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DAEN 690

Project Report

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Evaluation of Migratory Bird Population and Harvest Data

**About the Cover**

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Abstract

Abstract

The Fish & Wildlife Service’s (FWS) Division of Migratory Bird Management (DMBM) is tasked with safeguarding migratory bird populations. To support this mission, they collect and report bird harvest and hunter data – the data is used by federal and state agencies to set wildlife management policies. Though DMBM produces annual reports (called ‘Flyway Data Books’) to share data, these reports are manually created, the data is static (in PDFs), and there’s little analysis applied to the data. Thus, reporting is time consuming and prone to human error, technical/nontechnical end users don’t use the data, and insights that could inform policymaking are less likely to surface. This research explored three associated opportunities: (1) automate report creation; (2) enable self-service data access and analysis; and (3) apply novel analysis and visualization techniques. To automate report creation and enable self-service data access and analysis, the team used business process mapping and requirements techniques to assess automation feasibility and technology solutions. The team found that open-source Python libraries and free/low-cost data visualization solutions (e.g., Tableau) could accomplish these tasks. The team also applied novel analysis and visualization techniques – these included descriptive statistics and time series forecasting and choropleth maps. Though alternative statistics and visualizations yielded insights not yet reported, time series forecasting produced mixed results – notably, due to the dataset lacking variables likely to drive forecasts. The team’s work will enable DMBM to spend less time on data preparation and reporting, and more time on higher-value activities. And it will enable DMBM end users to create analysis to support custom, user-specific policy questions. Net-net, stakeholders responsible for managing bird populations can be equipped with more, and timelier, intelligence and make data-driven decisions.

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Report

# Section 1: Problem Definition

## 1.1 Background

The U.S. Fish & Wildlife Service is the federal agency responsible for the conservation and management of fish, wildlife, plants, and their habitats for the United States. Specifically, the Division of Migratory Bird Management (DMBM) works with partners to protect, restore, and conserve bird populations and their habitats for the benefit of future generations [1]. Over the course of history, birds have been killed for food, feathers, and science. The abuse of natural resources was the norm. Beginning in the early 1800’s, states began protecting birds with laws and individuals started to become educated on the benefits of birds. In 1818 Massachusetts passed the first state law to protect non-game bird species and in 1827 John James Audubon begin publication of his book The Birds of America. Throughout history, more laws were passed, organizations were formed, and the people of America became educated on the importance of birds. In 1918, Congress passed the Migratory Bird Treaty Act which implemented four international conservation treaties that the U.S. entered with Canada in 1916, Mexico in 1936, Japan in 1972, and Russia in 1976 [2]. The treaty was meant to help sustain populations of all protected migratory bird species. It was not until 2009 that there was the first comprehensive analysis of the state of our birds and how individuals can help with the troubling decline that was seen, this was called the State of the Birds Report. The decline of bird populations is an early signal that the health of our ecosystems is failing and a primary concern for the Division of Migratory Bird Management.

The Migratory Bird Program is tasked with safeguarding migratory bird populations through protection, restoration, and management. Bird management includes both population and habitat conservation, and in most cases, managing habitats has benefits for a variety of species. Some of the things the DMBM does to protect, manage, and restore our bird population is [3];

* Biologists and managers perform surveys and conduct other monitoring activities to determine the status of migratory bird populations.
* Collaborate with numerous partners to support important bird management plans, treaties, migratory bird join ventures, and initiatives including Partners in Flight, the U.S. Shorebird Plan, the North American Waterbird Plan, and the North American Waterfowl Management Plan.
* Oversee two bird habitat grant programs: the North American Wetlands Conservation Act and the Neotropical Migratory Bird Conservation Act
* Manage the Migratory Bird Hunting and Conservation Stamp Program, referred to as the “duck stamp”. Ninety-eight cents of each dollar spent on duck stamps directly contributes to habitat conservation.
* Support and sustain ethical hunting of waterfowl and other migratory game birds, as well as strive to foster and inspire birdwatching and other outdoor experiences related to birds.
* Conduct outreach and education programs for children and adults.

The DMBM collaborates with bird conservation partnerships that includes federal and state agencies, Tribes, universities, NGO’s, corporations, experts, and private landowners to manage birds and their habitats. The partnerships formulate and execute management plans, outlining explicit, strategic, and adaptable conservation actions to return and maintain species to health and sustainable levels. To help regulate migratory bird harvest throughout the four migration flyways, biological information such as survey data is provided.

Starting in the 1952-53 season, the U.S. Fish and Wildlife Service (FWS) has conducted a survey among Federal Duck Stamp purchasers to assess waterfowl hunting activities and harvest across the United States, a practice that continued until the 2001-02 season. This was replaced by a more comprehensive migratory game bird harvest survey system. In 1992, the FWS, in collaboration with State Fish and Wildlife Agencies, established the Migratory Bird Harvest Information Program (HIP), fully operational by 1999, which mandates that licensed migratory game bird hunters register annually in each state they hunt. States collect essential hunter information and their previous year's hunting activities, forwarding this to the FWS. Additionally, states ensure that hunters possess proof of compliance during hunting. This cohesive State-Federal effort enables the FWS to conduct detailed annual surveys on hunter activities and game bird harvests nationwide.

Since 1961, FWS has been conducting the Waterfowl Parts Survey, an annual initiative to monitor the species, age, and sex composition of duck and goose harvests. Hunters participating in this survey submit bird wings and specific feathers, along with the location and date of each harvest. This data, analyzed by FWS and State biologists, offers valuable insights into the demographics of the harvested birds. However, recent logistical challenges, such as supply chain shortages, have affected the distribution of necessary materials, leading to a reliance on hunters' leftover envelopes and alternative communication methods. The data from the Waterfowl Parts Survey, when combined with harvest estimates from the HIP waterfowl survey, are crucial for calculating species-specific harvest estimates and demographic ratios, which are then adjusted for state-level variations to provide comprehensive flyway and national figures. These long-term surveys have contributed to the annual population status reports for these species, supporting the FWS's data-driven approach to wildlife management and conservation. (Raftovich, Fleming, Chandler, & Cain, 2023)

In 2019, the United States Fish and Wildlife Service's Division of Migratory Bird Management (DMBM) outlined a Strategic Plan for the conservation and sustainable management of migratory birds (US FWS, 2019). This plan is anchored in four fundamental goals:

• Provide Leadership in Migratory Bird Conservation

• Conserve and Manage Sustainable Populations of Birds of Management Concern

• Conserve Habitat for Migratory Birds of Management Concern

• Manage Bird Data and Information for Use in Decision Making

At a time when data can be a powerful catalyst for change, the last goal recognizes the importance of collecting, managing, and interpreting avian data. The DMBM's strategic approach to data management involves not only the gathering and analysis of population, habitat, and conservation data but also ensuring that this information is accessible and actionable. Following a culture of data-driven decision-making, the Division ensures that its policies, conservation measures, and management plans are grounded in empirical evidence, offering the best possible outcomes for migratory birds and their habitats.

Annual data collection and analysis by DMBM form the backbone of strategies aimed at preserving migratory bird species while allowing for sustainable hunting and other human activities. This data, encompassing population and harvest information, helps shape federal and state regulations, ensuring the protection of migratory species while balancing ecological, recreational, and economic needs.

To effectively manage and protect migratory game birds, the DMBM operates within a structured framework known as Flyways – major geographical corridors that birds follow during migration. The United States is segmented into four main Flyways: the Pacific, Central, Mississippi, and Atlantic (Figure 1). Each Flyway is monitored and managed independently due to the distinct migratory patterns and species compositions within these corridors.

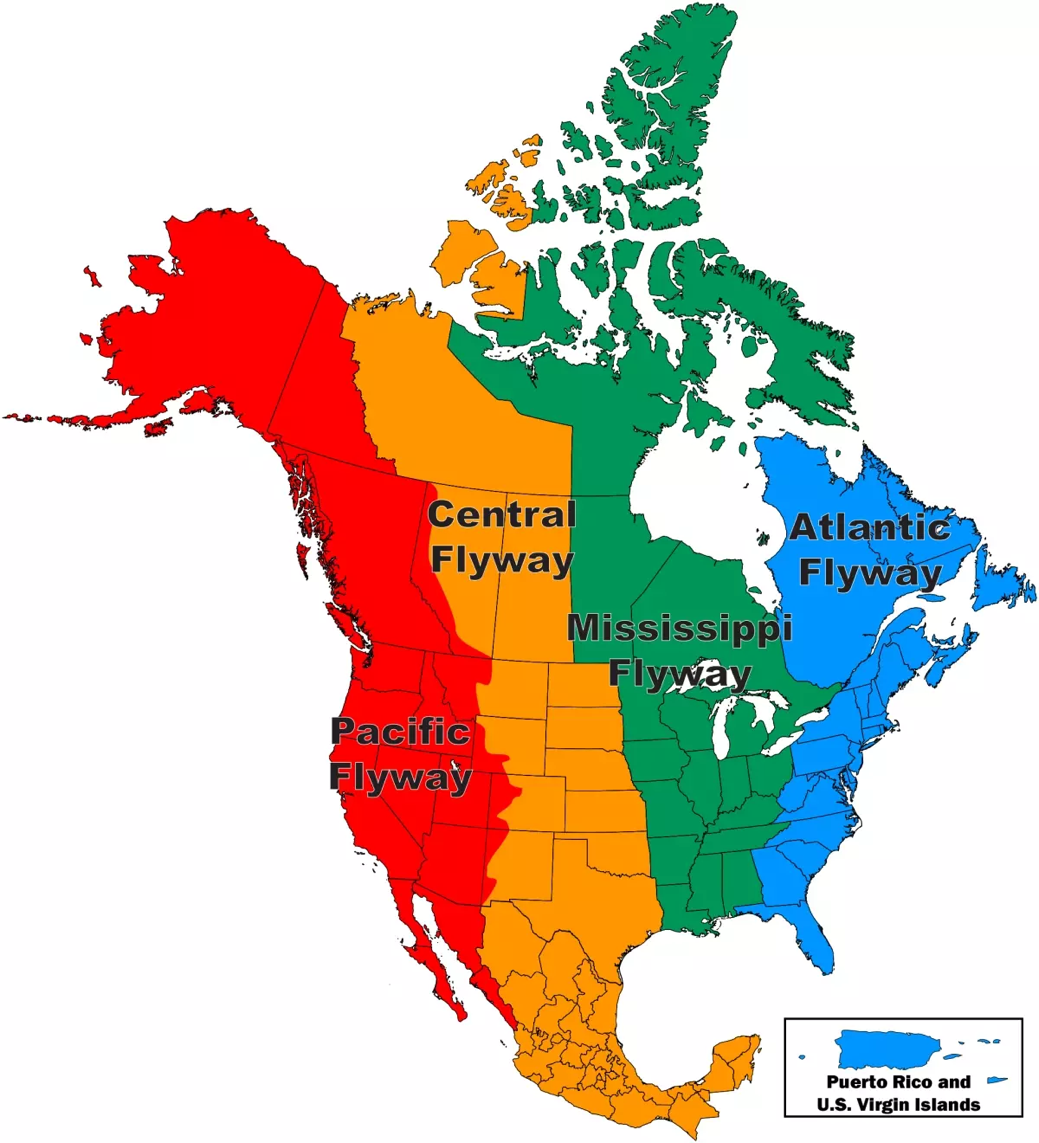


Figure 1: Map of US Flyways

**Photo By/Credit:** USFWS/USFWS

The USFWS – DMBM tracks bird movements along these four flyways and gathers other relevant data, including population counts, hunting and harvest statistics, which are compiled into “Flyway Data Books”. These data books serve as a comprehensive reference, offering insights into bird populations over time and guiding decision-making processes related to hunting regulations and conservation efforts. They are essential tools for biologists, conservationists, and policymakers, to ensure informed, data-driven decisions that align with the overarching goal of sustainable management and conservation of migratory game bird populations (Migratory Bird Flyway Data Books, n.d.).

The DMBM Annual Harvest Survey is a crucial source of data for the Flyway Data Books. The survey program has three steps ([Migratory Bird Harvest Surveys | What We Do | U.S. Fish & Wildlife Service (fws.gov))](https://www.fws.gov/program/migratory-bird-harvest-surveys/what-we-do):

* Step 1: Harvest Information Program (HIP)
  + This is a registration questionnaire that all migratory bird hunters must fill out when registering for their hunting license.
  + All registered hunters are required to complete HIP, and based on their responses, a smaller sample receives the Diary Survey and Parts Collection Survey (Steps 2 and 3).
* Step 2: Migratory Bird Hunter Survey (Diary Survey) <https://www.fws.gov/project/migratory-bird-hunter-survey-diary-survey>
  + Hunters selected for this are required to fill out a hunting diary form, which includes the date, county, and number of birds taken for every hunt.
  + These are important because they provide harvest estimates for the varied species.
* Step 3: Parts Collection Survey (Wing Survey) <https://www.fws.gov/project/migratory-bird-parts-collection-survey>
  + Hunters selected for this are required to collect information about harvest by species, age, and sex.
  + Some hunters volunteer to support the data collection by sending wings and tail feathers from the waterfowl they shoot each season.
  + Using these physical samples and information, the DMBM can determine the species, sex and age composition of each season’s duck harvest and the species and age composition of the goose harvest.

In addition, this data is used to estimate the harvest of each species or species group, the number of days hunted, the number of active hunters, and the number of birds bagged per hunter in each state for which there is a hunting season for that species or group ([Migratory Bird Harvest Surveys | About Us | U.S. Fish & Wildlife Service (fws.gov))](https://www.fws.gov/program/migratory-bird-harvest-surveys/about-us). The analysis of the harvest and hunter activity can then be used to determine the length of the hunting season and establish policy parameters such as season start and end dates, and the bag limits for hunters.

A map of the united states

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Figure 2: Visualization from Harvest Survey Results – by County

**Image By/Credit:** USFWS/USFWS

The Harvest Survey informs the US-FWS and its partners about high duck harvest areas, aiding in the allocation of resources for protecting and enhancing crucial waterfowl habitats. The survey covers 3,115 counties in the US and duck and goose harvests in 86% and 69% of these areas, respectively, for the past decade, with some regions having negligible harvests not captured by the survey (Harvest Survey Results, 2017).

## 1.2 Problem Space

The FWS’s Migratory Bird Program monitors game bird harvest in the United States – species monitored include doves and band-tailed pigeons; waterfowls; American woodcock; rails, gallinules, coots and snipe; and sandhill cranes. Among the Program’s responsibilities are producing annual reports (Flyway Data Books) on hunter activity and harvest estimates for these species. These reports include data from four administrative Flyway regions (Atlantic, Mississippi, Central and Pacific), sourced from national and state-partner monitoring programs. The reports are used by FWS personnel, state wildlife officials, media, and the public.

The FWS sees problems with how these reports have historically been/are currently created. These problems are described below and organized by producer (those creating reports) and user (those using reports) problems.

**Problem 1 (Efficiency):** Tools/Processes to Produce Harvest Reports Are Inefficient

The FWS seeks to produce reports in a timelier manner. The current process is manual – data is manually collected from multiple national/state sources, is manually cleaned/prepared, and then copy/pasted into an aggregate data table that’s used as the source for summary statistics and data tables included in Flyway Data Books.

**Problem 2 (Errors):** Tools/Processes to Produce Harvest Reports are Error Prone

Building on problem 1, manual processes also increase the likelihood of data errors. For instance, data from multiple sources can arrive in different formats or those inputting data can interpret/define data needs and standards differently. And even if these issues are addressed, the human element remains – humans are error prone.

**Problem 3 (Value):** Users Aren’t Able to Realize the Full Value of Harvest Reports

The reports are in PDF format, limiting users’ ability to extract and query data. Technical users cannot easily interact with the published data given the static format of reports. And even if reports were dynamic (e.g., published via a dashboard), nontechnical users might not be able to use the data. The result, data is not being used to its full potential to inform decisions or novel insights are not being discovered.

Finally, it should be noted, according to the FWS, problems 1 and 2 are the highest priority. They would like the ability to produce the data and data tables that currently exist in reports more efficiently and error-free. They seek to iterate on problem 3 once a solution to problems 1 and 2 is achieved.

## 1.3 Research

The initial research the group did was focused on understanding what the Division of Migratory Bird Management and Migratory Birds (DMBM) does and why it is important. Team members read through the U.S. Fish & Wildlife website, specifically the sections on Migratory Birds, to further understand the goals and objectives of the DMBM.

Our initial meeting with the U.S Fish & Wildlife Service contacts was on Wednesday 1/24/24 at 1:30 p.m. (EST). During the meeting, we asked various questions to further understand the goal and how we can develop a solution. These questions included:

* Where is the data? What format is it in?
  + The data is housed in a repository and the client will provide the data to us in a CSV format.
* What is the technical background of the user?
  + The technical background of the user is low code to no code.
  + The simplest end form is ideal for the user.
  + We will determine where to use PowerBI or Tableau.
* What is the overall goal and objective?
  + The first step will be to get the data source straight to tables.
  + To automate producing tables and create time series reports more efficiently and with less errors than they are currently able to do.
  + Help them create data books in a timely fashion and cut out the manual work for them.
  + Display data so that it is beneficial to the public and their partners/states.
  + Allow state partners to access the data and have some basic statistics/visual display

Our second Meeting with US Fish & Wildlife contacts was on Tuesday 1/30/24 at 1:30 p.m. (EST). During the second meeting, we were given the harvest data set to start exploratory analysis on.

