ponds and installing vegetative buffer zones to reduce wetland pollution. It also recommends expanding funding for programs that assist landowners in protecting wetlands on private property. Finally, **Section 6.6** calls for coordinated efforts at the federal, state, and local levels to complete restoration projects, strengthen wetland protection laws, and prevent further habitat destruction. Taken together, these strategies offer a path forward to support Wood Stork conservation and protect the wetlands they depend on.

6.2 Habitat Restoration and Protection of the Everglades

The destruction of wetlands in South Florida, especially in the Everglades, has forced Wood Storks to shift their migration north into Georgia and the Carolinas. To prevent further habitat loss and help stabilize their populations, restoration efforts must focus on rebuilding key foraging and nesting areas. This can be done by reintroducing native trees, improving wetland conditions, and expanding conservation programs that protect Wood Stork habitats from further destruction.One major issue is the loss of tree islands and cypress swamps, which are the main nesting sites for Wood Storks. Many of these areas have been destroyed due to land clearing and invasive species like Brazilian pepper trees, which crowd out native plants. To fix this, conservation efforts should focus on replanting native trees such as cypress and pond apple, which provide strong branches for nesting. In places where tree islands have completely disappeared, artificial nesting platforms could be placed in protected areas like Big Cypress National Preserve to encourage Wood Storks to stay in South Florida rather than migrate further north.

Foraging areas also need to be restored, as many wetlands have been drained for agriculture and development. Wood Storks rely on seasonal drying patterns in wetlands, which naturally concentrate fish into shallow pools, making it easier for them to catch food. However, human activity has disrupted these natural cycles, making food scarce during the breeding season. To help restore natural feeding conditions, water flow in key areas like the Kissimmee River and western Everglades should be adjusted to allow for seasonal flooding and drying. Additionally, private landowners could be encouraged to protect or restore small wetlands on their property by offering financial incentives, helping create more foraging opportunities without requiring large-scale land changes.

Another way to improve food availability is by introducing a fish stocking program in protected wetlands. The number of Wood Stork chicks that survive depends on how much food is available, and many wetlands no longer have enough fish. Stocking small, native fish species like killifish and mosquitofish in key foraging areas before the breeding season would make sure that Wood Storks have enough food supply. At the same time, removing invasive fish like armored catfish, which provide little nutrition, would help restore a better balance to the ecosystem. To make sure these efforts are successful, more funding and policy support are needed for wetland conservation programs. Many current restoration projects are limited by lack of money or conflicts over land use. Expanding federal and state funding for projects like the Comprehensive Everglades Restoration Plan (CERP) would help speed up wetland recovery. Additionally, stronger land protection policies could prevent important wetland areas from being developed in the future. Restoring and protecting Wood Stork habitats in Florida will help keep their populations stable and reduce the need for them to migrate further north. By rebuilding nesting areas, restoring natural feeding conditions, and increasing conservation efforts, Wood Storks will have the resources they need to thrive in their historical range. These efforts will also benefit other wetland species and help maintain the health of the Everglades, one of the most important ecosystems in North America.

6.3 Agricultural and Aquatic Land Use and Policies

The cost analysis performed in **Section 5.3** found that the expected economic loss for agriculture in the United States is increasing, and through ARIMA projections, this trend will continue in the future. To address the economic and ecological consequences of shifting Wood Stork migration patterns in the Southeast, specific agricultural strategies must focus on habitat restoration, pesticide reduction, and sustainable land management. First, creating incentivised wetland conservation easements, where farmers are compensated for restoring and maintaining wetlands near agricultural lands, would provide foraging grounds for Wood Storks, making sure they arrive in time to naturally regulate pest populations. The U.S. Department of Agriculture (USDA) could expand funding for programs like the Wetland Reserve Program (WRP) to prioritize lands adjacent to high impact agricultural zones in Florida, Georgia, and South Carolina, since in the Random Forest Regressor Model (**Section 4.5**), the flock was shown to have a shifting migration route into North Carolina over time. Additionally, rotational water-level management within rice fields and lowland croplands would stimulate natural wetland conditions, attracting Wood Storks and other birds to hunt for prey, reducing the need for chemical pesticides. A study by Depken et al. found that Wood Stork foraging success is significantly higher in managed wetlands with controlled water levels, showing a 40% increase in prey capture efficiency compared to unmanaged wetlands **[69]**. This suggests Farmers could implement a flood-dry rotation schedule based on Wood Stork migration timing, ensuring the presence of foraging grounds when birds are most needed for pest control.

To further decrease pesticide reliance and associated economic losses, agricultural policies should support the adoption of Integrated Pest Management (IPM) strategies that specifically account for Wood Stork migration patterns. One approach is to designate pesticide-free buffer zones near Wood Stork foraging habitats, preventing chemical contamination of wetland ecosystems and allowing natural predation to occur. Also, using precision spraying technology using AI-driven pest surveillance systems could be deployed to detect past outbreaks in real time, limiting pesticide use to necessary areas instead of broad applications. Farmers should be encouraged to use cover crops with insect-repelling plants, with commonly used plants being marigolds or mustard to help control pests naturally **[68]**. While mitigation strategies are put in place to gradually restore Wood Stork's to their lands. They can also bring in helpful insects like ladybugs or nematodes, which cut down on the need for pesticides that can hurt Wood Storks and the fish they eat. By protecting wetlands, using fewer chemicals, and relying more on natural pest control, farmers can help Wood Storks survive while also saving money and keeping their land healthier in the long run.

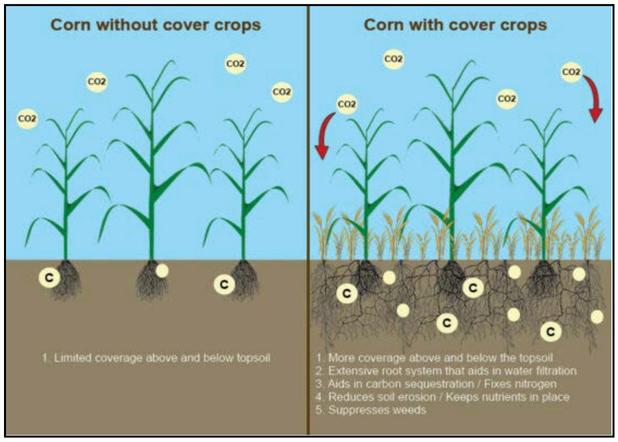


Figure 21: *This diagram shows how cover crops improve soil by increasing carbon storage, enhancing water filtration, reducing erosion, and retaining nutrients. As farmers adopt cover cropping, soil and water quality improve, creating better conditions for Wood Storks as they gradually return. Healthier wetlands will support stronger fish populations, ensuring long-term benefits for both agriculture and wildlife (Courtesy of Agri-Pulse)* [84].