Further collaborations with the group included:

* Comparing R and Python as project language for development and data exploration/analysis.
* Comparing the relative strengths and weaknesses of Power BI and Tableau as the intended platform for publishing interactive dashboard visualizations of the data.
* Considering different data storage/hosting options, including Google Drive/Collab environment, GitHub repository hosting, cloud services (Azure or AWS), SQL database hosted on local computer.

Later meetings were held to present team progress on proposed solutions and developing the visualization package with the end users in mind.

## 1.4 Solution Space

**Automated Data Aggregation and Report Generation with Python**

**Objective**: Streamline the data collection, cleaning, and preparation process to enhance efficiency and reduce errors.

* **Data Cleaning and Preparation**: Implement Python libraries like Pandas for data cleaning and manipulation. Scripts can be developed to automatically clean, merge, and standardize data from different sources according to predefined rules, significantly reducing manual effort and the potential for errors.
* **Automated Report Generation**: Use Python to create structured data tables and summaries that will serve as the basis for the Flyway Data Books. Automate the generation of CSV files that can be directly used for reporting or further analysis.

**Enhanced Table Presentation with HTML**

**Objective**: Improve the usability and accessibility of data tables for both technical and non-technical users.

* **Dynamic HTML Tables**: Develop HTML templates that can dynamically display data tables generated by Python scripts. These templates can be designed to be responsive and user-friendly.
* **Interactive Features**: Integrate JavaScript or use frameworks like DataTables to add interactivity to the HTML tables, such as sorting, filtering, and pagination. This will make it easier for users to navigate and find the specific data they need.

**Visual Analytics with Tableau**

**Objective**: Provide compelling visual insights and facilitate easier data interpretation for decision-making.

* **Tableau Dashboards**: Use Tableau to create interactive dashboards that visualize the data from the Python-generated tables. Design the dashboards to highlight key trends, patterns, and insights in the migratory bird harvest data across the four Flyway regions.
* **User Access and Sharing**: Publish the Tableau dashboards on a web platform where FWS personnel, state partners, media, and the public can access them. Ensure there are varying levels of access and interactivity tailored to the needs of different user groups.
* **Training and Documentation**: Provide documentation and training materials for FWS personnel and partners on how to use the Python tools, HTML interfaces, and Tableau dashboards. This will help maximize the adoption and effective use of the new systems.

**Implementation Considerations**

* **Iterative Development**: Start with a prototype focusing on a subset of the data or one Flyway region to test and refine the approach. Gather feedback from end-users to improve the system before full-scale implementation.
* **Scalability**: Design the system with scalability in mind so it can handle increasing amounts of data and potentially incorporate additional data sources in the future.

## 1.5 Project Objectives

**Objective 1:** Improve Efficiency in Harvest Report Production

* Learning Assumption: Upon project completion, the team anticipates acquiring insights into optimal methods for automated data collection and integration, enhancing overall efficiency.
* Solution Achievement Assumption: The team expects the solution to automate data collection, presenting a more efficient and streamlined process for integrating new data into the existing database.
* Understanding of the Problem Assumption: Completion of this project is assumed to provide a deeper understanding of challenges associated with manual data collection and opportunities for automation to enhance efficiency.
* Value Provided Assumption: The automated data collection solution is expected to deliver value by saving time, reducing manual efforts, and ensuring timely updates, benefiting the Migratory Bird Program and its stakeholders.

**Objective 2:** Enhance Accuracy in Harvest Reports

* Learning Assumption: The team assumes that the project will yield effective strategies for automated data validation and cleaning, leading to improved accuracy in the data processing pipeline.
* Solution Achievement Assumption: The solution is expected to automatically validate, clean, and ensure the data is analysis-ready, reducing errors and enhancing the reliability of harvest reports.
* Understanding of the Problem Assumption: Through this project, the team assumes they will deepen their understanding of challenges related to data errors and identify ways to mitigate these issues.
* Value Provided Assumption: The enhanced accuracy in harvest reports is anticipated to provide value by increasing the reliability of the data, supporting better-informed decision-making for the Migratory Bird Program and its stakeholders.

**Objective 3:** Streamline Harvest Report Creation

* Learning Assumption: Project completion is expected to provide insights into effective methods for automating the creation of harvest reports, reducing manual steps and minimizing human errors.
* Solution Achievement Assumption: The team anticipates that the solution will streamline the process for creating harvest reports, eliminating manual efforts, and decreasing the risk of errors in report generation.
* Understanding of the Problem Assumption: The team assumes that this project will deepen their understanding of inefficiencies in the current report creation process and identify opportunities for automation.
* Value Provided Assumption: The streamlined report creation process is assumed to provide value by saving time, reducing manual errors, and ensuring timely availability of accurate harvest reports.

**Objective 4:** Facilitate User Interaction with Data

* Learning Assumption: The completion of the project is anticipated to yield valuable insights into effective approaches for enabling user interaction with data, including the provision of tools or interfaces for data extraction and querying.
* Solution Achievement Assumption: The team assumes that the proposed solution will offer user-friendly tools or interfaces, allowing users to interact with the collected information and extract meaningful insights. This is expected to significantly enhance the overall usability of the data.
* Understanding of the Problem Assumption: Through the project, the team expects to deepen their understanding of the specific needs and challenges users face in interacting with data. This increased understanding will inform the design of a solution that effectively addresses these user-centric issues.
* Value Provided Assumption: Enabling robust user interaction with the data is presumed to deliver substantial value. By empowering stakeholders to extract insights and make well-informed decisions, the project aims to contribute to the development of a more engaged and informed user community.

**Objective 5:** Transition from PDF Reports to Dynamic Data Presentation

* Learning Assumption: The team assumes that by finishing this project, they will learn effective methods for transitioning from static PDF reports to dynamic data presentation formats.
* Solution Assumption: The team assumes that the solution will explore and implement dynamic data presentation formats, potentially using tools like PowerBI or Tableau, enhancing accessibility and usability.
* Understanding the Problem Assumption: The team assumes that this project will deepen their understanding of the limitations of static PDF reports and identify opportunities for adopting modern data presentation formats.
* Value Provided Assumption: The team assumes that transitioning to dynamic data presentation will provide value by offering more interactive and accessible ways of presenting data, catering to the diverse needs of stakeholders, and enhancing overall data utilization.

## 1.6 Primary User Stories

Based on the problems and opportunities defined by the FWS, we developed four high-level user stories to guide our project:

1. “As a User, I want to automatically collect and then integrate new data collected from national and sources into the existing database.”

2. “As a User, when the existing database is periodically updated, I want to automatically validate, clean and ensure the data is analysis ready.”

3. “As a User, I want to automatically create the exact data/data tables published in Flyway Data Books.”

4. “As a User, I want to enable key stakeholders to interact with the data so they can answer unique, evolving questions – i.e., enable users to extract and query data in ways Flyway Data Books don’t currently allow.”

## 1.7 Product Vision

Scenario 1

* **For**: The Migratory Bird Program.
* **Who**: The FWS, i.e., the project sponsors.
* **The**: Dashboard/tool.
* **Is a**: Automated solution.
* **That**: Enables the FWS to (a) automatically ingest and clean new data with historical data; (b) automatically update key metrics and return a PDF table of summary metrics; and (c) drill-down into summary metrics or perform ad hoc queries, and without needing technical data analysis skills.
* **Unlike**: The current solution, which is largely manual and output into static PDF tables.
* **Our product**: Reduces the amount of human intervention required to compile reports and increases the ease, and types, of analysis the FWS can perform.

Scenario 2

* **For**: End Users of the Migratory Bird Program.
* **Who**: End users, i.e., state and non-FWS-affiliated stakeholders.
* **The**: Dashboard/tool.
* **Is a**: Decision support tool.
* **That**: Enables non-FWS users to drill-down into summary metrics or perform ad hoc queries based on non-FWS reporting needs – i.e., it enables these users to use FWS data to its fullest potential.
* **Unlike**: The current solution, which is largely output into static PDF tables.
* **Our product**: Enables non-FWS users to interactively explore FWS data and acquire custom data/data analysis based on their unique decision-making needs.

# Section 2: Datasets

## 2.1 Overview

Migratory bird harvest data, collected by the Department of Migratory Bird Management (DMBM), serves as a comprehensive record of migratory bird hunting activities over an extensive period, from 1961 through 2022. It encompasses a wide array of data points, totaling nearly six million rows and 21 distinct features for each entry. The data reflects detailed information on the harvest of various bird species, capturing specifics such as the time and place of each harvest, the species involved, and the biological data of the birds including age and sex. This rich dataset is a testament to the rigorous data collection efforts aimed at understanding and managing bird populations.

The value of such a dataset lies in its potential applications. It is a significant asset for wildlife management and provides insights into the effects of environmental changes and hunting regulations on bird populations. The granularity allows for the examination of species-specific trends and can inform conservation efforts. Moreover, the data can be leveraged to assess the ecological impact of hunting on migratory patterns, contributing to the sustainable management of these important wildlife resources.

The second data set provided, vw\_harvest\_estimates.csv, includes harvest and hunting activity estimates for migratory game birds in 49 states, 4 flyways, and US totals. This dataset contains the estimated retrieved and unretrieved harvest, days hunted, number of active hunters, and bag per hunter, along with confidence intervals (expressed as percent of the estimate) and variance, for 13 species or species groups of migratory game birds surveyed in the Migratory Bird Hunter Diary Survey from 1999 to 2020, by state and management unit.

## 2.2 Field Descriptions

Figure 3: Dataset 1: WingData.csv (763 MB) - 5,900,720 rows with 21 features (dates: 1961 – 2022).

|  |  |  |
| --- | --- | --- |
| Variable Name | Type | Description |
| PartID | Integer | 10-digit internal identification code representing a single part (duck wing or goose tail) submitted by a hunter in the Parts Collection Survey. |
| Season | Integer | Year representing the beginning of the hunting season. |
| PCSHunterID | Integer | Unique 9-digit internal identification number of an individual hunter in the Parts Collection Survey. |
| harvest\_month | Integer | Month reported by the hunter in which the duck or goose was harvested. Blank if no month was provided by the hunter. |
| harvest\_day | Integer | Day reported by the hunter when the duck or goose was harvested. Blank if no day was provided by the hunter |
| harvest\_year | Integer | Year reported by the hunter when the duck or goose was harvested. |
| flyway\_code | Integer | Integer code for flyway associated with the location of harvest  1 = Atlantic, 2 = Mississippi, 3 = Central, 4 = Pacific, 5 = Alaska |
| flyway\_name | String | Flyway name associated with the location of harvest |
| flyway\_abbrev | String | Flyway abbreviation associated with the location of harvest |
| state\_code | Integer | Integer code for state where harvest occurred |
| state\_name | String | Full state name where harvest occurred |
| state | String | 2-character abbreviation for state in which the duck or goose was harvested. |
| aou\_number | Integer | American Ornithological Union (AOU) code used for uniquely identifying a species |
| species\_aou | String | 4-character AOU code corresponding to the species of duck wing or goose tail submitted by the hunter. |
| species\_name | String | Common name of the species of duck wing or goose tail submitted by the hunter. |
| age\_code | integer | 1-digit code corresponding to the estimated age of the duck or goose whose wing or tail was submitted. 0 = unknown age, 1 = adult (after hatch year bird), 2 = immature (hatch-year bird). |
| age\_char | String | Character code representing the age of the bird at harvest  U = unknown age, A = adult (after hatch year bird), I = immature (hatch-year bird). |
| sex\_code | Integer | 1-digit code corresponding to the sex of the duck or goose whose wing or tail was submitted. 0 = unknown sex, 4 = male, 5 = female |
| sex\_char | String | character code representing the sex of the species harvested. U = unknown sex, M = male, F = female |
| cohort |  | Identifier representing the age and sex cohort of the duck or goose whose wing or tail was submitted (Combination of Age and Sex variables). |
| harvest\_weight | Float | Weighted value reflecting the number of harvested birds of a given species represented by a particular duck wing or goose tail. The total estimated harvest of a given species (by state and by year) is estimated as the sum of the weighted value of all wings or tails of that species submitted in each state and year. |
| is\_duck | Integer | Code representing the species (see Appendix A) that belong to the category ‘duck’, 1= duck, 0 = not duck |

Figure 4: Dataset 2: vw\_harvest\_estimates.csv

|  |  |  |
| --- | --- | --- |
| Variable Name | Type | Description |
| sp\_group\_surveyed | String | 4-character code representing the survey instrument, i.e., the group of species represented on the survey form: WATF (waterfowl survey), which includes ducks, geese, sea ducks and brant; DOVE (dove and band-tailed pigeon survey), which includes mourning doves, white-winged doves, and band-tailed pigeons; AMWO (woodcock survey), which includes American woodcock; SCRG (snipe, coot, rail and gallinule survey, which includes Wilson’s snipe, American coot, rails, and gallinules); and CRAN (sandhill crane survey) which includes sandhill cranes. |
| sp\_group\_estimated | String | Common name of species or species group for which harvest estimates are calculated. This includes the individual species: mourning dove, white-winged dove, band-tailed pigeon, American woodcock, sandhill crane, Wilson's snipe, and American coot; and species groups: ducks, geese, sea ducks, brant, rails, and gallinules. |
| season | Integer | Year representing the beginning of the hunting season |
| mgmt\_unit | String | The management unit in which the state is located, which may differ depending upon the species. For waterfowl harvest estimates, the management units are defined as the flyways: AF = Atlantic Flyway, MF = Mississippi Flyway, CF = Central Flyway, PF = Pacific Flyway, AK = Alaska. For doves: EMU = eastern management unit, CMU = central management unit, WMU = western management unit. For band-tailed pigeons: FC = four corners states, PC = Pacific coast; for woodcock: EMR = eastern management region, CMR = central management region; US = continental United States (including Alaska) |
| survey\_state | String | 2-character abbreviation for the state for which the harvest estimate is calculated. This includes 49 states (all but Hawaii), as well as flyway and US totals. AF = Atlantic Flyway, MF = Mississippi Flyway, CF = Central Flyway, and PF = Pacific Flyway, and US totals. |
| survey\_state1 | String | Duplicate of survey\_state |
| state\_frame\_size | Integer | The total number of HIP registrations submitted to the USFWS by each state each year. |
| days\_hunted | Float | Estimate of the total number of days hunters hunted for a particular species or species group |
| CI\_ days\_hunted | Float | Confidence interval associated with the estimate of days hunted, expressed as a percentage of the estimate of days hunted |
| Var\_ days\_hunted | Float | Estimate of variance associated with the estimate of days hunted |
| retrieved | Float | Estimate of the number of birds shot and retrieved |
| CI\_ retrieved | Float | Confidence interval associated with the estimate of retrieved birds, expressed as a percentage of the estimate of retrieved birds |
| Var\_ retrieved | Float | Estimate of variance associated with the estimate of the number of retrieved birds |
| unretrieved | Float | Estimate of the number of birds that were knocked down within sight, but could not be retrieved |
| CI\_ unretrieved | Float | Confidence interval associated with the estimate of unretrieved birds, expressed as a percentage of the estimate of unretrieved birds |
| Var\_ unretrieved | Float | Estimate of variance associated with the estimate of the number of unretrieved birds |
| active\_hunters | Float | Estimate of the number of active hunters (those who hunted that species or species group at least one day during the hunting season) |
| CI\_ active\_hunters | Float | Confidence interval associated with the estimate of active hunters, expressed as a percentage of the estimate of active hunters |
| Var\_ active\_hunters | Float | Estimate of variance associated with the estimate of active hunters |
| bag\_per\_hunter | Float | Estimate of the number of birds shot and retrieved per hunter |
| CI\_bph | Float | Confidence interval associated with the estimate of bag per hunter, expressed as a percentage of the estimate of bag per hunter |
| Var\_bph | Float | Estimate of variance associated with the estimate of bag per hunter |
| status | Char | The status of the harvest estimate. P = Preliminary status\*, meaning that the estimate was calculated during the regulatory cycle following the hunting season, but has not been finalized. F = Finalized status, meaning that the estimate as well as the data used to produce it have been rigorously reviewed for errors, and corrected where necessary. |

\*Due to the short time between hunting seasons and the harvest regulations-setting process, preliminary estimates are initially calculated using state sample frame estimates and hunter response data that have not been rigorously reviewed, because of the substantial time involved to complete the review process.

## 2.3 Data Context

The U.S. Fish and Wildlife Service, Division of Migratory Bird Management conducts the annual Migratory Bird Parts Collection Survey, also known as the Wing Survey, to gather detailed information on the species and number of migratory birds harvested, which helps in assessing population health, setting hunting regulations, and guiding conservation efforts. The dataset for this project comes from the Wing Survey data, collected annually from 1961 to 2023, specifically for waterfowl in the four flyway regions: Atlantic, Mississippi, Central, and Pacific.

All registered hunters of migratory birds in the United States are required to register for the Harvest Information Program (HIP) and provide their name, address, and a description of their hunting activity from the previous year. Then, based on their HIP responses, a subset of hunters is sampled to participate in the Migratory Bird Hunter/Harvest Survey (Diary Survey) and the Parts Collection Survey (Wing Survey). Hunters selected for the Diary Survey receive a form to record the date, county, and number of birds harvested per hunt, across five different, independent surveys each targeting specific species or groups ( 1) doves and band-tailed pigeons, 2) waterfowl (ducks, sea ducks, geese, and brant), 3) American woodcock, 4) rails, gallinules, coots, snipe, and 5) sandhill cranes), providing essential harvest estimates for each.

The Wing Surveys, aimed at gathering data on the harvest's species, age, and sex, involve requesting selected hunters from the Diary Survey to submit bird parts, either a bird wing for most species or a goose tail feather, from each bird they have harvested. There are three independent Wing Surveys depending on the species being harvested: waterfowl, mourning dove, and woodcock, rail & band-tailed pigeons. Each year, hunters send in about 90,000 duck wings, 20,000 goose tails and wing tips, 10,000 dove wings, and 8,000 woodcock wings, in specially marked envelopes. Starting in September, envelopes with harvested bird parts arrive at flyway collection sites, are sorted by species, and frozen until state and federal biologists examine them during "wingbees" held in mid-November for doves, February for waterfowl/pigeons, and early April for woodcock/rails. At the wingbees, biologists identify duck species by unique color patterns on their wing feathers, such as the iridescent purple speculum of Mallards and the color variations in Northern Pintails, while geese species are distinguished by tail feather size and color. Furthermore, they determine the sex and age (adult or young-of-the-year) from wing characteristics, using color, shape, wear, or replacement of feathers to discern age differences, enabling the calculation of age ratios for each species. (U.S. Fish & Wildlife Service, 2024)

## 2.4 Data Quality Assessment

This section evaluates data quality according to the following criteria: completeness, uniqueness, accuracy, atomicity, and conformity.

Completeness – i.e., the extent the data contains the elements needed to complete the analysis.

For the most part, each record has a complete set of required information, such as the part for species identification, harvest location, and time of harvest. However, there are data missing for the following variables: PCSHunterID (7,064 n/a); harvest\_month (74,730 n/a); harvest\_day (94,043 n/a); species\_aou (1,583 n/a); and species\_name (1,583 n/a).

Uniqueness – i.e., the extent of duplication across variables or observations.

There are two variables are the most unique unique, PartID and PCSHunterID. For the former, each part (e.g., duck wing or goose tail) surveyed has a unique 10-digit internal identification code. Observations (rows) in the data set are uniquely identified by the PartID. And for the latter, each hunter participating in the FWS’s Parts Collection survey has a unique 9-digit internal identification number.

Figure 5 below shows unique values for each variable – as expected, PartID and PCSHunterID are most unique. Most variables are categorical (e.g., harvest\_month and sex\_char) so there is duplication across observations. And many of the variables are redundant, i.e., they contain the same information but are coded differently. For example, state\_name (full name of state) and state\_code (abbreviation of state) contains redundant information. The variable cohort is the concatenation of the variables for age and sex, with redundant information from those variables.

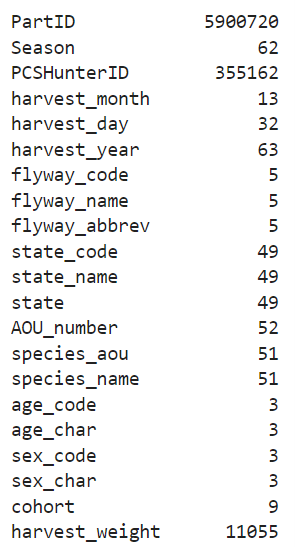


Figure 5: Unique Values per Field (WingData.csv)

Accuracy i.e., the extent data is error free and represents the real-world event it is supposed to depict.

Accuracy is difficult to assess – the data was gathered by/sent to the team from by the FWS, so the team must rely on the sponsor’s affirmation of data accuracy. Still, there are steps the team has/can take:

* Exploratory data analysis to spot data anomalies – e.g., look at unique values (like the above table) to see if there are inconsistencies/errors in how data are entered.
  + In addition to NA values mentioned above, there are values of zero for harvest\_day (4,608 rows) and harvest\_month (3563 rows), with considerable overlap, (3562 rows) with 0 for both day and month. There are another (594) entries for dates which may be errors as they fall outside the legal waterfowl hunting season; the earliest and latest dates allowed for hunting are September 1 and March 10, respectively.
* Corroborate FWS published data – e.g., ensure results produced by the FWS and team are replicable and that there are no discrepancies.
* Build domain expertise – e.g., learn more about the FWS’s mission and context that it uses the data to ensure all variables are needed and/or used/interpreted correctly.

Atomicity and other RDBM principles – i.e., the extent operations on the data all occur, or none occur.

To ensure data set transactions are isolated from each other, the team is using a single Google Colab file that loads/houses the original data set. This ensures a single source of truth for building out the solution for the sponsor – e.g., data cleaning, EDA, and other operations are inserted to ensure we are working on the same version of the data. As the team transitions to Tableau to evolve the product, the same process will be applied. Finally, the data adheres to ‘tidy’ principles, e.g., each cell contains only one piece of information (species\_name has a single, not multiple, species names).

Conformity – i.e., the extent that the data values are stored in a standard format.

EDA did not reveal nonconformity across the data. Data are consistently formatted – e.g., dates follow the same year (harvest\_year), month (harvest\_month), and day (harvest\_day) format. Data are consistently entered – e.g., state names (state\_name) and abbreviations (state\_code) are in the same upper-/lower-case format. And data are consistently coded – e.g., species names (species\_name) and codes (species\_aou) follow classification standards set by the American Ornithological Union. As noted above, some fields are redundant, with aou\_number (a unique four-digit number for each species\_, species\_aou (a unique four-character code for each species), and species\_name (the full, spelled out name corresponding to the AOU taxonomy standards).

## 2.5 Data Conditioning

Data conditioning is largely based on the findings from the data quality assessment (refer to 2.4 Data Quality Assessment) and analysis requirements (as these evolve, this section will be updated). Conditioning steps completed/under consideration so far include:

* **Imputing missing values**. The 1,583 NA values for the variables species\_aou and species\_name were able to be imputed using the values from the variable aou\_number, using the [USGS Species Table and Recommended Band Sizes](https://www.pwrc.usgs.gov/BBL/Bander_Portal/login/speclist.php) as a lookup table.
* **Recoding variables**. Several variables that should be coded with strings are numerically encoded, e.g., harvest\_month (1.0, 2.0, etc. Format, not Jan, Feb, etc.).
* **Binning variables**. The cohort variable shows nine categories, many of which are rare and/or unknown, making them candidates to re-bin. E.g., Combine ‘unknown male’ with a larger, meaningful category like ‘immature male’ OR combining male/female ‘unknowns’ into new unknown categories.

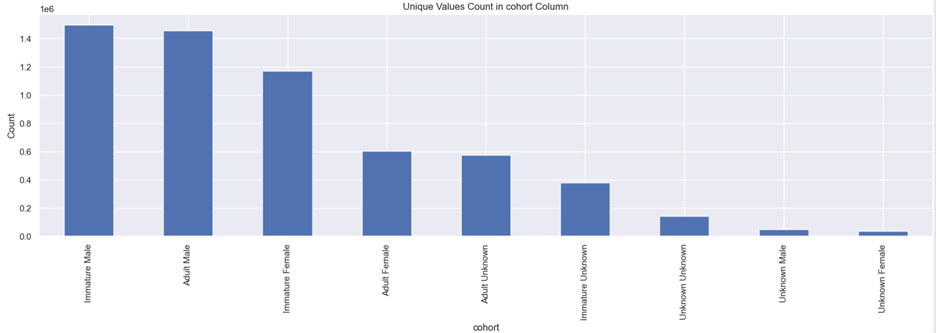


Figure 6: Unique Variables Count by Cohort

* **Addressing NA’s**. Though missing values are rare, there are some still present – the table below shows the percentage of NA‘s for each variable, most occur in harvest\_month and harvest\_day.

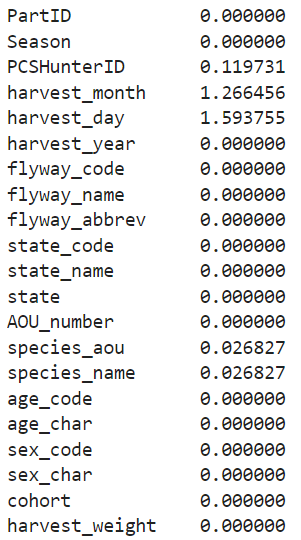


Figure 7: Percent of NA values by field

Though data exists covering dates from the 1960’s to present, the project sponsor’s requirements require the team to only use data from 1999 to present. So the NA values that predate 1990 are less of a concern. However, the heatmap of NAs below (white equals NAs) shows many NAs are upfront in the dataset (aka post-1990), meaning we will have to work with the sponsor to decide how to address them.

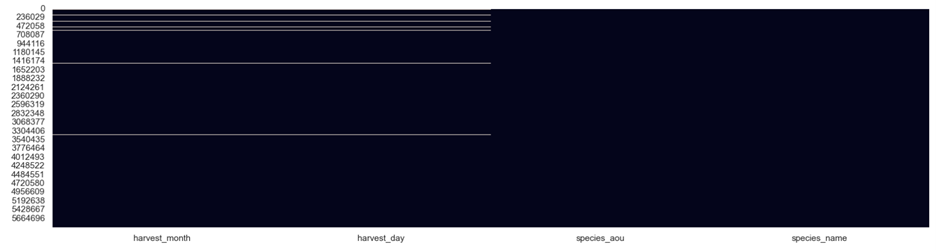


Figure 8: Heatmap of NA values by field

* **Other missing or NA values**. Since the data will be primarily aggregated on the year, state, species, and flyway variables, missing values for month and day will be ignored.
* **Create new variables**. A variable, **‘is\_duck’**, was created to facilitate the aggregation of data from species that belong to the duck category, specified by the client. All other aggregations could be done at the level of individual species.

## 2.6 Other Data Sources

The team used previous flyway data books produced by the Division of Migratory Bird Management to help us check and produce the tables they want for their new format of data books. As mentioned above, these data books serve as a comprehensive reference, offering insights into bird populations over time and guiding decision-making processes related to hunting regulations and conservation efforts.

During the first meeting, another data set was presented, the population data set. That data set was not utilized because another Capstone class is doing their project on the population data set.

To visualize flyway harvest data spatially in Tableau, the team uses flyway shapefile data downloaded from open data arcgis.com. The shapefile has flyway geometries with concise boundaries that are importable along with the harvest data in Tableau.

## 2.7 Storage Medium

The dataset and associated Python scripts for processing are stored in a public GitHub repository. This choice of storage medium offers several advantages:

Accessibility: By storing the data on GitHub, all team members and stakeholders have easy access to it. They can load the repository to their local machines and access the data and scripts as needed, regardless of their physical location.

Version Control: GitHub provides robust version control capabilities, allowing team members to track changes made to both the dataset and the processing scripts. This ensures that everyone is working with the most up-to-date versions of the data and code.

Git Large File Storage (LFS): Due to the size of the dataset file, GitHub's Large File Service (LFS) is utilized. Git LFS manages large files by storing a pointer file in the repository as a reference to the actual file, which is stored externally. GitHub oversees the pointer, allowing access to the large file upon cloning the repository by using the pointer as a guide to locate the file. This enables efficient storage and retrieval of large files while still leveraging GitHub's infrastructure for version control and collaboration.

Ease of Sharing: GitHub provides a platform for easy sharing and collaboration. Team members can share access to the repository with others and allow collaboration on data analysis and processing tasks.

Integration with Python: Python scripts can read the data from the URL reference from the GitHub repository (About Git Large File Storage, 2024). This means that data processing tasks can be automated and integrated directly with the version-controlled dataset, streamlining the analysis workflow.

## 2.8 Storage Security

In this context, the data is publicly available with no concern for confidentiality restrictions.

Public Accessibility: Since the data is stored on a public GitHub repository, it is accessible to anyone with the repository's URL. There are no access restrictions in place, allowing anyone to load the repository and access the data and scripts.

No Confidentiality Restrictions: The nature of the data does not require confidentiality restrictions. It is intended for public use and sharing among team members. Therefore, there is no need for additional security measures to restrict access to the data.

## 2.9 Storage Costs

The project team opted to use GitHub LFS for storing the large dataset file. GitHub LFS provides free storage for repositories up to 2 GB in size. Since the dataset file is 763 MB, it falls well within the free storage limit. Given that the dataset file size is comfortably covered by GitHub's free storage offering, there are no direct storage costs associated with hosting the dataset on GitHub.

# Section 3: Algorithms & Analysis / ML Model Exploration & Selection

## 3.1 Solution Approach

### 3.1.1 Systems Architecture

A diagram of a software development

Description automatically generated with medium confidence

Figure 9: Flowchart diagram of system architecture

The architecture of our system can be best represented by Figure 9 shown above. Our first step was to take the raw data provided to us by the client and conduct analysis of the data using the pandas library in Python. Once exploratory data analysis on the data was completed, we proceeded with cleaning the data where we saw fit, again using the pandas library. That included filtering any rows out where data components were missing, converting the harvest month and harvest day variables to integers, combining the variables for a date (day, month, year) into a single variable, and updating a few of the species codes in the dataset.

Once the data was analyzed and cleaned, there were two objectives that needed to be completed. The first objective was to generate Excel tables that the client could use as their data books. We used the pandas library to aggregate the data so that we could pass it through a Python script that would automatically generate these Excel tables for the client. This way the client can update the source file every year as new data are available in order for them to continue to generate new tables. The second objective was to build a public dashboard for the client. For this objective, we are using Tableau to apply analytics and build visualizations that we can put on a public dashboard.

### 3.1.2 Systems Security

The team carefully considered the integrity and security of the data systems. This section outlines our security framework and protocols for a system designed around the utilization of a public domain dataset, processed through Python and Google Colab, stored via Git Large File Storage (LFS), and visualized using Tableau Public Server. The objective is to ensure the security, transparency, integrity, and availability of the data and all analytics processes, to support the reliability of the insights derived from this system.

Given the large size of the dataset involved in our analysis, Git LFS is the key to our data storage strategy. Git LFS enhances our system by providing an efficient means to handle large files without compromising the operational efficiency of our version control repositories. Also, Git LFS interfaces with our code repository and allows us to centralize the code files, with password protected edit access to ensure that only authorized personnel can modify or access the stored data or code files. This minimizes the risk of unauthorized data corruption or alteration.

As a result, the system solution can be made portable to the client, such that they can host all datasets and code files within their secured network, as the analysis relies on data output generated by their internal server processes.

### 3.1.3 Systems Data Flows

The system data flows section outlines the flow of data within our project's architecture, including how data moves from its source to its destination, and how it is processed and analyzed, highlighting the tools and processes involved at each step. Below is the system data flows section.

The primary data sources for our project are the Wing Survey data and the hunter data provided by the U.S. Fish and Wildlife Service (FWS). These datasets are stored in a Git Large File Storage (LFS) repository on GitHub for collaborative access. The data for this analysis consists of CSV files containing harvest and hunter data. Users can download these CSV data files locally and execute table generation scripts to process and generate annual tables for harvest and hunter data. The data includes numeric variables such as year, month, age, day, harvest weight, and categorical variables like flyway code and sex code. Before analysis, categorical variables are converted into a numerical format using techniques like one-hot encoding.

Data processing begins by retrieving the datasets from the GitHub repository using Python scripts running on Google Colab. The Python scripts handle data cleaning, transformation, and aggregation to prepare the datasets for analysis. Conditional logic is applied to manage missing values, round numerical data, and generate new variables as needed. Once processed, the data is exported as CSV files, ready for further analysis.

The preprocessed datasets are used as inputs for analysis and modeling tasks. Algorithms are applied to analyze harvest trends, estimate future harvests using time series forecasting, and derive insights from the data. For time series forecasting, the ARIMA model is utilized to predict harvest weights for individual species over specific timeframes. The results of the analysis and modeling are stored in structured formats and can be exported for visualization.

Tableau Public Server is used for data visualization and dashboard creation. The data processed and analysis results are imported into Tableau for visualization. Tableau dashboards provided interactive visualizations of harvest trends, species distributions, and other relevant insights. We can interact with the dashboards to explore data dynamically and gain deeper insights into migratory bird populations and hunting activities.

The finalized dashboards are published on Tableau Public, making them accessible to FWS Stakeholders and other interested members, to provide online access to the dashboards to view the latest insights and trends. The dashboards serve as a valuable resource for decision-making, research, and conservation efforts related to migratory bird management.