Beyond pest regulation, Wood Storks play a role in aquatic ecosystem management and nutrient recycling, which directly impacts agricultural water quality and soil health. Data indicates that wading birds, including Wood Storks, contribute to a significant reduction in excess fish and amphibian populations in shallow wetlands, preventing algal blooms and maintaining balanced aquatic ecosystems [66][67]. Their foraging behavior, which involves stirring sediment and redistributing organic material, enhances water oxygenation and nutrient cycling, improving water quality for nearby agricultural use. Research shows that breeding wading birds in the Everglades, including Wood Storks, contribute approximately 7.6 tonnes of nitrogen and 1.2 tonnes of phosphorus annually through deposits [65]. Creating constructed wetlands near croplands that support Wood Stork feeding could improve these natural nutrient recycling processes while also cutting down on agricultural runoff. Since Wood Storks stir up sediments and help distribute organic matter when they forage in shallow waters, they play a big role in keeping aquatic ecosystems healthy. Restoring wetlands and protecting these birds would let farmers benefit from their ability to naturally fertilize soil and filter water, making farms more sustainable while reducing reliance on expensive chemical inputs.

6.4 Public Awareness and Community Engagement

As stated in the Introduction, Wood Storks act as natural pest-control for wetland ecosystems and beyond. Through their tactile foraging, they reduce the number of harmful disease carrying insects like mosquitoes, black flies, biting midges, etc [13]. With declining Wood Stork migration, the availability of Wood Storks to protect nearby communities from vector-borne diseases is at risk. Wetland heavy areas need nearby communities to be aware of this risk that directly affects them and their families. This can be done through implementing community engagement programs–such as workshops, school programs, local events, and more.

A study from the Afterschool Alliance found that while 73% of afterschool programs offer STEM-related activities, only 18% focus on environmental science or conservation topics. This disparity shows that while STEM is a priority, environmental awareness is not being equally emphasized in after-school settings [91]. On a larger scale, environmental science education is not consistently mandated across states. A National Wildlife Federation report revealed that only 30% of states require some form of environmental literacy in their K-12 education standards, and even in those states, implementation varies significantly between districts [92]. It is crucial that both parents and children of affected communities fully understand how Wood Stork migration influences their health.

Outside of school programs, state governments should sponsor environmental organizations that can host community awareness workshops and events. These events can inform communities about how shifts in migration timing, driven by climate change, affect food sources, habitat availability, and the public health of their communities. In fact, this strategy has already been tested in Costa Rica and Ethiopia. A study published by ElSevier et al. highlights how community-based programs focused on bird conservation and habitat restoration have had notable positive effects on both local ecosystems and bird populations. In regions like Costa Rica and Ethiopia, bird monitoring initiatives have successfully integrated ecological research and environmental education. These programs not only promote the conservation of migratory bird species. Through these efforts, bird populations have been better monitored, and restoration of critical habitats has directly supported migratory routes [65].

Community involvement and awareness is the foundation of real change because it brings people together to take action where it matters most. It's easy to think that big organizations or government policies are the only things that can make a difference, but real progress starts with individuals working as a group. Whether it's advocating for environmental policies, restoring natural habitats, or simply spreading awareness, local efforts create momentum that leads to lasting change. Without community action, issues like climate change or habitat destruction wouldn't get the attention they need. When people unite for a cause, they not only make an impact but also inspire others to step up. Real change doesn't just happen—it's built by communities that refuse to stay silent.

6.5 Climate Resilient Water Management

Through the SARIMA graphs of surface air temperature and precipitation for the states of interest in **Section 4.4**, it is evident that climate change is altering precipitation patterns and increasing temperatures, threatening the wetlands that Wood Storks rely on for foraging. Longer droughts can shrink wetland areas, while extreme rainfall events lead to water level fluctuations, disrupting prey availability. To maintain stable wetland conditions and support both Wood Storks and agriculture, targeted water management strategies must be implemented. Wetland restoration is essential for stabilizing Wood Stork foraging areas. Nearly 80% of wetlands in Florida, Georgia, and South Carolina have been altered due to drainage projects and water diversions. Reconnecting natural water flow through controlled releases and levee removal can restore seasonal flooding, ensuring that wetlands retain water during dry periods. In the Everglades, wetland restoration efforts have led to a 12% increase in wetland area and a 15% improvement in water retention [70]. Expanding similar projects across key Wood Stork habitats could restore over 500,000 acres of wetlands, providing stable food sources. The U.S. Army Corps of Engineers and local water management districts would oversee these restoration projects, with landowners participating through conservation programs.

Agricultural water use accounts for over 70% of freshwater consumption in the southeastern U.S., often reducing wetland water levels [71]. Implementing rotational flooding in rice fields and lowland crops can mimic natural wetland conditions, benefiting both farmers and wildlife. Research has shown that rotational flooding increases fish and insect populations by 40%, making wetlands more productive for Wood Stork foraging. If just 10% of rice farms in Florida and Georgia adopted this strategy, over 100,000 acres of seasonal wetland habitat could be maintained. This approach would be led by the USDA in collaboration with farmers through conservation incentive programs. Currently, only 15% of eligible landowners participate in federal wetland conservation programs due to funding limitations [72]. Increasing funding for the Wetlands Reserve Program (WRP) by $50 million annually could expand protection to an additional 500,000 acres of wetlands. Providing tax incentives for wetland conservation, similar to a successful Louisiana program that restored 250,000 acres, could encourage more farmers to participate [73]. These programs would be managed by the USDA and state agricultural agencies, ensuring that wetlands adjacent to agricultural lands remain intact.

Increased rainfall variability due to climate change has led to a 27% rise in extreme rainfall events in the Southeast, causing wetland flooding and contamination. Runoff from agricultural lands carries pesticides and fertilizers into wetlands, harming fish populations and reducing prey availability for Wood Storks. Expanding the use of stormwater retention ponds and vegetative buffer zones could mitigate these impacts. Retention ponds reduce runoff by 60%, while buffer zones filter out 85% of pollutants before they reach wetlands [74]. Implementing these measures in high-risk agricultural areas could protect hundreds of thousands of acres of wetland habitat. State environmental agencies and local conservation groups would oversee adoption and enforcement of these practices.

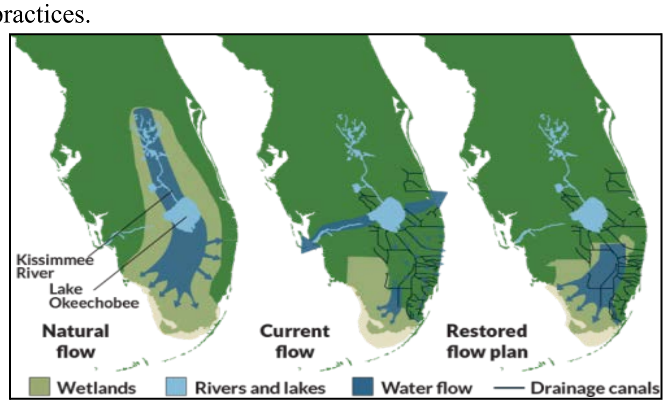


Figure 22: *In 2000, The Comprehensive Everglades Restoration Plan was authorized, making it the largest hydrologic restoration project ever undertaken in the United States. However, this plan still has a long time to develop further due to funding shortfalls, bureaucratic delays, and the complexity of large-scale ecosystem restoration. As of 2023, only approximately 30% of the plan's projects have been completed, with key components like water flow restoration and wetland rehabilitation still facing obstacles. The slow progress threatens critical habitats for migratory birds like the Wood Stork,*

whose breeding success has already declined by more than 50% in some areas due to habitat degradation and inconsistent water levels (Courtesy of Florida Museum) [83].