### 3.1.4 Algorithms & Analysis

The algorithm used for the first phase of the project analyzes data collected from the Wing Survey on migratory bird harvests across different flyways in the United States. This algorithm responds to the stakeholders' stated goal to automate the production of tables to publish in the Flyway Databooks. Users can request a specific timeframe, in this case of the most recent Flyway Databooks spanning from 1999 to 2021, and the algorithm aggregates data for each species within the predefined flyways (Atlantic, Mississippi, Central, and Pacific) by applying a series of analytical steps.

Initially, the dataset is filtered to isolate responses relevant for each bird species within a designated flyway and timeframe. This subset undergoes further processing, where the harvest weight is rounded to the nearest hundred, followed by an aggregation and pivoting operation to summarize the data by season and state to facilitate a more granular analysis of harvest trends.

The core of the algorithm involves the computation of total harvest weights by flyway, by aggregating data for each flyway, thereby enabling the derivation of a cumulative total representing the entire U.S. This is achieved through a function that iteratively sums the harvest weights across all flyways, including Alaska, and subsequently merges these totals with the pivoted dataset to provide a comprehensive overview of harvest patterns.

The algorithm uses dynamic generation of time periods for analysis, beginning with the first year specified and adjusting subsequent periods to terminate in years ending with 0 or 5. This adjustment ensures that each period aligns with other FWS published reports. The algorithm calculates averages for each of these periods and integrates the results into the final dataset which is then sorted and prepared for export as a CSV file for further processing.

The algorithm automatically generates all tables for all species across all flyways, saving time and promoting standardization of the results. This process uses a function that loops over each species and flyway, culminating in the generation of detailed tables that can be exported as CSV files or written to an Excel file (.XLSX). These tables not only provide insights into the harvest patterns of various species across different regions but also produce more structured data for analysis, so that the findings are accessible and informative for stakeholders interested in migratory bird management and conservation efforts.

A similar algorithm is used for the analysis of the hunter data set, specifically targeting various bird species or groups of species across multiple flyways. The algorithm also operates within a defined time frame and parameterizes the approach to filtering, aggregating, and analyzing data based on specified parameters including flyway designation, species (ducks, geese, seaducks, or brant), and the value categories for each table (Days Hunted, Active Hunters, and Harvest per Hunter).

As in the previous algorithm, this process selects records from the dataset that match specified criteria - flyway, species, and time period - to form the basis for subsequent analyses. Then, the algorithm incorporates conditional logic to manage data rounding operations, depending on the specified aggregator value. For Days Hunted and Active Hunters, rounding is performed to the nearest hundred, whereas Harvest per Hunter values are rounded to one decimal place, adapting to the nature of the data being processed.

The program then uses pivot tables to aggregate the specified values by flyway and calculate averages with the same dynamic time periods as in the harvest data algorithm, to then generate tables and output them as csv files with a standardized naming convention.

For both the harvest weight and hunter data calculation scripts, a user command-line interface (CLI) “wrapper” is implemented. The goal of CLI is to provide an easy-to-use interface for executing the scripts. Both of the scripts come prepackaged with input options accompanied by a fully documented user help menu.

Figure 10: HarvestDataGen.py CLI Interface  
A screenshot of a computer screen

Description automatically generated

* FILENAME is a required argument that must be passed in. This is the harvest data CSV file.
* There are 4 available command-line options:
  + Option **flyway** --> *"Atlantic Flyway"*
  + Option **season --> *"****1999:2021"*
  + Option **species\_name -->** *"Duck:(Mallard|American Black Duck|Wigeon), Snow Goose, Black Scoter"*.
  + Option **species\_aou -->***"Duck:(ABDU|AGWT|AMWI|COGO|BAGO),BBWD,STEI"*

Figure 11: HunterDataGen.py CLI Interface  
A screen shot of a computer

Description automatically generated

* FILENAME is a required argument that must be passed in. This is the hunter data CSV file.
* There are three available command-line options:
  + Option **flyway** --> *”AF"*
  + Option **season --> *"****1999:2021"*
  + Option **species\_group -->** *"brant,ducks,geese,sea ducks*

## 3.2 Machine Learning

### 3.2.1 Model Exploration

This study leveraged historical datasets from the Department of Migratory Bird Management (DMBM) to forecast pivotal dynamics within wildlife management: the hunter population and the harvest population. Specifically, we developed five distinct types of ARIMA models to analyze and forecast the following scenarios: harvest population by species, harvest population by species and state, harvest population by species and flyway region, hunter population by species, and hunter population by species and state. These models were chosen to capture the multifaceted nature of hunting activities and the population trends of species across different geographical delineations.

The ARIMA (AutoRegressive Integrated Moving Average) model stands out for its comprehensive approach to time series forecasting, capable of handling data that exhibits trends, seasonality, and non-stationarity. Our decision to employ ARIMA models was predicated on their flexibility and proven efficacy in modeling time-dependent data, such as the DMBM's records of hunter and harvest populations.

As the project client was interested in producing short term predictions of trends in the harvest data, we attempted to use a time series prediction algorithm for forecasting wild bird harvest data by species, using the ARIMA model from the *statsmodels* Python library. This code begins by loading and preprocessing the data, including converting the ‘Season’ column to datetime format and sorting it in chronological order to prepare for the time series analysis.

The ARIMA model works by analyzing autocorrelations between past and present values, along with correlations between past errors and present values, and integrating the time series if it does not exhibit stationarity. The ARIMA model has three hyperparameters (p, d, q) that control the model’s complexity. The first parameter 'p' specifies the number of lag observations, 'd' is the degree of differencing, and 'q' is the size of the moving average window. The model used for the predictions used (3,1,3) as values for the hyperparameters. (Korstanje, 2021)

Before proceeding with the analysis, the datasets were subjected to crucial preprocessing steps, including the conversion of the 'season' attribute to datetime format and chronological sorting. These steps ensured the integrity of the time series, enabling accurate and reliable forecasting. The data set was split into training and testing datasets, with the last two data points left for testing. After fitting the model to the training data, the algorithm predicts harvest weights for the test period and calculates forecasting accuracy using the metrics Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE).

The algorithm applies the model to each individual species and evaluates each forecast separately, then makes a prediction for the next year’s harvest value. The species-specific results of the model, including the forecast and accuracy metrics, are stored in a Pandas DataFrame and can also be exported to an Excel file.

### 3.2.2 Model Selection

For each scenario, the ARIMA model's parameters—denoted as ARIMA(p, d, q)—were chosen based on the dataset's characteristics. The parameters represent:

* **p (AutoRegressive terms)**: This parameter specifies the number of lagged observations in the model. It captures the dependency between an observation and a certain number of lagged observations.
* **d (Differencing order)**: The d parameter indicates the number of times the data has been differenced to achieve stationarity. Stationarity is a crucial aspect of time series analysis, ensuring that the series' statistical properties do not change over time.
* **q (Moving Average terms)**: The q parameter defines the size of the moving average window. It models the relationship between an observation and a residual error from a moving average model applied to lagged observations.

An order of (3, 1, 3) was selected across the models to effectively capture the historical data's complexity. This configuration was derived from a comprehensive analysis involving autocorrelation and partial autocorrelation functions, alongside extensive testing for optimizing the forecasts.

The study's focus on leveraging ARIMA for forecasting purposes, driven by the specific nature of the DMBM datasets, negated the exploration of alternative models. The ARIMA model's established track record in similar forecasting scenarios reaffirmed its selection as the sole analytical framework for this analysis.

# Section 4: Visualizations / ML Model Training, Evaluation, & Validation

## 4.1 Overview

Visualizations are a crucial component of our project. Instead of just giving out big chunks of data, visualizations make it easy for everyone to understand what is going on with migratory birds.

First off, they make complicated data simple to understand. There is tons of data every year about different kinds of bird species, Harvest Weights, Harvest Year, Age, Sex, and other information related to bird species. Visualizations help us turn all that data into clear pictures and graphs, so people can see what's happening without getting lost in numbers. This helps a lot when deciding on things like hunting rules and how to manage bird populations.

Visualizations also give us a big picture view. The US FWS has been collecting data since the 1960s, so there is a great deal of data to process. Visuals help us see trends over time, spot any anomalies, and figure out what needs attention.

Furthermore, visualizations help democratize the data – they are for everyone. By showing data in pictures, we let everyone, from state agencies to regular folks, see what is going on. This transparency helps build trust because people can see the data for themselves and know decisions are being made based on solid evidence.

In addition to using Tableau for creating visuals, we have developed a public dashboard to display these graphics. This dashboard serves as a central hub for accessing and exploring the visual representations of migratory bird data. With the public dashboard, stakeholders, researchers, and the public can easily access the latest insights and trends regarding bird Harvesting with Seasons and Time.

After thorough discussions with our clients, we have opted for Tableau for the following reasons:

* Ease of Use: Tableau offers a user-friendly interface, making it accessible for our team to create visually compelling dashboards with minimal technical expertise.
* Versatility: Tableau provides a wide range of visualization options, allowing us to represent complex data sets in various formats such as charts, graphs, and maps.
* Interactivity: With Tableau, we can develop interactive dashboards that empower users to explore data dynamically, enhancing engagement and facilitating deeper insights.
* Scalability: Tableau is highly scalable, accommodating large datasets and allowing integration with our existing infrastructure, ensuring our visualizations can grow alongside our project.
* Accessibility: Tableau Public provides a platform for sharing visualizations with a wider audience, promoting transparency, and enabling public engagement with our project

## 4.2 Visualizations

For this project, we have constructed three dashboards using Tableau and published them on a public dashboard platform. These dashboards include the Hunter Dashboard and two Harvest Dashboards. Below is a detailed report of each dashboard:

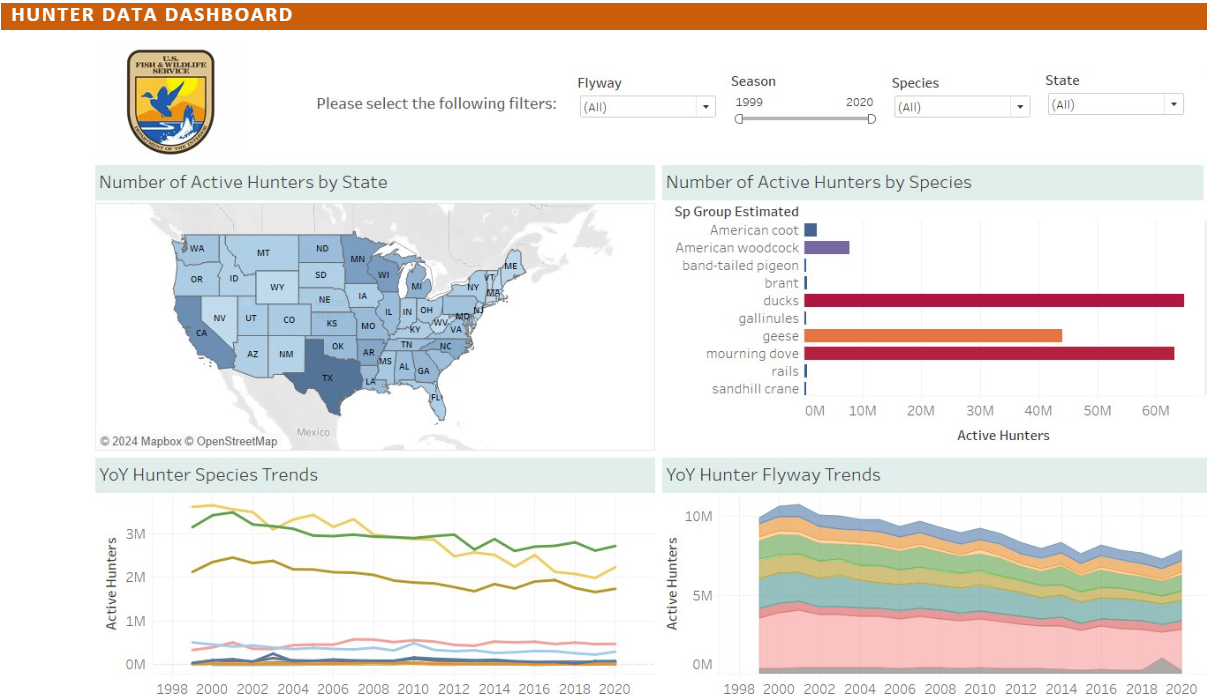


Figure 12: Hunter Data Visualization Dashboard

The Hunter Dashboard presents a comprehensive overview of the distribution of active hunters across various states and species.

The US state map graph is important in understanding the geographical concentration of hunters and identifying regions of high hunting activity. Additionally, it helps in targeted strategies for resource allocation, conservation efforts, and regulatory measures. Questions that can be derived from this graph include:

* Which states exhibit the highest and lowest numbers of active hunters?
* Are there any notable trends or patterns in hunting activity across different regions?

The Species Distribution Graph provides insights into the number of active hunters for each hunted species. This visualization helps in understanding the popularity of distinct species among hunters and aids in monitoring species-specific hunting pressure. Some Questions from this graph may include:

* Which species are the most hunted?
* Are there any significant variations in hunting preferences across different regions or flyways?

The YoY Hunter Species Trends graph offers a perspective on hunting activity by season. This visualization is important for tracking changes in hunting patterns over time, identifying seasonal trends, and forecasting future hunting dynamics. It enables stakeholders to adapt management strategies in response to evolving hunting behaviors. A few Questions that can be explored through this graph include:

* How have hunting trends for specific species evolved over multiple seasons?
* Are there any recurring patterns or fluctuations in hunting activity throughout the year?

The YoY Flyway Trends graph illustrates hunter harvest trends across different flyways for each season. This graph is essential for understanding the spatial distribution of hunting activity and its impact on migratory bird populations. By analyzing flyway-specific trends, stakeholders can assess the effectiveness of conservation measures and identify areas requiring targeted intervention. Questions and insights derived from this graph may include:

* How do hunting harvests vary across different flyways and seasons?
* Are there any flyways experiencing hunting pressure or declines in bird populations?

In conclusion, the dashboard provides valuable tools for analyzing hunting data and gaining insights into various aspects of hunting activity, species distribution, and trends over time. By leveraging the filter options, stakeholders can customize their analysis to address specific queries and make data-driven decisions for sustainable hunting management and conservation efforts.

Users can explore hunting data trends using filters to analyze by flyway, bird species hunted, state you, or year. With these filters, users can focus on what interests them the most, whether a particular region, species, or time period, and also make comparisons between several regions or species. This way stakeholders can get a deeper understanding of the data and make smart choices about managing hunting.

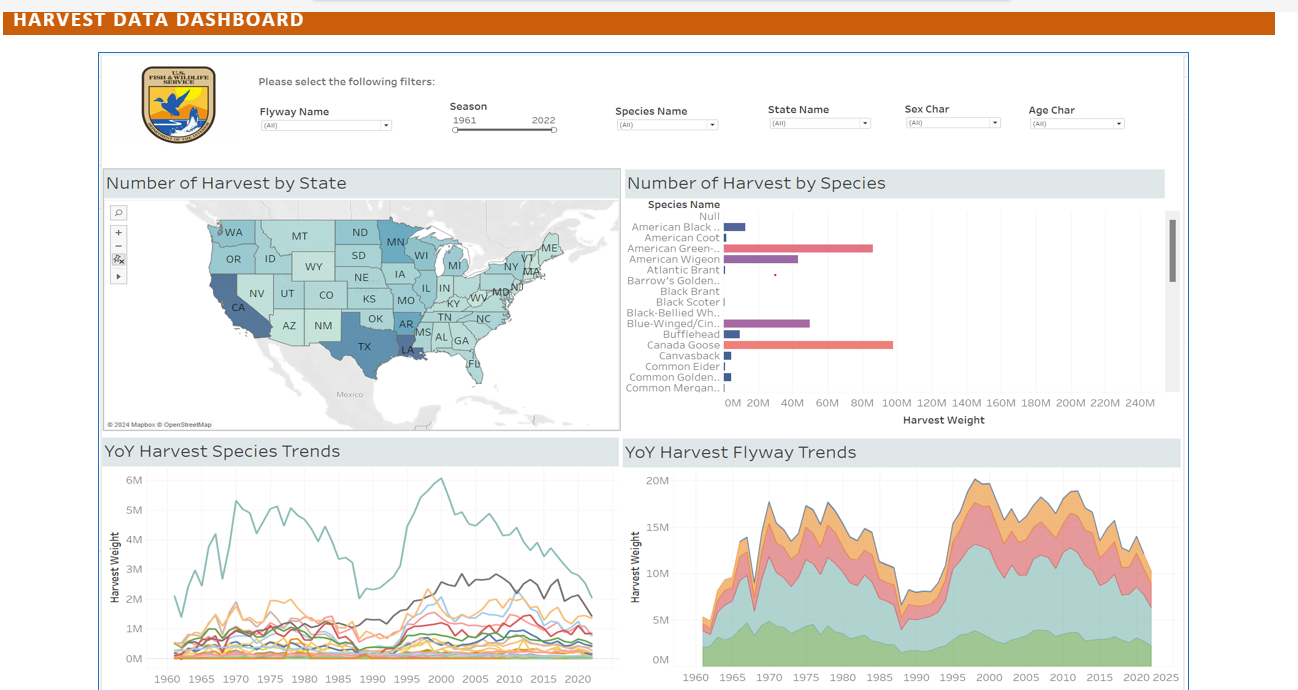


Figure 13: Harvest Data Visualization Dashboard 1

The Harvest Dashboard 1, seen above, provides insights into the total number of harvests across different states and species, as well as harvest trends over time. The dashboard has interactive filters, enabling users to customize their analysis based on flyway, species, state, or season. Each graph has a purpose in understanding hunting harvests.

The US State Map graph shows the total number of harvests in each state, offering a visual representation of harvest activity across the country. This graph is useful for identifying regions with high harvest and by selecting the species filter we can look at the distribution of harvested game species. Questions arising from this graph include:

* Which states exhibit the highest and lowest numbers of total harvests?
* b) Are there any geographical patterns or trends in hunting harvests across different regions?

The Total Harvests by Species graph represents a bar graph which shows the number of total harvests for each hunted species. This visualization enables users to understand the relative popularity of different species and assess their contribution to overall harvest weights. Questions derived from this graph may include:

* Which species are harvested the most?
* Are there any notable fluctuations or trends in the harvest numbers of specific species over time?

The Harvest Species Trends by Season graph shows the seasonal variation in harvest trends for distinct species. This graph is essential for monitoring changes in harvest activity throughout the year and identifying seasonal patterns in species harvests. Questions that can be explored through this graph include:

* How do harvest trends for specific species vary across different seasons?
* Are there any consistent seasonal peaks or declines in species harvests?

The YoY Flyway Trends graph presents harvest trends by flyway for each season, offering insights into spatial variations in hunting harvests over time. This graph is important for understanding the impact of Harvest weights and trends within different. Questions and insights drawn from this graph may include:

* How do harvest trends differ across various flyways and seasons?
* Are there any flyways experiencing significant changes in harvest levels over time?
* Harvest weights of species populations within each flyway?

The Harvest Dashboard 1 provides an overview of hunting harvests, helps us to explore total harvests by state and species, as well as harvest trends by season and flyway. With interactive filtering options, we can customize the analysis questions to address specific inquiries and gain insights relevant to Harvest information.

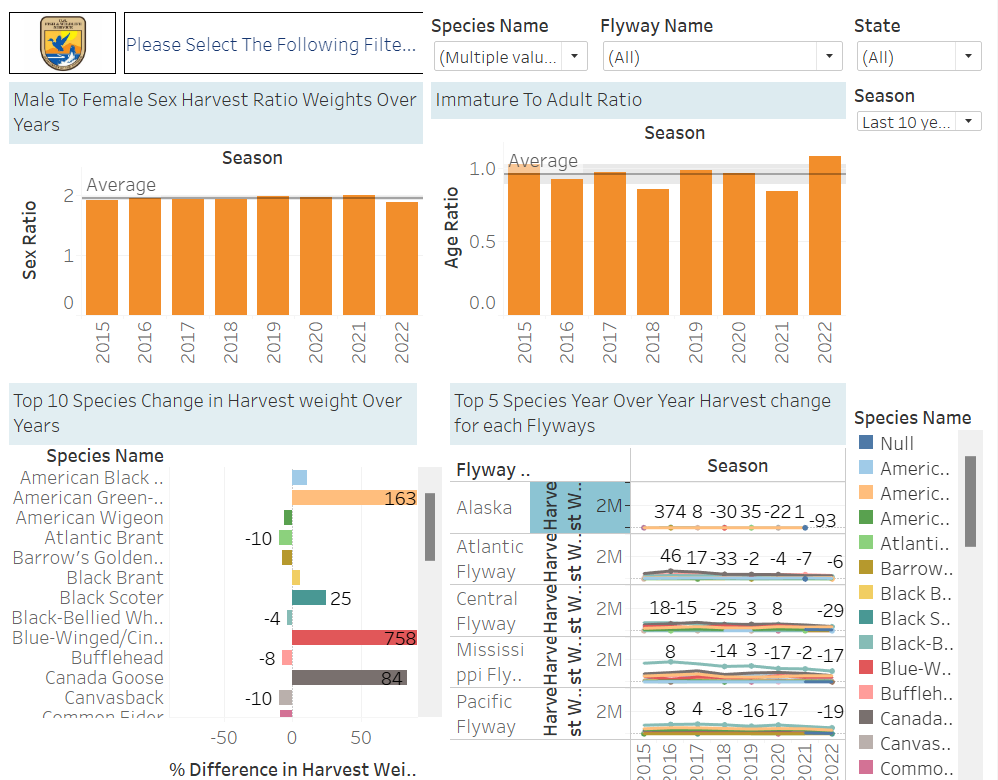


Figure 14: Harvest Data Visualization Dashboard 2

The Harvest Dashboard 2 offers an overview of harvests, focusing on key metrics such as harvest weight, age distribution, species trends, and year-over-year (YoY) changes. With interactive filtering options, users can customize their analysis based on questions regarding season, sex, age, species, state, and flyway. Each graph provides valuable insights into harvest dynamics.

* 1. Male To Female Sex Harvest Ratio Weights over years:

The graph here we observe the harvest weights in the male to female sex ratio over the years. It highlights whether the harvest distribution between the sexes.

By comparing the male to female sex ratios, the graph reveals how the balance of harvested males and females has changed over time. This information is crucial for understanding harvest population dynamics. Questions from this graph may include:

a**) Sex Ratio Dynamics**: Are there any trends or fluctuations in the male to female sex ratio over the years? Check if the ratio remains stable, or are there periods of imbalance?

b) By using the filters tailor the visuals for different states, flyways, species.

2) Immature to Adult Harvest Weights Over Years:

The Immature to Adult Harvest Weights Over Years graph presents harvest weight data categorized by age of species, allows users to explore changes in harvest weights over time. By filtering the data by season, State, Flyways, or Species we can observe age-specific harvest trends and assess the impact of hunting on different age groups within the population. Insights and questions from this graph may include:

* How does the age ratio between immature and adult specimens vary across different seasons for different States, Species, Flyways?
* Are there any significant differences in harvest weight trends for different age groups of the species?

The Species Change in Harvest Weight Over Years graph displays the percentage change in harvest weight for distinct species over the past decade. This graph provides valuable insights into long-term trends in species-specific harvests, highlighting changes in population dynamics and harvest pressure. Insights and questions derived from this graph may include:

* Which species have experienced the most significant increases or decreases in harvest numbers over the past ten years?
* What factors contribute to changes in harvest amounts for specific species, and how can these trends inform conservation strategies?

The Species Year Over Year Harvest Change for Each Flyway graph displays year-over-year harvest trends and percentage differences in harvests for species within each flyway. By filtering the data by species, state, or season, we can analyze flyway-specific harvest dynamics. Insights and questions from this graph may include:

* How do harvest trends vary between distinct species within each flyway?
* Are there any consistent patterns or fluctuations in year-over-year harvest percentage changes for specific species?

The Harvest Dashboard 2 offers a robust set of tools for analyzing harvest data, allowing users to explore harvest weight, age distribution, species trends, and flyway-specific dynamics. By using interactive filtering options, stakeholders can customize their analysis to address specific inquiries and make data-driven decisions for sustainable hunting management and conservation efforts.

## 4.3 Machine Learning

### 4.3.1 Model Training

The training of the ARIMA models aimed at forecasting two main outcomes: hunter populations by species, and species hunted (harvest population), across different geographical and administrative categorizations, using historical data provided by the Department of Migratory Bird Management (DMBM). This section delineates the systematic approach adopted for training the models, which is segmented into data preparation, model fitting, and validation stages.

#### Data Preparation

The initial step in our model training process involved preparing the DMBM's dataset for analysis. This preparation entailed several key actions:

* **Data Loading**: The dataset was provided by the DMBM and included historical records of hunter and harvest populations.
* **Preprocessing**: To facilitate time series analysis, the 'season' column was converted into datetime format. This conversion was crucial for ensuring the temporal sequence of the data was accurately maintained. Following this, the data was sorted based on the 'season' column to align the series chronologically, a necessary step for time series forecasting.

For each of the five scenarios—harvest by species, harvest by species and state, harvest by species and flyway region, hunters by species, and hunters by species and state—the data was grouped accordingly. This grouping involved summing the 'active\_hunters' or the relevant count metric based on the model's focus, either by species alone or in conjunction with state or flyway regions.

#### Model Fitting

With the data prepared, we proceeded to fit an ARIMA model for each scenario. The ARIMA (p, d, q) model, where p denotes the number of lag observations (autoregressive terms), d the degree of differencing (to ensure stationarity), and q the size of the moving average window, was employed. Based on preliminary analyses and the specific dynamics of each dataset, a generalized order of (3, 1, 3) was chosen for all models. This decision was grounded in the aim to capture the nuanced patterns and dependencies in the time series data.

The fitting process included:

* **Training Data Selection**: For each species (or species-state/flyway combination), the data was further split, reserving the last two seasons as a test set to evaluate the model's forecasting performance, while the remainder constituted the training set.
* **ARIMA Model Training**: The ARIMA model was trained on the training set for each scenario, using the historical 'active\_hunters' count or the equivalent harvest metric as the target variable. This training involved estimating the parameters of the ARIMA model that best captured the underlying time series patterns within the training data.

### 4.3.2 Model Evaluation

The segmentation of the datasets into training and testing subsets enabled the evaluation of the ARIMA models' predictive performance, with the future dynamics' forecasts, including next year's predictions, providing accuracy measures for the models' performance.

To evaluate the accuracy and reliability of our forecasts, three key metrics were utilized:

* **Root Mean Square Error (RMSE)**: This metric measures the average magnitude of the errors between the predicted values and the actual values. It does this by squaring the errors, averaging them, and then taking the square root. The RMSE is particularly useful in emphasizing larger errors, making it a stringent measure of prediction accuracy.
* **Mean Absolute Error (MAE)**: MAE calculates the average absolute difference between predicted values and actual values, offering a straightforward interpretation of prediction accuracy. Unlike RMSE, MAE does not square the errors before averaging, which means it gives equal weight to all errors, making it robust to outliers.
* **Mean Absolute Percentage Error (MAPE)**: MAPE expresses the error as a percentage of the actual values, providing a relative measure of the prediction errors. This metric is particularly valuable for comparing the accuracy of models across different scales or datasets.

Utilizing RMSE, MAE, and MAPE allowed for a comprehensive assessment of our ARIMA models' performance. These metrics not only quantified the models' predictive accuracy but also highlighted areas for potential improvement, guiding further refinements.

### 4.3.3 Model Validation

In the model validation phase, we confirmed the model's predictive reliability and generalizability using independent datasets not previously exposed to during training. We employed a hold-out validation method, where a portion of the data was reserved exclusively for this validation process. The performance metrics on this validation set closely mirrored the evaluation metrics (RMSE, MAE, MAPE), indicating consistency and stability in the model's predictive quality. This suggests the model's ability to generalize well to new data, reinforcing its potential utility in practical applications. Additionally, periodic re-validation is recommended to ensure the model adapts to new patterns and remains robust over time.

# Section 5: Findings

The results of the time series models and evaluations of their predictions are outlined in the following section. The ARIMA model had mixed results as regards the accuracy of predictions, especially at the more granular levels of the data. At more general levels, the model had more success, but was limited by the lack of informative predictors in the available dataset.