By restoring wetlands, improving irrigation efficiency, expanding conservation incentives, and enhancing stormwater management, these strategies ensure that Wood Stork foraging grounds remain stable despite climate change. These efforts also benefit farmers by preserving water supplies, reducing pesticide reliance, and maintaining soil health, creating a balanced idea to improve ecological and agricultural sustainability.

6.6 Federal and Local Governmental Policy Implementation

Protecting Wood Stork migration patterns requires action at the federal, state, and local levels to conserve wetlands and restore their habitats. As Wood Storks move farther north because of habitat loss in Florida, government policies are needed to protect their traditional breeding and feeding areas. Without action, the Everglades could stop being their main nesting site, forcing them into areas that might not support them as well in the long run. At the federal level, the U.S. Fish and Wildlife Service (USFWS) lists the Wood Stork as Threatened under the Endangered Species Act (ESA), which is supposed to protect it from habitat destruction. However, Florida has lost nearly 44% of its wetlands since the early 1900s [75]**.** The Comprehensive Everglades Restoration Plan (CERP), a federal program launched in 2000, was designed to restore 18,000 square miles of wetlands, including important Wood Stork foraging areas [76]. While CERP has improved water flow in some regions, only 60% of planned projects have been finished because of funding issues. Completing these projects could help restore key Wood Stork habitats, especially in Southwest Florida, where nesting success has dropped by 35% in the last 20 years due to habitat loss [82]. Expanding the Wetlands Reserve Easement (WRE) program, which has already protected 2.7 million acres of wetlands across the U.S., could also encourage private landowners to keep wetlands intact instead of developing them [77].

State governments in Florida, Georgia, and South Carolina are responsible for protecting wetlands through laws that address local environmental challenges. In Florida, the Rural and Family Lands Protection Program helps private landowners keep wetlands undeveloped and has protected 64,000 acres of wetland habitat so far [78]**.** However, demand for this program is higher than its current budget allows, meaning many important wetland areas remain unprotected. Increasing funding by $50 million per year could preserve another 100,000 acres, helping maintain Wood Stork breeding sites [79]. Additionally, state governments should strengthen wetland permitting laws to prevent the destruction of natural wetlands in exchange for artificial replacements, which often do not provide the same ecological benefits for Wood Storks.

At the local level, cities and conservation groups can help protect Wood Stork habitats by enforcing zoning laws, conservation easements, and wetland restoration projects. For example, Corkscrew Swamp Sanctuary in South Florida, a 13,000-acre preserve, has long been a key Wood Stork nesting site. However, nesting success has fallen by 80% since the 1960s due to habitat degradation [80]. Increasing local funding for removing invasive species and restoring tree islands could help improve nesting conditions. In Miami-Dade County, stormwater retention projects have lowered wetland pollution by 40%, improving water quality in important feeding areas [81]. Expanding these projects in other parts of Florida and the Southeast could further help Wood Storks find reliable food sources.

To keep Wood Stork populations stable in Florida and prevent further migration shifts into the Carolinas, action at all levels of government is needed. Federal agencies should complete ongoing restoration projects and increase funding for conservation programs. State governments must pass stricter wetland protection laws and expand financial incentives for private landowners to protect wetland habitats. Locally, stronger land-use regulations and wetland restoration efforts can further improve habitat quality. With a coordinated approach, policymakers can help restore stable nesting and foraging conditions for Wood Storks, making sure their populations remain strong in their traditional range.

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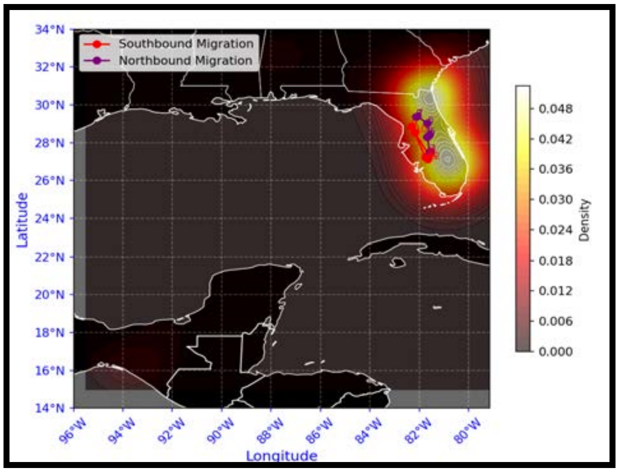
Appendix

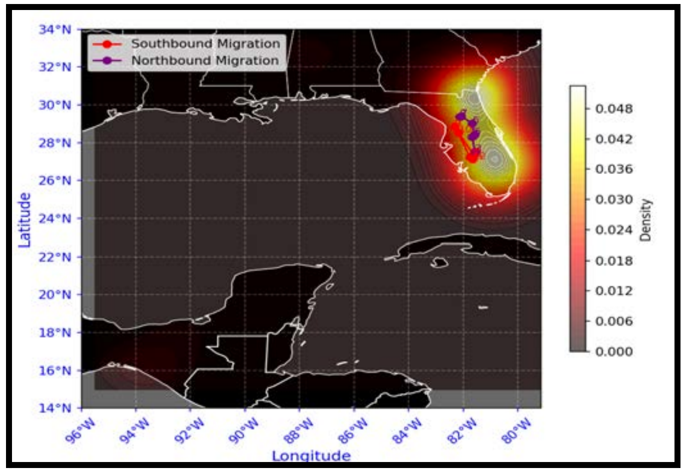
Appendix 1: Kernel Density Estimation

Remaining Graphs of the Kernel Density Estimation

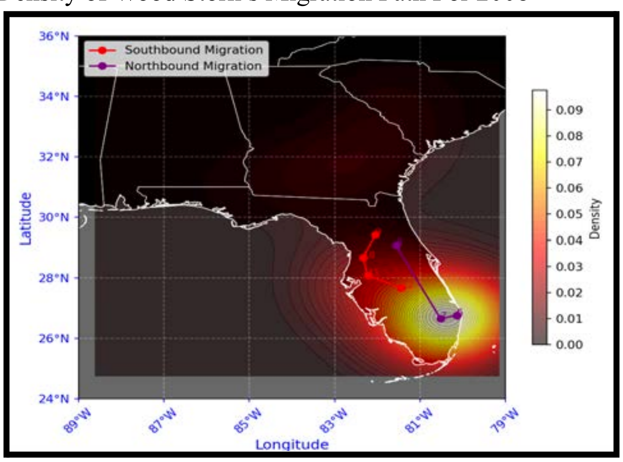
Kernel Density of Wood Stork's Migration Path For 2004



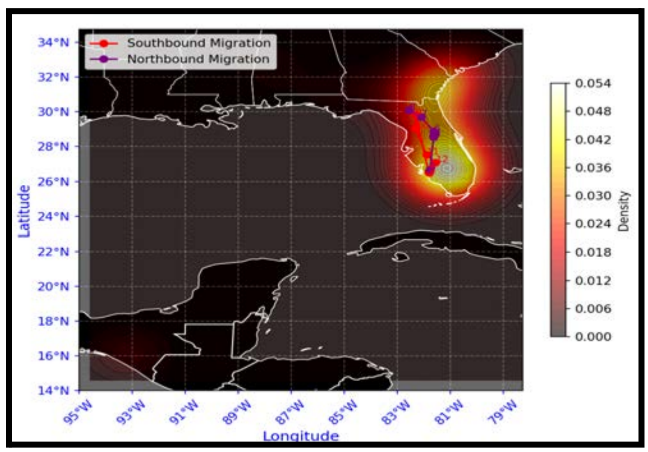
Kernel Density of Wood Stork's Migration Path For 2006



Kernel Density of Wood Stork's Migration Path For 2008

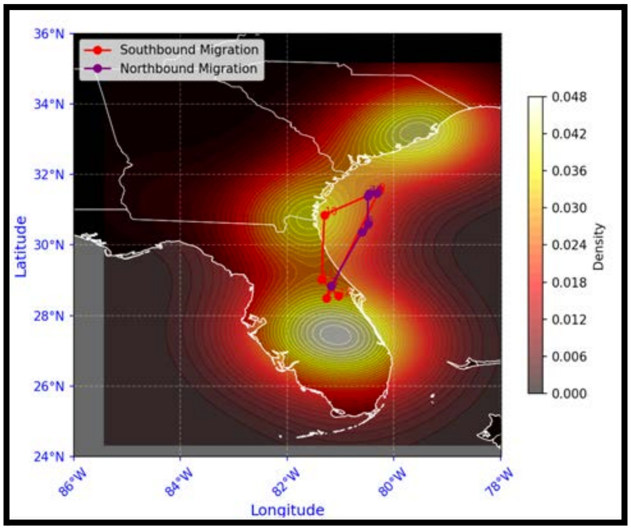


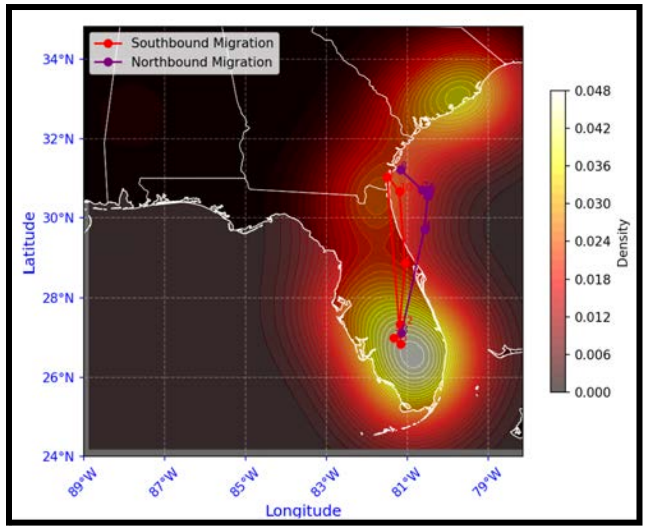
Kernel Density of Wood Stork's Migration Path For 2010



Kernel Density of Wood Stork's Migration Path For 2012

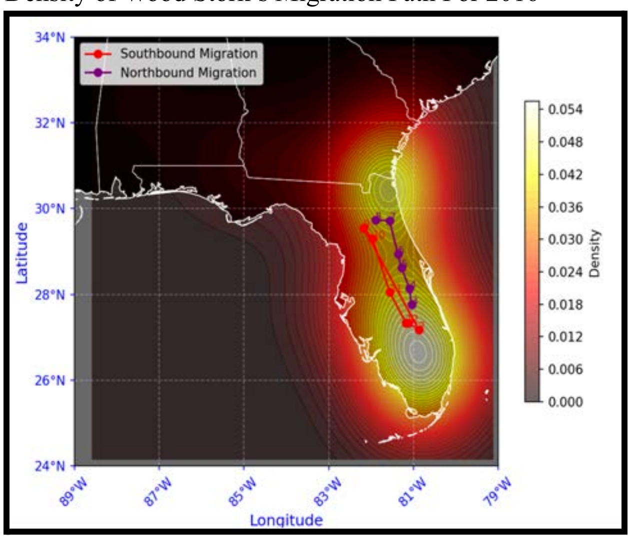
Kernel Density of Wood Stork's Migration Path For 2014

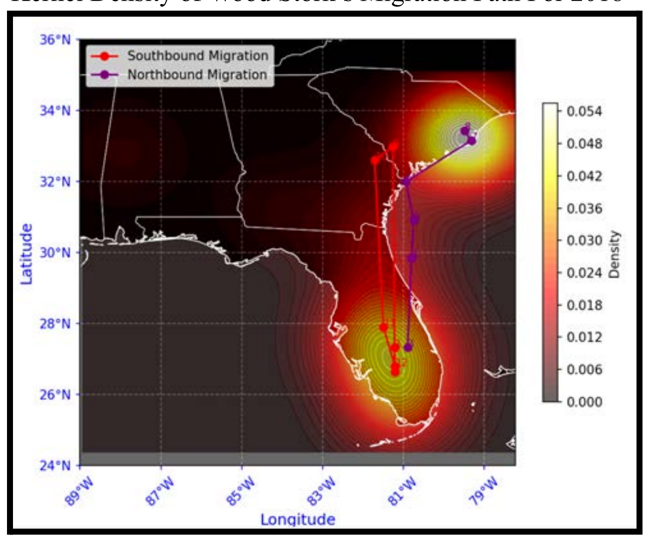




Kernel Density of Wood Stork's Migration Path For 2016

Kernel Density of Wood Stork's Migration Path For 2018





Kernel Density Estimation Code

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.neighbors import KernelDensity

import cartopy.crs as ccrs
import cartopy.feature as cfeature
from cartopy.mpl.ticker import LongitudeFormatter, LatitudeFormatter
import matplotlib.ticker as mticker

data_path = r'C:\Users\ssagi\Downloads\wood_stork2.csv'
df = pd.read_csv(data_path)

df['timestamp'] = pd.to_datetime(df['timestamp'])
df.sort_values('timestamp', inplace=True)

df['year'] = df['timestamp'].dt.year
df['month_num'] = df['timestamp'].dt.month
```

```
# Example migration windows
southward_months = [9, 10, 11, 12, 1, 2]

northward_months = [3, 4, 5, 6, 7, 8]

def get_monthly_path(group_year, months):
  monthly_data = group_year.groupby('month_num')
  path_points = []
  for m in months:
     if m in monthly_data.groups:
        coords = monthly_data.get_group(m)[['location-lat','location-long']].values
        mean_lat = np.mean(coords[:, 0])
        mean_lon = np.mean(coords[:, 1])
        path_points.append((m, mean_lat, mean_lon))
  return path_points

for year, group_year in df.groupby('year'):
  if len(group_year) < 2:
     continue

  south_path = get_monthly_path(group_year, southward_months)
  north_path = get_monthly_path(group_year, northward_months)

  lat_all = group_year['location-lat'].values
  lon_all = group_year['location-long'].values
  coords_all = np.column_stack((lat_all, lon_all))