Figure 15: Harvest Weight Forecasting by Species and State

| **State** | **Species** | **Prediction** | **RMSE** | **MAE** |
| --- | --- | --- | --- | --- |
| WY | Northern Pintail | 395.54194 | 41.01440816 | 30.43088876 |
| NJ | American Wigeon | 376.4764518 | 54.61089249 | 45.08635424 |
| AK | Gadwall | 453.8110639 | 72.26490234 | 70.32601422 |
| WY | American Green-Winged Teal | 1710.462156 | 83.62369305 | 81.06936792 |
| WV | American Black Duck | 331.9788332 | 89.6078066 | 85.69397509 |
| UT | Bufflehead | 1936.607086 | 106.8406996 | 101.7951823 |
| DE | American Wigeon | 272.6011392 | 136.4738313 | 119.3560689 |
| NY | Northern Pintail | 2149.460442 | 143.773506 | 141.4920038 |
| OH | Common Goldeneye | 1562.938975 | 160.1406411 | 143.3477332 |
| OR | Eurasian Wigeon | 210.2956425 | 185.4222118 | 141.1002551 |
| NY | Blue-Winged/Cinnamon Teal | 1538.989476 | 185.6629465 | 144.8448924 |
| ME | Common Merganser | 287.4203632 | 196.0283355 | 195.8280666 |
| ME | Common Goldeneye | 534.3846691 | 198.5736914 | 174.5548122 |
| MA | Hooded Merganser | 407.3176953 | 200.8004342 | 175.0031044 |
| MI | Hooded Merganser | 5103.524831 | 202.8568977 | 161.1755054 |
| VT | Ring-Necked Duck | 223.316175 | 226.2753314 | 182.6058846 |
| NJ | Lesser Scaup | 591.0098467 | 236.9101526 | 215.3686633 |
| NH | American Black Duck | 1133.912448 | 251.0491449 | 224.7856094 |
| AK | Barrow's Goldeneye | 1336.943211 | 268.9647028 | 262.9263372 |
| VA | Mallard X Black Duck Hybrid | 689.4303223 | 291.6892086 | 247.9710568 |
| AZ | Ring-Necked Duck | 1222.563884 | 297.362174 | 289.0518157 |
| NY | Mallard (Domestic) | 300.885967 | 298.93169 | 291.5208248 |
| FL | Northern Pintail | 1438.312668 | 302.3648444 | 240.3531493 |
| NH | American Green-Winged Teal | 353.9218152 | 318.2901186 | 269.5910936 |
| SC | Northern Pintail | 1415.587122 | 327.6278033 | 286.1643556 |
| WV | Mallard | 2329.569083 | 329.0920516 | 310.3382964 |
| NY | Gadwall | 1943.49216 | 331.3694668 | 322.8629319 |
| OK | Lesser Scaup | 1748.065386 | 334.9747972 | 314.6310454 |
| SD | Ruddy Duck | 1240.984655 | 335.9625127 | 245.5136509 |
| NV | Canada Goose | 5156.923695 | 337.9149907 | 318.6422622 |
| NV | Ruddy Duck | 562.9099564 | 345.6826262 | 345.5939461 |
| CT | American Green-Winged Teal | 149.3395306 | 362.1896909 | 360.4681142 |
| WA | Redhead | 2117.756015 | 367.4622041 | 348.4616801 |
| ME | Hooded Merganser | 926.0727282 | 372.5625247 | 352.0093172 |
| WY | Northern Shoveler | 728.1105799 | 377.5411336 | 325.6021065 |
| PA | Bufflehead | 2510.110612 | 380.7094963 | 328.6943847 |
| AZ | American Wigeon | 2005.938595 | 383.6225828 | 317.148469 |
| MA | Surf Scoter | 914.8417536 | 385.9196959 | 359.4344707 |
| AK | Northern Pintail | 4597.820126 | 394.5846747 | 366.3859464 |
| PA | Ring-Necked Duck | 367.8803272 | 400.0474645 | 299.5689031 |
| IN | American Black Duck | 1040.986275 | 403.0954452 | 352.9529166 |
| OK | Wood Duck | 8365.688879 | 410.2253046 | 409.9873032 |
| AZ | Bufflehead | 701.8569849 | 422.6253836 | 340.2068288 |
| PA | Hooded Merganser | 954.9175787 | 433.5085155 | 431.1196336 |
| KS | Lesser Scaup | 1375.255737 | 441.0119745 | 400.4269216 |
| AZ | Gadwall | 1392.438293 | 444.5902554 | 412.4228059 |
| NH | Hooded Merganser | 335.386592 | 444.6686078 | 330.0651341 |
| WY | Blue-Winged/Cinnamon Teal | 1305.779998 | 448.2077394 | 396.7919399 |
| NY | Mallard X Black Duck Hybrid | 203.8911073 | 451.3220252 | 373.6799165 |
| NV | Blue-Winged/Cinnamon Teal | 555.8241037 | 454.4248145 | 411.308425 |
| WV | Wood Duck | 1519.975264 | 459.7748288 | 327.2598249 |
| AZ | Blue-Winged/Cinnamon Teal | 906.9359597 | 462.7230049 | 336.8819026 |
| FL | Gadwall | 674.8291083 | 468.3519821 | 466.5598301 |
| AK | Greater Scaup | 453.4312141 | 480.6844325 | 419.8008623 |
| AZ | Canada Goose | 1371.003036 | 516.4735402 | 469.9226383 |
| LA | Snow Goose (white) | 12239.47711 | 545.5490491 | 432.5692185 |
| IN | American Wigeon | 1261.341022 | 550.807656 | 501.8031696 |
| MI | Gadwall | 4468.582907 | 553.7609301 | 510.9111511 |
| MD | American Green-Winged Teal | 7639.276683 | 556.4396466 | 551.2842955 |
| NM | Northern Pintail | 1032.936569 | 567.426354 | 563.2207891 |
| OH | Hooded Merganser | 1429.772073 | 577.0876927 | 531.9633653 |
| AZ | Northern Pintail | 25.59169825 | 593.6252155 | 586.7514957 |
| NY | Lesser Scaup | 1420.546226 | 611.6141704 | 611.2411853 |
| RI | Mallard | 876.4275669 | 618.7788714 | 547.6060007 |
| RI | American Black Duck | 802.1533178 | 626.239285 | 623.9462961 |
| NJ | Greater Scaup | 465.2954094 | 629.3635772 | 450.7255585 |
| ND | Northern Pintail | 16709.16338 | 631.1247446 | 560.7391581 |
| NY | Hooded Merganser | 2072.240711 | 634.5630608 | 631.6374677 |
| CO | Northern Pintail | 2065.947401 | 643.2195282 | 634.8024396 |
| PA | American Green-Winged Teal | 1596.894419 | 651.4252969 | 499.5463356 |
| OH | Lesser Scaup | 1441.400463 | 662.4387228 | 494.6319746 |
| MD | Northern Pintail | 1731.174343 | 673.6282221 | 505.248383 |
| AK | Bufflehead | 1385.200777 | 681.8955435 | 678.5388069 |
| NV | Northern Shoveler | 4077.56664 | 682.3307893 | 644.1258338 |
| AZ | Northern Shoveler | 1661.840972 | 684.8017103 | 551.7342307 |
| AL | Northern Shoveler | 1702.204433 | 686.0733767 | 511.5429738 |
| MA | Wood Duck | 3673.800777 | 687.9545544 | 501.0973456 |
| OK | Bufflehead | 358.0600234 | 694.4445738 | 582.8617469 |
| SC | Blue-Winged/Cinnamon Teal | 8623.579576 | 695.1206037 | 634.9941771 |
| WY | American Wigeon | 2369.02833 | 697.2137569 | 602.9287242 |
| SC | American Black Duck | 1082.156603 | 704.9370417 | 701.3067926 |
| MA | American Green-Winged Teal | 421.0475049 | 705.3315178 | 677.1666852 |
| SC | American Wigeon | 821.7735087 | 725.908666 | 622.3326167 |
| NH | Mallard | 4074.392217 | 740.5902629 | 659.3507616 |
| DE | Northern Pintail | 1443.285072 | 758.4610867 | 747.4449573 |
| MT | Blue-Winged/Cinnamon Teal | 1928.846141 | 783.0929734 | 674.6840784 |
| NY | Greater Scaup | 2402.773591 | 785.5621427 | 756.5786989 |
| OK | Snow Goose (white) | 3517.675513 | 791.7410447 | 754.1717764 |
| MD | American Wigeon | 1747.222688 | 792.0261098 | 787.71592 |
| AK | Common Goldeneye | 1498.852012 | 806.6764369 | 743.5266475 |
| VT | Wood Duck | 3847.295729 | 814.6219798 | 814.2133129 |
| ID | Redhead | 1447.288826 | 817.0521549 | 774.2101551 |
| PA | American Black Duck | 2437.733688 | 820.3018391 | 731.4112392 |
| NY | Red-Breasted Merganser | 2198.588548 | 826.5216986 | 683.1368279 |
| CT | Wood Duck | 2376.952105 | 827.5079066 | 793.371338 |
| VA | Ring-Necked Duck | 7240.28432 | 842.1416893 | 822.4967787 |
| IN | Ring-Necked Duck | 2610.534177 | 842.3749832 | 753.0565587 |
| NJ | Mallard | 7201.140811 | 844.2953379 | 754.0875979 |
| WA | Bufflehead | 9449.507719 | 855.947343 | 854.7299254 |
| VT | Common Goldeneye | 1343.824255 | 861.6725908 | 687.0723982 |
| VA | Lesser Scaup | 2281.466115 | 869.0139988 | 770.0011506 |
| NY | Ring-Necked Duck | 1656.288528 | 869.3634162 | 799.5237938 |
| VT | American Green-Winged Teal | 2326.038605 | 873.2770743 | 846.1539616 |
| VA | Northern Pintail | 1479.658781 | 881.1209524 | 878.3101917 |
| IA | Northern Pintail | 4036.844406 | 903.757271 | 690.3554938 |
| NJ | Hooded Merganser | 2491.606063 | 912.2138273 | 911.9705035 |
| MT | Northern Pintail | 2263.270119 | 917.736876 | 836.3040643 |
| WA | Lesser Scaup | 8300.455801 | 934.8264785 | 809.5871613 |
| NJ | Wood Duck | 4165.691752 | 946.9282872 | 685.4370005 |
| MN | American Wigeon | 14652.1735 | 965.3917953 | 689.9466371 |
| NV | Northern Pintail | 2695.273733 | 968.5778053 | 943.6366466 |
| AK | American Green-Winged Teal | 5474.435101 | 969.0363844 | 899.1112039 |
| FL | American Wigeon | 508.8255628 | 972.7539506 | 961.1433925 |
| UT | Redhead | 2857.262681 | 980.896837 | 696.9366253 |
| ME | Ring-Necked Duck | 1405.704622 | 987.5001469 | 986.9397179 |
| CA | Common Goldeneye | 3684.866619 | 1007.82731 | 977.7390239 |
| VA | Hooded Merganser | 2413.882645 | 1029.819123 | 851.704941 |
| NV | Redhead | 1339.733492 | 1030.969812 | 1030.574176 |
| KS | Wood Duck | 3965.952817 | 1031.463741 | 1022.183557 |
| CO | Northern Shoveler | 1851.644924 | 1034.523397 | 948.6728421 |
| GA | Hooded Merganser | 3173.438527 | 1052.32132 | 809.0410666 |
| ME | American Black Duck | 2990.617354 | 1063.873289 | 876.5417329 |
| OH | Northern Shoveler | 2198.123435 | 1083.339876 | 1036.869722 |
| NM | Northern Shoveler | 2098.494274 | 1085.695715 | 1023.312657 |
| MT | Lesser Scaup | 1545.646586 | 1096.374077 | 1095.265477 |
| CT | American Black Duck | 2014.11066 | 1119.534879 | 1017.645523 |
| IL | Hooded Merganser | 2870.663289 | 1124.966529 | 1040.102377 |
| MN | Greater Scaup | 2177.423806 | 1132.293717 | 1006.006678 |
| FL | Hooded Merganser | 256.1018009 | 1152.553266 | 1150.770567 |
| OR | Wood Duck | 5858.372732 | 1155.221697 | 943.3669029 |
| VT | American Black Duck | 2237.198719 | 1163.071957 | 1135.924531 |
| AL | American Green-Winged Teal | 5861.541399 | 1170.869928 | 1107.422826 |
| CO | Common Goldeneye | 1292.344597 | 1187.51485 | 1060.085903 |
| NE | Ring-Necked Duck | 1946.136492 | 1189.383754 | 1186.600291 |
| OH | American Black Duck | 3353.752201 | 1202.313649 | 1174.170149 |
| CA | Greater Scaup | 1426.313508 | 1208.016832 | 866.2631944 |
| ID | Wood Duck | 3709.905763 | 1219.1519 | 1146.37225 |
| VA | American Wigeon | 80.13986471 | 1225.442124 | 1225.435548 |
| WI | American Black Duck | 1006.463783 | 1226.380567 | 924.0697249 |
| OH | Bufflehead | 2887.831062 | 1297.330231 | 974.6561191 |
| IL | Northern Shoveler | 6248.765384 | 1301.230951 | 1068.59702 |
| NV | American Green-Winged Teal | 9838.467894 | 1304.835724 | 1199.859431 |
| WI | Hooded Merganser | 3869.596442 | 1309.807887 | 1261.118351 |
| SD | Ring-Necked Duck | 4651.120266 | 1356.438737 | 1334.631198 |
| KS | Ring-Necked Duck | 4346.633932 | 1357.41787 | 1193.492526 |
| MI | Northern Shoveler | 1227.10498 | 1376.178589 | 1158.417332 |
| WI | Northern Shoveler | 4257.343798 | 1376.526708 | 1210.277127 |
| IN | Northern Pintail | 847.5854016 | 1398.683826 | 1261.38898 |
| FL | Mallard | 165.9267545 | 1400.017854 | 1159.94812 |
| MS | American Wigeon | 1537.010611 | 1401.487339 | 1327.803095 |
| WY | Common Goldeneye | 1810.672187 | 1410.683276 | 1365.360064 |
| DE | Snow Goose (white) | -89.05385639 | 1412.802106 | 1412.799231 |
| NH | Wood Duck | 4011.567061 | 1419.900474 | 1378.698855 |
| SD | American Wigeon | 9566.724441 | 1431.055844 | 1073.103295 |
| MA | Bufflehead | 3091.176221 | 1432.884356 | 1406.709646 |
| IL | Redhead | 2913.921296 | 1454.89597 | 1251.494878 |
| VA | American Green-Winged Teal | 7611.074911 | 1459.784082 | 1179.173582 |
| ID | Northern Shoveler | 2362.84365 | 1470.536595 | 1158.539315 |
| CT | Mallard | 3863.081521 | 1494.991129 | 1066.494372 |
| NV | Gadwall | 5054.467025 | 1536.413076 | 1413.979353 |
| NV | American Wigeon | 2616.373436 | 1537.422109 | 1459.460799 |
| SC | Northern Shoveler | 2827.553505 | 1583.203872 | 1338.171766 |
| TN | American Wigeon | 5212.589205 | 1609.943439 | 1280.242996 |
| ID | Ring-Necked Duck | 3033.799868 | 1615.039199 | 1548.961097 |
| ME | Bufflehead | 2056.369229 | 1633.839202 | 1399.110498 |
| PA | Wood Duck | 11067.79641 | 1640.719718 | 1569.931686 |
| NM | Canada Goose | 4940.350373 | 1662.539072 | 1661.531765 |
| NE | Northern Pintail | 2847.672013 | 1687.192858 | 1449.845468 |
| MI | Northern Pintail | 5807.846071 | 1687.547019 | 1322.935726 |
| MI | American Green-Winged Teal | 15515.74421 | 1688.092576 | 1686.430375 |
| SC | Gadwall | 6475.108767 | 1692.776052 | 1692.716639 |
| AZ | Mallard | 4602.536942 | 1707.794207 | 1507.004003 |
| DE | Wood Duck | 3513.301568 | 1725.514282 | 1646.663567 |
| SC | Hooded Merganser | 2424.923971 | 1727.062335 | 1678.703269 |
| UT | Ruddy Duck | 2464.860232 | 1736.412493 | 1723.775819 |
| MO | Snow Goose (blue) | 830.5784743 | 1741.006317 | 1716.870892 |
| ME | Wood Duck | 6355.496525 | 1742.995657 | 1703.2135 |
| MI | American Wigeon | 5957.060452 | 1745.087584 | 1339.76719 |
| IN | Wood Duck | 8007.681876 | 1764.655756 | 1684.148154 |
| IL | Northern Pintail | 4661.777659 | 1764.736668 | 1699.035734 |
| NY | American Wigeon | 3463.668412 | 1779.262875 | 1546.314297 |
| PA | Gadwall | 851.1538835 | 1829.357826 | 1643.190773 |
| FL | Northern Shoveler | 3612.238486 | 1830.721149 | 1768.53825 |
| AK | American Wigeon | 6997.474846 | 1836.605562 | 1463.798214 |
| NY | American Green-Winged Teal | 8109.736578 | 1841.398852 | 1560.845828 |
| IL | American Black Duck | 2021.89356 | 1845.020277 | 1843.098027 |
| MS | Hooded Merganser | 1732.992268 | 1853.768377 | 1689.79763 |
| TX | Hooded Merganser | 3038.188076 | 1868.031679 | 1363.437409 |
| WY | Gadwall | 3370.102905 | 1895.980732 | 1648.762762 |
| WI | Northern Pintail | 6446.455745 | 1898.71415 | 1780.267946 |
| SD | Bufflehead | 5940.456483 | 1926.248904 | 1916.193067 |
| SD | Northern Pintail | 7422.731093 | 1928.698377 | 1917.716867 |
| ME | American Green-Winged Teal | 3104.80684 | 1934.888789 | 1841.213443 |
| ME | Mallard | 9478.201417 | 1938.308064 | 1936.114492 |
| MD | Gadwall | 5903.583726 | 1938.32831 | 1459.114404 |
| WI | Common Goldeneye | 6833.316215 | 1971.012256 | 1845.262603 |
| LA | Hooded Merganser | 5366.456195 | 1994.704218 | 1908.930951 |
| KS | American Wigeon | 6090.511821 | 2000.997219 | 1712.208392 |
| AZ | American Green-Winged Teal | 2154.986817 | 2001.567227 | 1864.145936 |
| WA | Common Goldeneye | 2771.203896 | 2108.864794 | 2035.058546 |
| MA | American Black Duck | 3891.435174 | 2136.302761 | 2006.393239 |
| NE | American Wigeon | 6130.384109 | 2143.124548 | 2141.099516 |
| NM | American Green-Winged Teal | 3767.019097 | 2157.200653 | 2126.408081 |
| WA | Ring-Necked Duck | 11694.08249 | 2180.09195 | 2105.012744 |
| OH | Northern Pintail | 1656.633342 | 2199.127934 | 2149.880857 |
| OR | Bufflehead | 5679.004129 | 2217.416838 | 2193.426704 |
| WY | Canada Goose | 23414.68706 | 2228.50887 | 1602.999461 |
| KS | Snow Goose (blue) | 2363.498703 | 2235.454826 | 2227.810008 |
| NY | Common Goldeneye | 3903.389092 | 2236.636047 | 2035.756224 |
| NC | American Black Duck | 4627.971482 | 2267.637227 | 1622.622642 |
| OR | Lesser Scaup | 5149.15843 | 2271.484905 | 1841.152778 |
| IA | Northern Shoveler | 5027.436305 | 2287.428004 | 2269.212618 |
| ID | Northern Pintail | 4500.404997 | 2305.181826 | 2277.799496 |
| TX | Northern Pintail | 34365.4181 | 2308.124201 | 2080.846665 |
| TX | Bufflehead | 5203.795799 | 2311.006009 | 1746.434279 |
| UT | Lesser Scaup | 2611.230715 | 2315.471467 | 2192.990158 |
| KY | American Black Duck | 2439.322012 | 2336.206932 | 2054.736512 |
| WI | Ring-Necked Duck | 10890.17324 | 2338.068857 | 1758.846663 |
| OH | Gadwall | 3922.767616 | 2347.278903 | 2184.784946 |
| GA | Mallard | 6975.649016 | 2359.703723 | 1770.149145 |
| NE | Wood Duck | 4028.73911 | 2368.558957 | 2367.241088 |
| MS | Ring-Necked Duck | 6024.975289 | 2369.807987 | 2171.989145 |
| IN | Gadwall | 6247.525395 | 2377.366872 | 2353.279775 |
| MA | Common Eider | 5355.87877 | 2385.133629 | 2250.056251 |
| DE | American Black Duck | 4873.459472 | 2407.795556 | 2288.598357 |
| UT | Blue-Winged/Cinnamon Teal | 7096.887208 | 2408.980646 | 2376.996992 |
| AR | American Wigeon | 11398.04509 | 2411.38898 | 2076.92591 |
| VA | Bufflehead | 15060.23473 | 2420.504492 | 2154.143987 |
| IA | Lesser Scaup | 3090.706182 | 2475.698807 | 2412.304572 |
| WA | Greater Scaup | 4841.758267 | 2543.946623 | 2505.323888 |
| SD | Blue-Winged/Cinnamon Teal | 20396.3795 | 2557.33111 | 2186.159675 |
| KY | Gadwall | 11651.39699 | 2558.649809 | 2219.701094 |
| IL | Common Goldeneye | 2696.717301 | 2563.531177 | 2366.742587 |
| NJ | Snow Goose (white) | 3712.085974 | 2580.849693 | 2580.843669 |
| WA | American Green-Winged Teal | 44170.98298 | 2585.589931 | 2582.328356 |
| MI | Ring-Necked Duck | 8256.248842 | 2608.025477 | 1969.601246 |
| TN | Canada Goose | 16137.09639 | 2647.426184 | 2157.708571 |
| WI | Redhead | 7507.917772 | 2663.41282 | 2627.282487 |
| ND | Ring-Necked Duck | 8338.863308 | 2677.640072 | 2477.144056 |
| OR | Gadwall | 9818.117854 | 2681.996423 | 2220.533078 |
| AL | Mallard | 8875.648678 | 2705.808807 | 2065.885327 |
| MT | Northern Shoveler | 4054.429004 | 2724.718529 | 2439.30608 |
| OK | Redhead | 3668.052681 | 2756.664344 | 2697.573769 |
| IA | American Wigeon | 4442.274023 | 2757.698596 | 2587.936025 |
| IL | Blue-Winged/Cinnamon Teal | 17184.49131 | 2790.811257 | 2745.629074 |
| NY | Redhead | 3961.014688 | 2799.55849 | 2585.635549 |
| OH | American Wigeon | 1462.317258 | 2807.621871 | 2246.638803 |
| MO | Gadwall | 37236.11933 | 2815.976029 | 2455.338574 |
| OH | Blue-Winged/Cinnamon Teal | 6911.349059 | 2834.96069 | 2831.292395 |
| CO | American Wigeon | 5965.891882 | 2849.237176 | 2576.909205 |
| MI | Mallard | 89549.72944 | 2861.044909 | 2140.714749 |
| KY | American Green-Winged Teal | 5623.789113 | 2861.988356 | 2521.33347 |
| OH | American Green-Winged Teal | 5047.482624 | 2877.045989 | 2800.816779 |
| NC | Northern Pintail | 6046.245676 | 2949.672755 | 2798.560458 |
| FL | Mottled Duck | 9546.947347 | 3001.356772 | 3001.133233 |
| NC | Hooded Merganser | 11658.32055 | 3019.976086 | 2539.461835 |
| WA | Northern Pintail | 24609.91606 | 3020.082127 | 2925.409322 |
| MA | Mallard | 7071.646508 | 3023.927933 | 2986.52387 |
| AR | Ring-Necked Duck | 14492.05553 | 3028.364725 | 2277.353707 |
| AL | Lesser Scaup | 4277.089442 | 3047.453692 | 3014.254229 |
| VT | Mallard | 7396.296043 | 3058.211072 | 2997.331216 |
| FL | Lesser Scaup | 10988.21689 | 3068.28506 | 2543.162096 |
| IA | American Green-Winged Teal | 27523.88337 | 3069.716539 | 3034.831286 |
| NY | Bufflehead | 8140.903653 | 3124.100157 | 3055.038947 |
| CA | Lesser Scaup | 11658.93379 | 3128.224668 | 3113.929036 |
| OR | Ring-Necked Duck | 6762.917617 | 3137.951842 | 2996.121409 |
| MN | Lesser Scaup | 8221.055677 | 3147.357932 | 3102.701202 |
| NC | Ring-Necked Duck | 13215.10629 | 3157.251012 | 2942.766541 |
| SD | Wood Duck | 6174.880947 | 3175.482933 | 3058.02084 |
| MO | Ring-Necked Duck | 7217.377137 | 3247.152378 | 2721.732211 |
| WI | Gadwall | 14358.58038 | 3263.50862 | 3199.552007 |
| NE | Northern Shoveler | 5456.132433 | 3291.30982 | 3288.626889 |
| SD | Redhead | 7569.35914 | 3304.728173 | 2381.732775 |
| WA | Gadwall | 12841.33848 | 3320.805701 | 2862.976716 |
| MO | Lesser Scaup | 4578.105391 | 3325.127848 | 3312.144132 |
| NJ | Bufflehead | 11842.13524 | 3334.046513 | 2383.004735 |
| IA | Gadwall | 9927.779184 | 3357.448557 | 3076.326429 |
| CA | Ruddy Duck | 1929.771196 | 3358.830469 | 3065.294657 |
| IL | American Wigeon | 1811.061698 | 3375.02564 | 3269.686088 |
| NE | Gadwall | 8937.84162 | 3436.490153 | 2641.850985 |
| MD | American Black Duck | 9312.741976 | 3450.335541 | 2522.280348 |
| MI | American Black Duck | 9510.286519 | 3458.112539 | 2829.420114 |
| NE | American Green-Winged Teal | 22946.26264 | 3462.756306 | 3030.929248 |
| SD | Lesser Scaup | 5568.200812 | 3481.913223 | 3480.433703 |
| MO | Wood Duck | 5759.345247 | 3515.894212 | 3118.080253 |
| NY | American Black Duck | 10563.9251 | 3516.171663 | 2988.632731 |
| ID | Gadwall | 9530.557768 | 3561.773185 | 3533.400943 |
| NM | Gadwall | 4253.558407 | 3562.252627 | 3479.711846 |
| MI | Lesser Scaup | 6287.226925 | 3569.114363 | 3557.657797 |
| VA | American Black Duck | 10611.60119 | 3621.076218 | 3130.59236 |
| MI | Common Goldeneye | 1255.236697 | 3633.364499 | 3089.492913 |
| OR | Northern Pintail | 28493.57974 | 3699.073374 | 3601.187169 |
| KS | Redhead | 5172.984845 | 3732.22964 | 3682.613181 |
| GA | American Green-Winged Teal | 3940.494405 | 3742.595053 | 3291.359191 |
| NM | American Wigeon | 5820.87619 | 3744.73501 | 3738.778173 |
| MO | Snow Goose (white) | 886.9850335 | 3746.421652 | 2953.401745 |
| CA | Redhead | 7924.348137 | 3758.894571 | 3755.728801 |
| TX | Blue-Winged/Cinnamon Teal | 205687.162 | 3784.125979 | 3247.865601 |
| NC | Northern Shoveler | 3379.44257 | 3879.314782 | 3692.810734 |
| MN | Common Goldeneye | 8407.135606 | 3894.536775 | 3439.205155 |
| IL | Ring-Necked Duck | 8654.342699 | 3929.047883 | 3916.313469 |
| WI | American Wigeon | 8139.862364 | 3953.183977 | 3951.730831 |
| MD | Lesser Scaup | 6855.207863 | 3994.267571 | 3974.0398 |
| NJ | American Green-Winged Teal | 1592.32638 | 4005.840295 | 2967.058629 |
| DE | American Green-Winged Teal | 8133.947253 | 4020.081066 | 3643.592199 |
| MO | Blue-Winged/Cinnamon Teal | 21440.54074 | 4028.421176 | 3664.871801 |
| LA | Snow Goose (blue) | 432.2911421 | 4132.328483 | 3515.540777 |
| RI | Canada Goose | 6071.627535 | 4150.953326 | 4150.517623 |
| OR | Greater Scaup | 5948.801417 | 4175.487157 | 3080.542028 |
| MN | Northern Shoveler | 7884.440149 | 4191.925051 | 4011.957197 |
| CO | American Green-Winged Teal | 12027.65772 | 4195.64297 | 3816.586431 |
| MS | Northern Pintail | 5469.121981 | 4222.326643 | 3807.155677 |
| VA | Gadwall | 9670.341855 | 4265.451121 | 4013.651841 |
| NC | American Green-Winged Teal | 29311.31867 | 4311.386664 | 4310.998924 |
| AK | Mallard | 14381.60902 | 4325.81507 | 4261.325463 |
| KS | Northern Pintail | 7796.769228 | 4396.019191 | 3186.285393 |
| IL | Lesser Scaup | 5401.161223 | 4396.81268 | 3700.010292 |
| ME | Common Eider | 5431.83802 | 4414.610406 | 4322.477846 |
| FL | American Green-Winged Teal | 3362.694976 | 4459.846242 | 3841.711756 |
| MA | Canada Goose | 9910.320596 | 4471.228381 | 4405.234113 |
| MD | Wood Duck | 11705.4664 | 4544.416313 | 4505.135575 |
| IA | Ring-Necked Duck | 5914.293737 | 4554.413536 | 4524.726488 |
| ID | Canada Goose | 52915.05721 | 4644.426449 | 3950.762112 |
| SD | American Green-Winged Teal | 17885.78635 | 4679.521296 | 3805.306484 |
| ID | American Green-Winged Teal | 14884.16941 | 4694.362265 | 3967.692502 |
| TX | Canvasback | 6107.76696 | 4727.481378 | 4676.761234 |
| ND | American Wigeon | 19800.53183 | 4742.323382 | 4278.650659 |
| SD | Northern Shoveler | 11061.93178 | 4778.308632 | 4505.881568 |
| KS | Snow Goose (white) | 12111.90828 | 4852.773394 | 3740.751686 |
| MN | Hooded Merganser | 10538.00303 | 4883.613885 | 4623.000461 |
| MT | Common Goldeneye | 7422.870771 | 4945.525869 | 4945.438612 |
| NC | American Wigeon | 12603.10126 | 4961.15381 | 3968.262436 |
| SD | Snow Goose (blue) | 7682.880869 | 4970.198036 | 4782.046522 |
| PA | Mallard | 21469.59451 | 4983.187666 | 4931.646768 |
| OK | Blue-Winged/Cinnamon Teal | 12901.61876 | 5010.769379 | 4652.980663 |
| ID | Common Goldeneye | 12483.23578 | 5035.598783 | 4361.759106 |
| OK | Northern Pintail | 9217.078766 | 5104.458195 | 3918.448824 |
| TN | Ring-Necked Duck | 6954.306033 | 5143.845862 | 4977.917294 |
| MT | American Green-Winged Teal | 7550.759145 | 5166.249324 | 4868.188251 |
| NJ | American Black Duck | 6595.167965 | 5216.965027 | 3907.019173 |
| NV | Mallard | 9677.328284 | 5242.075901 | 5239.078867 |
| MI | Blue-Winged/Cinnamon Teal | 4831.118598 | 5245.307576 | 5097.096826 |
| IL | Gadwall | 16907.38498 | 5288.832126 | 4182.247183 |
| MO | Northern Shoveler | 17590.16168 | 5302.060874 | 4561.163115 |
| MI | Greater Scaup | 7323.274388 | 5339.172492 | 5338.676572 |
| KS | Canada Goose | 87920.15503 | 5363.329243 | 4725.071963 |
| WA | Northern Shoveler | 10228.30472 | 5382.821758 | 4540.748707 |
| DE | Mallard | 9030.543647 | 5388.527882 | 3830.455699 |
| NC | Lesser Scaup | 11922.84314 | 5418.330495 | 3877.935147 |
| OR | Northern Shoveler | 14916.56821 | 5436.072376 | 4900.706002 |
| NC | Gadwall | 14680.07094 | 5510.565579 | 5418.693416 |
| CA | Wood Duck | 14693.37838 | 5533.146163 | 4538.862041 |
| NC | Canada Goose | 34528.76675 | 5555.345933 | 4444.525762 |
| TN | Mallard | 72715.16714 | 5563.895215 | 5405.71448 |
| ND | Snow Goose (blue) | 10459.54048 | 5584.216715 | 4871.991595 |
| TX | Wood Duck | 35057.83955 | 5618.0755 | 5523.908638 |
| ID | American Wigeon | 18999.71081 | 5639.971921 | 4533.554767 |
| SC | Mallard | 10502.75898 | 5742.417423 | 5697.300014 |
| CT | Canada Goose | 10053.91717 | 5755.001811 | 5665.501269 |
| ND | Bufflehead | 10594.75595 | 5766.29925 | 5766.092739 |
| IN | American Green-Winged Teal | 3744.46158 | 5788.821922 | 5320.026181 |
| MD | Bufflehead | 15657.25464 | 5854.38907 | 5716.870223 |
| FL | Wood Duck | 19341.91373 | 6050.531263 | 4760.307656 |
| UT | Northern Pintail | 14968.40644 | 6052.398984 | 4446.417873 |
| MO | Northern Pintail | 6602.376405 | 6092.188509 | 5735.658365 |
| AK | Canada Goose | 6853.929345 | 6153.547053 | 6148.607537 |
| CA | Ring-Necked Duck | 26287.47191 | 6217.972091 | 6217.918173 |
| UT | Canada Goose | 23424.99148 | 6280.399487 | 5304.979658 |
| DE | Canada Goose | 7734.615942 | 6281.699493 | 4829.397849 |
| WI | Greater Scaup | 10541.13471 | 6306.574848 | 5872.794733 |
| IL | Bufflehead | 11362.41565 | 6355.331111 | 5738.770388 |
| WI | Lesser Scaup | 10270.0696 | 6374.733675 | 6014.304813 |
| AR | Northern Pintail | 19241.31845 | 6411.728199 | 5917.659543 |
| AL | Canada Goose | 17631.38044 | 6424.874373 | 5512.854106 |
| MN | Bufflehead | 12480.00399 | 6448.808985 | 6267.56045 |
| NY | Long-Tailed Duck | 9209.360595 | 6483.672823 | 6349.931173 |
| SC | Ring-Necked Duck | 17230.87086 | 6513.52179 | 6207.286615 |
| GA | Ring-Necked Duck | 10301.91866 | 6719.282096 | 5756.26835 |
| CO | Gadwall | 12413.15339 | 6759.458883 | 6757.67978 |
| VA | Mallard | 30475.82517 | 6823.543182 | 6808.936227 |
| NM | Mallard | 12363.92554 | 7015.220961 | 6832.02752 |
| KS | Northern Shoveler | 10509.24402 | 7114.004145 | 7000.776897 |
| OK | Northern Shoveler | 5713.851385 | 7150.382909 | 5201.498314 |
| AL | Gadwall | 20941.03051 | 7296.081192 | 7119.067344 |
| FL | Blue-Winged/Cinnamon Teal | 44679.98572 | 7300.91193 | 7125.414665 |
| MO | American Wigeon | 2141.357647 | 7370.927038 | 5936.895203 |
| NC | Wood Duck | 98420.5883 | 7404.890928 | 6158.420848 |
| MN | Northern Pintail | 8494.994643 | 7546.203084 | 6478.190238 |
| KS | American Green-Winged Teal | 22396.41233 | 7642.918137 | 6951.283726 |
| SD | Gadwall | 33925.72473 | 7854.467302 | 7781.597874 |
| MT | American Wigeon | 14312.19363 | 7930.49232 | 7908.685522 |
| TX | Mottled Duck | 5895.732106 | 7970.087216 | 6566.808395 |
| LA | Greater White-Fronted Goose | 30081.60531 | 8080.386662 | 7928.256076 |
| NY | Wood Duck | 20228.77201 | 8144.871238 | 7064.693971 |
| IL | American Green-Winged Teal | 16462.18958 | 8302.375057 | 8275.035221 |
| WY | Mallard | 15903.61112 | 8416.943956 | 6573.492112 |
| MT | Gadwall | 13218.78464 | 8470.059766 | 8298.232195 |
| MI | Redhead | 15412.28975 | 8530.878486 | 8202.819752 |
| NJ | Canada Goose | 21700.60548 | 8639.070463 | 8123.62179 |
| CA | Bufflehead | 13696.73913 | 8655.763432 | 6185.150287 |
| VA | Wood Duck | 21781.89971 | 8794.824069 | 6981.003246 |
| KY | Wood Duck | 9414.539468 | 8880.363488 | 8251.555116 |
| WI | Bufflehead | 19193.27185 | 8948.364859 | 8946.656289 |
| MD | Mallard | 35658.23624 | 9065.481003 | 8871.120034 |
| LA | Northern Shoveler | 33025.4611 | 9229.780792 | 7598.515277 |
| OK | Ring-Necked Duck | 25246.67602 | 9253.906001 | 9252.288362 |
| MI | Wood Duck | 41627.84135 | 9327.770149 | 9128.490296 |
| KS | Greater White-Fronted Goose | 11429.29429 | 9492.273909 | 8839.337855 |
| AL | Ring-Necked Duck | 13177.35815 | 9673.452568 | 7942.184768 |
| UT | American Green-Winged Teal | 30065.61207 | 9728.80569 | 8824.114049 |
| TX | Snow Goose (blue) | 6144.531709 | 9840.744138 | 8567.046567 |
| UT | Northern Shoveler | 22420.17857 | 9868.08585 | 8675.899265 |
| OH | Wood Duck | 19123.22531 | 9922.749461 | 9812.522272 |
| MS | American Green-Winged Teal | 28718.7786 | 9978.157735 | 7598.855674 |
| KY | Mallard | 60100.22775 | 10096.07093 | 9383.472445 |
| OK | American Wigeon | 24041.98052 | 10179.45539 | 7684.53528 |
| NY | Canada Goose | 64781.10756 | 10251.77339 | 8662.512431 |
| IL | Wood Duck | 23463.02152 | 10333.42622 | 9569.191216 |
| MO | Canada Goose | 36356.97179 | 10357.41379 | 10341.50494 |
| FL | Ring-Necked Duck | 53171.54597 | 10392.79037 | 10334.91629 |
| MS | Wood Duck | 28582.0161 | 10644.5719 | 10630.3277 |
| OR | American Wigeon | 63576.36382 | 10707.6951 | 9246.027473 |
| TX | Ring-Necked Duck | 59365.71731 | 10757.38223 | 8897.268143 |
| ND | Snow Goose (white) | 17730.865 | 10884.56501 | 9865.528108 |
| UT | American Wigeon | 26155.55281 | 11043.67291 | 10013.80692 |
| SD | Snow Goose (white) | 15438.75989 | 11198.03002 | 10047.73739 |
| ND | Northern Shoveler | 26720.54989 | 11239.2663 | 10177.79781 |
| KY | Canada Goose | 19738.77217 | 11364.02184 | 10840.12659 |
| IA | Wood Duck | 20389.96843 | 11565.89563 | 11537.92398 |
| NE | Blue-Winged/Cinnamon Teal | 37215.8341 | 11657.04311 | 10641.66785 |
| WI | Wood Duck | 94090.99447 | 11789.61049 | 11218.20637 |
| CO | Mallard | 39748.52103 | 11847.18359 | 11042.00141 |
| MN | Gadwall | 22787.25524 | 11901.10698 | 11520.32514 |
| MI | Bufflehead | 23338.92417 | 12242.96983 | 12085.73974 |
| KS | Gadwall | 20888.22545 | 12258.84073 | 9028.975123 |
| OR | American Green-Winged Teal | 43318.65968 | 12444.1749 | 11593.77968 |
| LA | Mottled Duck | 17949.06114 | 12604.28754 | 12426.03608 |
| NE | Canada Goose | 106138.5146 | 12750.12754 | 12525.9065 |
| NC | Bufflehead | 11737.10882 | 12890.22652 | 11625.14273 |
| NY | Mallard | 43082.68898 | 12921.43146 | 12794.64107 |
| VA | Canada Goose | 31169.5583 | 13043.48116 | 12817.40598 |
| SC | American Green-Winged Teal | 11567.96094 | 13219.3481 | 10307.90688 |
| IN | Mallard | 44790.28602 | 13244.67893 | 12662.14228 |
| NC | Mallard | 39887.62584 | 13270.94046 | 12604.13159 |
| SC | Wood Duck | 72303.22312 | 13584.93604 | 10530.40543 |
| WA | American Wigeon | 69260.94017 | 14054.52423 | 12459.92275 |
| CA | Snow Goose (white) | 78306.16263 | 14135.45418 | 13678.79089 |
| ND | Redhead | 23639.58423 | 14301.60144 | 13254.18435 |
| ND | Blue-Winged/Cinnamon Teal | 33869.98816 | 14358.76124 | 10693.20807 |
| LA | Northern Pintail | 22598.25535 | 14427.98274 | 10359.9882 |
| OK | American Green-Winged Teal | 32806.57284 | 14678.23839 | 14560.56534 |
| CA | Northern Pintail | 96005.26818 | 14915.77574 | 13940.59278 |
| ND | American Green-Winged Teal | 30981.80612 | 14928.57126 | 14808.18715 |
| WI | American Green-Winged Teal | 32213.09933 | 15057.69452 | 12547.41846 |
| CA | Gadwall | 54352.33495 | 15060.38482 | 14597.04309 |
| IL | Mallard | 74079.96431 | 15398.70435 | 14079.30353 |
| CA | Northern Shoveler | 172493.858 | 16007.06491 | 13787.31489 |
| IA | Mallard | 39055.36393 | 16210.73935 | 16205.95723 |
| MN | Redhead | 20581.99292 | 16258.05254 | 16130.04795 |
| OH | Mallard | 46411.53478 | 16300.88875 | 14806.30663 |
| TX | Lesser Scaup | 33119.29004 | 17466.8589 | 17440.46276 |
| IN | Canada Goose | 52380.70192 | 17629.32974 | 15900.54956 |
| AR | Mallard | 364539.3286 | 17658.99692 | 14485.34272 |
| ND | Lesser Scaup | 19660.00293 | 17691.86488 | 17578.57537 |
| AR | Northern Shoveler | 52988.19132 | 17827.00805 | 17041.54473 |
| TN | Gadwall | 48762.11926 | 17899.90097 | 12878.29447 |
| AL | Wood Duck | 66762.15797 | 17965.24738 | 15287.68672 |
| TX | Northern Shoveler | 63421.74186 | 18021.18603 | 16478.80091 |
| MO | American Green-Winged Teal | 33885.18957 | 18092.78357 | 16685.75464 |
| AR | American Green-Winged Teal | 150177.8281 | 18460.46051 | 18406.38342 |
| MS | Mallard | 37609.12424 | 18763.89756 | 15723.15352 |
| TX | Mallard | 55783.16695 | 19105.59536 | 19105.52086 |
| WA | Canada Goose | 51747.17165 | 20120.52445 | 20113.82084 |
| GA | Wood Duck | 78254.38963 | 20216.87714 | 19773.17078 |
| MT | Canada Goose | 64120.72908 | 20265.99111 | 14529.82133 |
| OK | Canada Goose | 64182.96728 | 20767.56495 | 15921.04772 |
| SD | Canada Goose | 84845.03911 | 20868.76531 | 19218.34904 |
| NE | Mallard | 54671.43836 | 20874.015 | 15458.6469 |
| CA | Blue-Winged/Cinnamon Teal | 35858.64708 | 21240.51061 | 21240.26233 |
| LA | American Wigeon | 30187.98916 | 21265.96683 | 21265.35878 |
| KS | Blue-Winged/Cinnamon Teal | 24983.66954 | 21313.70289 | 16311.09382 |
| CA | Greater White-Fronted Goose | 73695.41585 | 21562.56708 | 20545.65104 |
| UT | Gadwall | 0 | 21774.60255 | 19999.08125 |
| MS | Gadwall | 43247.96795 | 21863.12872 | 21756.07027 |
| CO | Canada Goose | 59395.75323 | 22130.66183 | 20327.14109 |
| WI | Blue-Winged/Cinnamon Teal | 53091.12431 | 22362.71277 | 21102.15309 |
| ND | Gadwall | 73175.9429 | 22933.23264 | 20539.98178 |
| OR | Mallard | 115936.4935 | 23612.23367 | 23328.10505 |
| TX | American Wigeon | 63702.93836 | 24432.4739 | 23789.18469 |
| TX | Canada Goose | 35041.90011 | 24665.65747 | 21645.83366 |
| MN | American Green-Winged Teal | 37003.89302 | 25148.87714 | 21169.6337 |
| TN | Wood Duck | 25102.04984 | 25267.23956 | 20759.50297 |
| LA | Ring-Necked Duck | 45893.17475 | 25926.88215 | 25563.06662 |
| WI | Mallard | 114155.7476 | 26584.64691 | 25090.24749 |
| IL | Canada Goose | 90593.67612 | 26615.64222 | 26479.80693 |
| SD | Mallard | 62949.33004 | 27075.68239 | 26749.81867 |
| ID | Mallard | 120639.6469 | 27993.61909 | 27933.79069 |
| CA | Canada Goose | 54751.09676 | 28265.90164 | 28025.25384 |
| MN | Canada Goose | 161395.9675 | 28393.7839 | 26754.06242 |
| MN | Ring-Necked Duck | 68852.42095 | 28840.52676 | 23163.22265 |
| MO | Mallard | 152211.5536 | 29055.82179 | 28844.78937 |
| OR | Canada Goose | 47025.37908 | 29233.5906 | 29191.4252 |
| IA | Blue-Winged/Cinnamon Teal | 56392.66774 | 29311.77751 | 29071.90186 |
| IA | Canada Goose | 57955.14148 | 30073.67172 | 29817.5727 |
| MN | Mallard | 95485.92975 | 30297.06011 | 26356.68527 |
| MN | Blue-Winged/Cinnamon Teal | 91348.45217 | 31077.92144 | 26466.68699 |
| KS | Mallard | 76222.16872 | 32350.10996 | 26537.29352 |
| TX | Greater White-Fronted Goose | 46677.2026 | 32682.0788 | 32526.55584 |
| AR | Wood Duck | 71744.8485 | 35025.47099 | 34686.8592 |
| LA | Wood Duck | 64956.55931 | 35077.78438 | 32344.47239 |
| UT | Mallard | 66025.50569 | 35782.84063 | 35148.42055 |
| MN | Wood Duck | 110336.0118 | 36183.56679 | 35186.11212 |
| LA | Blue-Winged/Cinnamon Teal | 247857.2985 | 36515.74248 | 36232.23243 |
| TX | Redhead | 66773.30689 | 38095.27329 | 32151.9815 |
| OK | Mallard | 134047.372 | 38128.6883 | 35038.44718 |
| TX | Snow Goose (white) | 57487.75284 | 38211.85539 | 37807.82238 |
| ND | Canada Goose | 119376.7103 | 38347.65042 | 36105.45927 |
| WI | Canada Goose | 159299.2322 | 39756.02987 | 37687.70294 |
| PA | Canada Goose | 85014.72058 | 40512.7711 | 40154.61004 |
| OK | Gadwall | 86208.90478 | 44382.11418 | 41856.56669 |
| TX | American Green-Winged Teal | 167711.471 | 47509.60688 | 45583.13073 |
| CA | American Wigeon | 172276.4867 | 48984.52266 | 46452.47509 |
| ND | Mallard | 131914.7487 | 50749.10549 | 50504.46869 |
| MI | Canada Goose | 141639.1478 | 50852.54053 | 39442.44074 |
| CA | American Green-Winged Teal | 265230.7981 | 51569.78553 | 47295.07013 |
| LA | Lesser Scaup | 50601.59893 | 51758.52462 | 49094.31663 |
| MT | Mallard | 103142.0539 | 56123.53695 | 55751.06005 |
| LA | American Green-Winged Teal | 74847.99407 | 58411.20789 | 57793.28221 |
| AR | Gadwall | 188825.0213 | 61357.54209 | 56844.64429 |
| LA | Mallard | 84850.69473 | 65146.01414 | 65076.84515 |
| MD | Canada Goose | 1659.484565 | 65596.37075 | 64207.93725 |
| CA | Mallard | 153054.7296 | 77012.33857 | 76263.01378 |
| WA | Mallard | 231172.2813 | 78856.49068 | 72985.92861 |
| LA | Gadwall | 169774.2162 | 110605.518 | 109118.5447 |
| TX | Gadwall | 249663.9777 | 122547.319 | 111885.0514 |