  # Fit KDE
  bandwidth = 1.0
  kde = KernelDensity(kernel='gaussian', bandwidth=bandwidth).fit(coords_all)

  # Tighter margin: ±1 around data
  lat_min, lat_max = lat_all.min() - 1, lat_all.max() + 1
  lon_min, lon_max = lon_all.min() - 1, lon_all.max() + 1

  grid_size = 100
  lat_lin = np.linspace(lat_min, lat_max, grid_size)
  lon_lin = np.linspace(lon_min, lon_max, grid_size)
  lon_mesh, lat_mesh = np.meshgrid(lon_lin, lat_lin)

  # Evaluate KDE
  grid_coords = np.column_stack([lat_mesh.ravel(), lon_mesh.ravel()])
  log_density = kde.score_samples(grid_coords)
  density = np.exp(log_density).reshape(lat_mesh.shape)

  # ---------------------------
  # Create a SQUARE figure
  # ---------------------------
  fig = plt.figure(figsize=(8, 8))  # Square figure
  ax = plt.axes(projection=ccrs.PlateCarree())
  ax.set_facecolor('black')

  # Let Cartopy fill that square figure
  ax.set_aspect("auto")  # or "equal", but may cause cropping if lat/lon ratio is far from 1:1

  # Zoom to data region
  ax.set_extent([lon_min, lon_max, lat_min, lat_max], crs=ccrs.PlateCarree())
```

```
# Dark-themed map
ax.add_feature(cfeature.LAND, facecolor='black', edgecolor='white')
ax.add_feature(cfeature.OCEAN, facecolor='dimgray')
ax.add_feature(cfeature.BORDERS, edgecolor='white')
ax.add_feature(cfeature.STATES, edgecolor='white', linewidth=0.5)
ax.coastlines(color='white', linewidth=0.7)

# Contourf
cf = ax.contourf(
    lon_mesh, lat_mesh, density,
    levels=45, cmap='hot', alpha=0.6,
    transform=ccrs.PlateCarree()
)
cbar = plt.colorbar(cf, ax=ax, orientation='vertical', shrink=0.7)
cbar.set_label('Density')

def plot_path(path_list, color, label):
    if not path_list:
        return
    path_list_sorted = sorted(path_list, key=lambda x: x[0])
    lats = [pt[1] for pt in path_list_sorted]
    lons = [pt[2] for pt in path_list_sorted]
    ax.plot(
        lons, lats, marker='o', color=color, label=label,
        transform=ccrs.PlateCarree()
    )
    for (m, lat_val, lon_val) in path_list_sorted:
        ax.text(
            lon_val, lat_val, f'{m}', fontsize=8, color=color,
            transform=ccrs.PlateCarree()
        )

plot_path(south_path, 'red', 'Southbound Migration')
plot_path(north_path, 'purple', 'Northbound Migration')

ax.set_title(f'Wood Stork Migration Heat Map & Paths for Year {year}',
             color='white', fontsize=14)

# Numeric x/y ticks (every 2 degrees, for example)
x_ticks = np.arange(np.floor(lon_min), np.ceil(lon_max)+1, 2)
y_ticks = np.arange(np.floor(lat_min), np.ceil(lat_max)+1, 2)

ax.set_xticks(x_ticks, crs=ccrs.PlateCarree())
ax.set_yticks(y_ticks, crs=ccrs.PlateCarree())

ax.xaxis.set_major_formatter(LongitudeFormatter())
ax.yaxis.set_major_formatter(LatitudeFormatter())

ax.set_xlabel('Longitude', fontsize=12, color='blue')
ax.set_ylabel('Latitude', fontsize=12, color='blue')

plt.setp(ax.xaxis.get_majorticklabels(), rotation=45)
ax.tick_params(axis='x', colors='blue', labelsize=10)
ax.tick_params(axis='y', colors='blue', labelsize=10)

ax.grid(True, color='white', alpha=0.3, linestyle='--')

plt.legend(loc='upper left')
```

```
plt.show()
```

Appendix 2: ARIMA

Auto-Regressive Integrated Moving Average Code

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.arima.model import ARIMA

# Data
years = [1987, 1992, 1997, 2002, 2007, 2012, 2017]
economic_loss = [4054640000, 6473000000, 9005000000, 8316000000, 10517000000, 12629000000, 14989000000]

# Convert to pandas Series
data = pd.Series(economic_loss, index=pd.to_datetime(years, format='%Y'))

# Fit ARIMA model (AutoRegressive order=1, Differencing order=1, Moving Average order=1)
model = ARIMA(data, order=(1,1,1))
model_fit = model.fit()

# Forecast future values
future_years = [2022, 2027, 2032]
future_index = pd.to_datetime(future_years, format='%Y')
forecast = model_fit.forecast(steps=len(future_years))

# Plot results
plt.figure(figsize=(10,5))
plt.plot(data, label='Historical Data', marker='o')
plt.plot(future_index, forecast, label='Forecast', marker='o', linestyle='dashed', color='red')
plt.xlabel('Year')
plt.ylabel('Expected Economic Loss ($)')
plt.legend()
plt.title('ARIMA Forecast of Expected Economic Loss for Agriculture in the United States')
plt.show()

# Print forecasted values
forecast_df = pd.DataFrame({'Year': future_years, 'Forecasted Loss ($)': forecast.values})
print(forecast_df)
```

Appendix 3: SARIMA

Contains SARIMA, stats analysis of SARMA, and 95% confidence intervals

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.statespace.sarimax import SARIMAX

# -------------------------------
# CONFIGURATION
```

```
# -------------------------------
target_states = [
    "Alabama, United States", "Mississippi, United States", "West Virginia, United States",
    "Georgia, United States", "Florida, United States", "South Carolina, United States",
    "North Carolina, United States", "Virginia, United States", "Maryland, United States",
]

temp_excel_file = "Temperature Data.xlsx"
precip_excel_file = "Precipitation Data.xlsx"

# The decades that exist in your data
historical_decades = [
    "1951-1960", "1961-1970", "1971-1980",
    "1981-1990", "1991-2000", "2001-2010", "2011-2020"
]

# We'll read all sheets at once for speed
temp_sheets = pd.read_excel(temp_excel_file, sheet_name=None, engine="openpyxl")
precip_sheets = pd.read_excel(precip_excel_file, sheet_name=None, engine="openpyxl")

# -------------------------------
# FUNCTIONS
# -------------------------------

def build_time_series_for_state(sheet_name, data_dict):
    """
    Reads the DataFrame for 'sheet_name' from 'data_dict',
    skips the first 25 rows, and flattens all decades (1951-2020)
    into a single monthly time series using NumPy indexing.
    Returns a 1D NumPy array or None if data is missing.
    """
    if sheet_name not in data_dict:
        print(f"Sheet '{sheet_name}' not found. Skipping...")
        return None

    df = data_dict[sheet_name].copy()
    df = df.iloc[25:].reset_index(drop=True)  # skip first 25 summary rows
    df.columns = df.columns.str.strip()

    arr = df.values  # shape ~ (some_rows, some_cols)
    col_map = {col_name: i for i, col_name in enumerate(df.columns)}

    all_values = []
    for decade in historical_decades:
        if decade in col_map:
            col_idx = col_map[decade]
            for year_offset in range(10):  # 10 years
                for month_idx in range(12):  # 12 months
                    row_idx = (year_offset * 12) + month_idx
                    if row_idx < arr.shape[0]:
                        val = arr[row_idx, col_idx]
                    else:
                        val = np.nan
                    all_values.append(val)
        else:
```

```
        # If that decade doesn't exist, fill with 10*12=120 NaNs
        all_values.extend([np.nan]*120)

    if all(pd.isna(all_values)):
        print(f"All values for '{sheet_name}' are NaN.")
        return None

    return np.array(all_values, dtype=float)

def forecast_sarima_temp(values):
    """
    1) Interpolate missing data for temperature (no log transform).
    2) Fit SARIMA(2,1,2)x(1,1,1,12) (adjust if you like).
    3) Forecast 120 months.
    4) Plot residual diagnostics.
    Returns (hist_values, forecast_values, lower_ci, upper_ci, results).
    """
    # Fill missing
    series = pd.Series(values).interpolate().bfill().ffill()
    hist_array = series.to_numpy()

    # Fit SARIMA
    # Example: More AR terms might let the model amplify short-term cycles
    model = SARIMAX(
        hist_array,
        order=(5,0,3),              # Increase AR, MA, remove differencing
        seasonal_order=(1,0,1,12),  # Lighter seasonal differencing
        enforce_stationarity=False, # Avoid LU errors if needed
        enforce_invertibility=False
    )
    results = model.fit(disp=False)

    results = model.fit(disp=False)

    # Residual diagnostics
    results.plot_diagnostics(figsize=(10,8))
    plt.suptitle("Temperature Model Diagnostics", y=1.02)
    plt.show()

    # Forecast 120 months
    steps = 120
    forecast_obj = results.get_forecast(steps=steps)

    forecast_mean = np.array(forecast_obj.predicted_mean)
    conf_int = np.array(forecast_obj.conf_int(alpha=0.05))
    lower_ci = conf_int[:, 0]
    upper_ci = conf_int[:, 1]

    return hist_array, forecast_mean, lower_ci, upper_ci, results

def forecast_sarima_precip(values):
    """
    1) Interpolate missing data for precipitation.
    2) Fit SARIMA(3,0,3)x(1,0,1,12) with NO log transform.
    3) Forecast 36 months.
```

```
    4) Return original-scale results.
    """
    # Fill missing values
    series = pd.Series(values).interpolate().bfill().ffill()

    # Fit SARIMA without log transform
    model = SARIMAX(
        series,
        order=(6,0,1),          # Lower AR/MA terms
        enforce_stationarity=True,
        enforce_invertibility=False
    )
    results = model.fit(disp=False)

    # Residual diagnostics
    results.plot_diagnostics(figsize=(10,8))
    plt.suptitle("Precipitation Model Diagnostics", y=1.02)
    plt.show()

    # Forecast 36 months
    steps = 36
    forecast_obj = results.get_forecast(steps=steps)

    forecast_mean = np.array(forecast_obj.predicted_mean)

    conf_int = np.array(forecast_obj.conf_int(alpha=0.05))
    lower_ci = conf_int[:, 0]
    upper_ci = conf_int[:, 1]

    return series.to_numpy(), forecast_mean, lower_ci, upper_ci, results

# -------------------------------
# MAIN
# -------------------------------
predicted_temp_data = {}
predicted_precip_data = {}

for state in target_states:
    print(f"\nProcessing '{state}'...")

    temp_values = build_time_series_for_state(state, temp_sheets)
    precip_values = build_time_series_for_state(state, precip_sheets)

    if temp_values is None or precip_values is None:
        print(f"Skipping '{state}' due to missing data.")
        continue

    # Forecast temperature (no log transform)
    hist_temp, f_temp, temp_lower, temp_upper, temp_results = forecast_sarima_temp(temp_values)
    # Forecast precipitation (log transform)
    hist_precip, f_precip, precip_lower, precip_upper, precip_results = forecast_sarima_precip(precip_values)

    # ---------------------
    # PLOT TEMPERATURE
    # ---------------------
```

```
    x_hist_t = range(len(hist_temp))
    x_forecast_t = range(len(hist_temp), len(hist_temp) + len(f_temp))

    plt.figure(figsize=(10,5))
    plt.plot(x_hist_t, hist_temp, label="Actual Temperature", color="blue")
    plt.plot(x_forecast_t, f_temp, label="Forecasted Temperature", color="red", linestyle="--")
    plt.fill_between(x_forecast_t, temp_lower, temp_upper, color="pink", alpha=0.3, label="95% CI")
    plt.xlabel("Months (index)")
    plt.ylabel("Temperature")
    plt.title(f"SARIMA Temperature Forecast - {state}")
    plt.legend()
    plt.grid(True)
    plt.show()

    # ---------------------
    # PLOT PRECIPITATION
    # ---------------------
    x_hist_p = range(len(hist_precip))
    x_forecast_p = range(len(hist_precip), len(hist_precip) + len(f_precip))

    plt.figure(figsize=(10,5))
    plt.plot(x_hist_p, hist_precip, label="Actual Precipitation", color="green")
    plt.plot(x_forecast_p, f_precip, label="Forecasted Precipitation", color="orange", linestyle="--")
    plt.fill_between(x_forecast_p, precip_lower, precip_upper, color="lightgreen", alpha=0.3, label="95% CI")
    plt.xlabel("Months (index)")
    plt.ylabel("Precipitation")
    plt.title(f"SARIMA Precipitation Forecast - {state}")
    plt.legend()
    plt.grid(True)
    plt.show()

    # ---------------------
    # SAVE RESULTS TO DATAFRAMES
    # ---------------------
    df_temp = pd.DataFrame({
        "MonthIndex": list(x_hist_t) + list(x_forecast_t),
        "Value": list(hist_temp) + list(f_temp),
        "Lower95": [np.nan]*len(hist_temp) + list(temp_lower),
        "Upper95": [np.nan]*len(hist_temp) + list(temp_upper)
    })
    df_precip = pd.DataFrame({
        "MonthIndex": list(x_hist_p) + list(x_forecast_p),
        "Value": list(hist_precip) + list(f_precip),
        "Lower95": [np.nan]*len(hist_precip) + list(precip_lower),
        "Upper95": [np.nan]*len(hist_precip) + list(precip_upper)
    })

    predicted_temp_data[state] = df_temp
    predicted_precip_data[state] = df_precip

# -------------------------------
# SAVE RESULTS TO EXCEL
# -------------------------------
if predicted_temp_data:
    with pd.ExcelWriter("Predicted_Temperature_Data.xlsx") as writer:
```

```
        for sheet, df in predicted_temp_data.items():
            df.to_excel(writer, sheet_name=sheet, index=False)

if predicted_precip_data:
    with pd.ExcelWriter("Predicted_Precipitation_Data.xlsx") as writer:
        for sheet, df in predicted_precip_data.items():
            df.to_excel(writer, sheet_name=sheet, index=False)

print("\nAll forecasts complete. Results saved to Excel!")
```

Appendix 4: Random Forest Regression

Random Forest Regressor Code

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import cartopy.crs as ccrs
import cartopy.feature as cfeature
from cartopy.mpl.ticker import LongitudeFormatter, LatitudeFormatter

from sklearn.ensemble import RandomForestRegressor

data_path = r'C:\Users\YourName\Downloads\wood_stork_data_2004_2035.csv'
df = pd.read_csv(data_path)
df.columns = df.columns.str.strip()

print("Columns in CSV:", df.columns.tolist())
# Must have: 'year', 'month_num', 'location-lat', 'location-long',
#            'average_temperature', 'average_precipitation'

df.sort_values(['year','month_num'], inplace=True, ignore_index=True)

# Split historical vs. future
df_hist = df[(df['year'] >= 2004) & (df['year'] <= 2019)].copy()
df_future = df[(df['year'] >= 2020) & (df['year'] <= 2035)].copy()

# For historical, drop missing lat/long
df_hist.dropna(subset=['location-lat','location-long'], inplace=True)


df_pred = df_future.copy()
df_pred['location-lat'] = np.nan
df_pred['location-long'] = np.nan

def train_month_model(df_hist, df_pred, target_year, month):
    """
    Gathers all rows for this 'month' from:
      - df_hist (2004..2019)
```

```
      - df_pred for years < target_year that have already been predicted
    Then trains a RandomForestRegressor that maps:
      (year_offset, temperature, precipitation) -> (lat, lon).
    Returns (model, f_min, f_range) or (None,None,None) if insufficient data.
    """

    # 1) Gather historical for that month
    df_hist_m = df_hist[df_hist['month_num'] == month].copy()
    # 2) Gather predicted for that month, up to year < target_year
    df_pred_m = df_pred[(df_pred['month_num'] == month) & (df_pred['year'] < target_year)].copy()
    # Drop rows that have not yet been predicted
    df_pred_m = df_pred_m.dropna(subset=['location-lat','location-long'])

    # Combine
    df_m = pd.concat([df_hist_m, df_pred_m], ignore_index=True)
    df_m.sort_values('year', inplace=True)

    # If <2 data points, can't train
    if len(df_m) < 2:
        return None, None, None

    # Build features/targets
    feats_list = []
    targs_list = []
    for idx, row in df_m.iterrows():
        year_offset = row['year'] - 2004
        temp_val    = row['average_temperature']
        prec_val    = row['average_precipitation']
        lat_val     = row['location-lat']
        lon_val     = row['location-long']
        feats_list.append([year_offset, temp_val, prec_val])
        targs_list.append([lat_val, lon_val])

    feats = np.array(feats_list, dtype=np.float32)  # shape (N,3)
    targs = np.array(targs_list, dtype=np.float32)  # shape (N,2)

    # Feature scaling
    f_min = feats.min(axis=0)
    f_max = feats.max(axis=0)
    f_range = (f_max - f_min) + 1e-9
    feats_scaled = (feats - f_min) / f_range

    if len(feats_scaled) < 2:
        return None, None, None

    # Train a multi-output RandomForest
    rf = RandomForestRegressor(n_estimators=50, random_state=42)
    rf.fit(feats_scaled, targs)  # targs shape => (N,2) => multi-output

    return rf, f_min, f_range

for year in range(2020, 2036):
    for month in range(1, 13):
```

```
        # Train a model for (month) using data up to year-1
        model_m, f_min_m, f_range_m = train_month_model(df_hist, df_pred, year, month)
        if model_m is None:
            # skip if insufficient data
            continue

        # Find row in df_pred for (year, month)
        row_idx = df_pred[(df_pred['year']==year) & (df_pred['month_num']==month)].index
        if len(row_idx) != 1:
            continue
        idx_r = row_idx[0]

        # Build feature => (year_offset, temperature, precipitation)
        row_data = df_pred.loc[idx_r]
        year_offset = row_data['year'] - 2004
        temp_val    = row_data['average_temperature']
        prec_val    = row_data['average_precipitation']

        # scale
        feats = np.array([year_offset, temp_val, prec_val], dtype=np.float32)
        feats_scaled = (feats - f_min_m)/f_range_m
        feats_scaled = feats_scaled.reshape(1,3)

        pred_latlon = model_m.predict(feats_scaled)  # shape (1,2)
        lat_val = pred_latlon[0,0]
        lon_val = pred_latlon[0,1]

        # store in df_pred
        df_pred.loc[idx_r, 'location-lat'] = lat_val
        df_pred.loc[idx_r, 'location-long'] = lon_val

df_pred_filled = df_pred.dropna(subset=['location-lat','location-long']).copy()
print("Predicted lat/long for future rows:\n", df_pred_filled.head(15))

lat_hist = df_hist['location-lat'].values
lon_hist = df_hist['location-long'].values
lat_fut  = df_pred_filled['location-lat'].values
lon_fut  = df_pred_filled['location-long'].values

lat_min = min(lat_hist.min(), lat_fut.min()) - 1
lat_max = max(lat_hist.max(), lat_fut.max()) + 1
lon_min = min(lon_hist.min(), lon_fut.min()) - 1
lon_max = max(lon_hist.max(), lon_fut.max()) + 1

def get_direction_color(m):
    # months 9..2 => red => southbound, else => blue => northbound
    if m in [9,10,11,12,1,2]:
        return 'red'
    else:
        return 'blue'

import cartopy.crs as ccrs
import cartopy.feature as cfeature
```

```
for yr in range(2020, 2036):
    df_yr = df_pred_filled[df_pred_filled['year'] == yr].copy()
    df_yr.sort_values('month_num', inplace=True)
    if len(df_yr) < 1:
        continue

    fig = plt.figure(figsize=(8,6))
    ax = plt.axes(projection=ccrs.PlateCarree())
    ax.set_facecolor('black')
    ax.set_extent([lon_min, lon_max, lat_min, lat_max], crs=ccrs.PlateCarree())

    ax.add_feature(cfeature.LAND, facecolor='black', edgecolor='white')
    ax.add_feature(cfeature.OCEAN, facecolor='dimgray')
    ax.add_feature(cfeature.BORDERS, edgecolor='white')
    ax.add_feature(cfeature.STATES, edgecolor='white', linewidth=0.5)
    ax.coastlines(color='white', linewidth=0.7)

    prev_lat, prev_lon = None, None
    for idx, row in df_yr.iterrows():
        mo = row['month_num']
        lat_c = row['location-lat']
        lon_c = row['location-long']
        color = get_direction_color(mo)

        ax.plot(lon_c, lat_c, marker='o', color=color, transform=ccrs.PlateCarree())
        ax.text(lon_c, lat_c, f"{int(mo)}", fontsize=8, color=color, transform=ccrs.PlateCarree())

        if prev_lat is not None:
            ax.plot([prev_lon, lon_c], [prev_lat, lat_c],
                    color=color, linewidth=2, transform=ccrs.PlateCarree())
        prev_lat, prev_lon = lat_c, lon_c

    ax.set_title(f"Month-by-Month Path (RandomForest) for Year {yr}", color='white', fontsize=14)
    ax.gridlines(draw_labels=True, color='gray', linestyle='--')
    plt.show()

df_pred_filled.to_csv(r'C:\Users\YourName\Downloads\wood_stork_future_randomforest.csv', index=False)
print("Saved final predictions to CSV.")
```

Appendix 5: Wetland Graphs for Comparison with Urbanization Graphs

```
!pip install geopandas fiona rasterio shapely matplotlib
%pip install dask-geopandas

import geopandas as gpd
import matplotlib.pyplot as plt

from google.colab import drive
drive.mount('/content/drive')
```

```
import geopandas as gpd
import dask_geopandas as dgpd
import matplotlib.pyplot as plt

# Load dataset lazily from Parquet
file_path = "SC_Wetlands.parquet"
dask_gdf = dgpd.read_parquet(file_path)

# Define relevant wetland types and colors
wetland_types = {
    "Freshwater Emergent Wetland": "red",
    "Freshwater Forested/Shrub Wetland": "orange",  # Light green
}

# Filter dataset without fully loading it into memory
filtered_dask_gdf = dask_gdf[dask_gdf["WETLAND_TYPE"].isin(wetland_types.keys())]

# Compute only the filtered subset
filtered_gdf = filtered_dask_gdf.compute()

# Simplify geometries (optional, reduces file size)
filtered_gdf["geometry"] = filtered_gdf["geometry"].simplify(tolerance=0.001)

# Optimize data types
filtered_gdf["WETLAND_TYPE"] = filtered_gdf["WETLAND_TYPE"].astype("category")

# Ensure CRS is WGS 84 (EPSG:4326)
if filtered_gdf.crs is not None and filtered_gdf.crs.to_epsg() != 4326:
    filtered_gdf = filtered_gdf.to_crs(epsg=4326)

# PLOT BOTH LAYERS
# ================================
fig, ax = plt.subplots(figsize=(10, 8))

# Plot wetlands
filtered_gdf.plot(column="WETLAND_TYPE", cmap="viridis", legend=True, alpha=0.6, ax=ax)


# Add legend and show
plt.legend()
plt.title("Wetlands")
plt.show()


import dask_geopandas as dgpd
import geopandas as gpd
```

```
import gc
import matplotlib.pyplot as plt

file_path = "/content/drive/MyDrive/FL_Wetlands.parquet"

# Load only required columns in smaller chunks
columns_to_load = ["WETLAND_TYPE", "geometry"]
dask_gdf = dgpd.read_parquet(file_path, columns=columns_to_load, npartitions=10)

# Optimize data types early
dask_gdf["WETLAND_TYPE"] = dask_gdf["WETLAND_TYPE"].astype("category")

# Define wetland types and their colors
wetland_types = {
    "Freshwater Emergent Wetland": "red",
    "Freshwater Forested/Shrub Wetland": "green",  # Light green
}

# Filter dataset lazily to include only the relevant wetland types
filtered_dask_gdf = dask_gdf[dask_gdf["WETLAND_TYPE"].isin(wetland_types.keys())]

# Process partitions with a copy to avoid SettingWithCopyWarning
def process_partition(partition):
    partition = partition.copy()  # Ensure we modify a copy
    partition.loc[:, "geometry"] = partition["geometry"].simplify(tolerance=0.005)
    return partition

# Compute only the filtered subset
filtered_gdf = filtered_dask_gdf.map_partitions(process_partition).compute()

# Free memory
del dask_gdf, filtered_dask_gdf
gc.collect()

fig, ax = plt.subplots(figsize=(10, 8))

# Plot wetlands
filtered_gdf.plot(column="WETLAND_TYPE", cmap="viridis", legend=True, alpha=0.6, ax=ax)


# Add legend and show
plt.legend()
plt.title("Wetlands")
plt.show()



import dask_geopandas as dgpd
```

```
import geopandas as gpd
import gc
import matplotlib.pyplot as plt

file_path = "/content/NC_Wetlands.parquet"

# Load only required columns in smaller chunks
columns_to_load = ["WETLAND_TYPE", "geometry"]
dask_gdf = dgpd.read_parquet(file_path, columns=columns_to_load, npartitions=10)

# Optimize data types early
dask_gdf["WETLAND_TYPE"] = dask_gdf["WETLAND_TYPE"].astype("category")

# Define wetland types and their colors
wetland_types = {
    "Freshwater Emergent Wetland": "green",
    "Freshwater Forested/Shrub Wetland": "#90EE90",  # Light green
}

# Filter dataset lazily to include only the relevant wetland types
filtered_dask_gdf = dask_gdf[dask_gdf["WETLAND_TYPE"].isin(wetland_types.keys())]

# Process partitions with a copy to avoid SettingWithCopyWarning
def process_partition(partition):
    partition = partition.copy()  # Ensure we modify a copy
    partition.loc[:, "geometry"] = partition["geometry"].simplify(tolerance=0.005)
    return partition

# Compute only the filtered subset
filtered_gdf = filtered_dask_gdf.map_partitions(process_partition).compute()

# Free memory
del dask_gdf, filtered_dask_gdf
gc.collect()
fig, ax = plt.subplots(figsize=(10, 8))

# Plot wetlands
filtered_gdf.plot(column="WETLAND_TYPE", cmap="viridis", legend=True, alpha=0.6, ax=ax)


# Add legend and show
plt.legend()
plt.title("Wetlands")
plt.show()


import dask_geopandas as dgpd
import geopandas as gpd
```

```
import gc
import matplotlib.pyplot as plt

file_path = "/content/GA_Wetlands.parquet"

# Load only required columns in smaller chunks
columns_to_load = ["WETLAND_TYPE", "geometry"]
dask_gdf = dgpd.read_parquet(file_path, columns=columns_to_load, npartitions=10)

# Optimize data types early
dask_gdf["WETLAND_TYPE"] = dask_gdf["WETLAND_TYPE"].astype("category")

# Define wetland types and their colors
wetland_types = {
    "Freshwater Emergent Wetland": "green",
    "Freshwater Forested/Shrub Wetland": "#90EE90",  # Light green
}

# Filter dataset lazily to include only the relevant wetland types
filtered_dask_gdf = dask_gdf[dask_gdf["WETLAND_TYPE"].isin(wetland_types.keys())]

# Process partitions with a copy to avoid SettingWithCopyWarning
def process_partition(partition):
    partition = partition.copy()  # Ensure we modify a copy
    partition.loc[:, "geometry"] = partition["geometry"].simplify(tolerance=0.005)
    return partition

# Compute only the filtered subset
filtered_gdf = filtered_dask_gdf.map_partitions(process_partition).compute()

# Free memory
del dask_gdf, filtered_dask_gdf
gc.collect()

fig, ax = plt.subplots(figsize=(10, 8))

# Plot wetlands
filtered_gdf.plot(column="WETLAND_TYPE", cmap="viridis", legend=True, alpha=0.6, ax=ax)


# Add legend and show
plt.legend()
plt.title("Wetlands")
plt.show()
```