The ARIMA model's forecasts for harvest weights across different states and species indicate varied levels of predictive accuracy. Some species-state pairings, like the Northern Pintail in Wyoming, show a strong alignment between predicted and actual values, as suggested by their low RMSE and MAE metrics. In contrast, other pairings, such as the Gadwall in Texas, display significant prediction errors, which may reflect the challenges of accounting for local ecological variations and species-specific factors in the models.

The inconsistency highlighted by the range of MAPE values across the dataset suggests that while the model offers precise forecasts in certain cases, it struggles in others. This variation in forecast accuracy points to the potential necessity for model enhancements, possibly through incorporating localized environmental data or adjusting the model to capture the intricacies of hunting patterns and species population dynamics more accurately.

Figure 16: Harvest Weight Forecasting by Species and Flyway Region

| **Flyway Region** | **Species** | **Prediction** | **RMSE** | **MAE** | **MAPE** |
| --- | --- | --- | --- | --- | --- |
| Mississippi Flyway | Ring-Necked Duck | 144089.58 | 13315.19 | 10462.40 | 6.59 |
| Central Flyway | American Green-Winged Teal | 303737.38 | 25681.39 | 25201.87 | 7.43 |
| Pacific Flyway | Snow Goose (white) | 111280.01 | 9456.10 | 8882.56 | 7.54 |
| Atlantic Flyway | Common Merganser | 7283.71 | 538.40 | 538.38 | 7.55 |
| Pacific Flyway | Ring-Necked Duck | 50315.88 | 4367.14 | 3717.26 | 7.99 |
| Pacific Flyway | Hooded Merganser | 4918.49 | 371.48 | 357.79 | 8.08 |
| Atlantic Flyway | Canada Goose | 309290.57 | 30896.63 | 25815.75 | 8.88 |
| Atlantic Flyway | Wood Duck | 385195.84 | 41939.47 | 31752.95 | 10.06 |
| Atlantic Flyway | Hooded Merganser | 26730.14 | 3275.11 | 3084.51 | 10.76 |
| Central Flyway | American Wigeon | 140168.22 | 14601.39 | 13481.28 | 10.94 |
| Atlantic Flyway | Blue-Winged/Cinnamon Teal | 62904.15 | 6885.30 | 6851.01 | 11.51 |
| Central Flyway | Bufflehead | 23723.56 | 2573.22 | 2364.72 | 11.57 |
| Pacific Flyway | Northern Shoveler | 188999.78 | 36958.98 | 27955.52 | 11.74 |
| Atlantic Flyway | Ring-Necked Duck | 104466.52 | 11139.88 | 10828.64 | 11.75 |
| Pacific Flyway | Bufflehead | 36818.36 | 7068.48 | 5394.34 | 11.75 |
| Mississippi Flyway | Mallard | 1220872.29 | 157349.46 | 128070.91 | 12.73 |
| Atlantic Flyway | American Green-Winged Teal | 99453.78 | 16780.46 | 15266.57 | 12.84 |
| Central Flyway | Hooded Merganser | 6077.01 | 843.75 | 728.06 | 14.31 |
| Alaska | Barrow's Goldeneye | 1368.90 | 201.97 | 201.40 | 15.07 |
| Mississippi Flyway | Canada Goose | 747990.83 | 122543.06 | 98628.91 | 16.69 |
| Atlantic Flyway | Northern Shoveler | 17855.83 | 3268.62 | 3045.47 | 17.24 |
| Central Flyway | Blue-Winged/Cinnamon Teal | 368867.05 | 60155.50 | 58538.83 | 17.32 |
| Mississippi Flyway | Northern Shoveler | 118585.09 | 21725.33 | 21325.16 | 17.80 |
| Pacific Flyway | Ruddy Duck | 5183.77 | 2020.68 | 1573.17 | 18.24 |
| Atlantic Flyway | American Wigeon | 18445.05 | 7319.90 | 5218.04 | 18.27 |
| Mississippi Flyway | Northern Pintail | 78337.52 | 38493.30 | 27692.69 | 21.13 |
| Pacific Flyway | Wood Duck | 21774.43 | 4921.99 | 4805.91 | 21.19 |
| Mississippi Flyway | Canvasback | 24634.64 | 4844.69 | 4830.61 | 21.54 |
| Central Flyway | Wood Duck | 61230.02 | 11795.43 | 11230.86 | 21.72 |
| Central Flyway | Northern Pintail | 91590.57 | 16056.27 | 15985.01 | 21.73 |
| Pacific Flyway | American Wigeon | 399499.51 | 72922.96 | 67195.17 | 22.08 |
| Pacific Flyway | American Green-Winged Teal | 452597.13 | 97007.51 | 72389.29 | 22.13 |
| Pacific Flyway | Northern Pintail | 181568.15 | 29911.03 | 29872.29 | 22.21 |
| Central Flyway | Ring-Necked Duck | 104205.26 | 20144.09 | 18982.86 | 22.80 |
| Alaska | American Wigeon | 6886.16 | 1179.77 | 1179.72 | 23.66 |
| Mississippi Flyway | American Green-Winged Teal | 448358.92 | 135328.33 | 133985.45 | 23.98 |
| Pacific Flyway | Common Goldeneye | 30281.56 | 6528.72 | 5505.85 | 24.22 |
| Atlantic Flyway | Gadwall | 38494.02 | 11733.75 | 11279.12 | 25.38 |
| Pacific Flyway | Mallard | 706058.74 | 180473.52 | 149325.42 | 27.19 |
| Alaska | American Green-Winged Teal | 3869.11 | 1691.15 | 1684.37 | 27.82 |
| Atlantic Flyway | Mallard | 229005.31 | 49153.24 | 49153.23 | 28.16 |
| Mississippi Flyway | American Wigeon | 50543.06 | 24176.54 | 22225.70 | 29.11 |
| Pacific Flyway | Barrow's Goldeneye | 1861.54 | 1208.92 | 985.34 | 29.62 |
| Alaska | Northern Pintail | 3009.44 | 1483.30 | 1436.68 | 29.83 |
| Mississippi Flyway | Blue-Winged/Cinnamon Teal | 599048.47 | 135104.93 | 126349.48 | 29.85 |
| Alaska | Mallard | 16815.06 | 4210.37 | 3490.81 | 30.52 |
| Alaska | Greater Scaup | 966.57 | 232.86 | 197.83 | 30.69 |
| Central Flyway | Canada Goose | 605360.61 | 145138.09 | 135806.83 | 32.51 |
| Central Flyway | Mallard | 579450.29 | 141728.17 | 129177.81 | 33.06 |
| Atlantic Flyway | American Black Duck | 69596.16 | 20994.08 | 17927.29 | 33.68 |
| Mississippi Flyway | Wood Duck | 563202.32 | 166714.31 | 141145.38 | 34.17 |
| Atlantic Flyway | Mallard X Black Duck Hybrid | 1818.80 | 1194.27 | 1137.57 | 34.35 |
| Mississippi Flyway | American Black Duck | 16355.23 | 4805.38 | 4344.28 | 35.75 |
| Atlantic Flyway | Northern Pintail | 18557.35 | 4438.01 | 3703.19 | 35.78 |
| Mississippi Flyway | Greater White-Fronted Goose | 98134.88 | 40264.17 | 40011.49 | 38.97 |
| Central Flyway | Common Goldeneye | 12304.94 | 8163.34 | 8054.88 | 39.47 |
| Pacific Flyway | Lesser Scaup | 26879.94 | 9017.82 | 8185.80 | 40.71 |
| Mississippi Flyway | Common Goldeneye | 27793.72 | 8731.56 | 8514.79 | 40.94 |
| Pacific Flyway | Surf Scoter | 1873.48 | 857.69 | 825.15 | 41.31 |
| Atlantic Flyway | Mottled Duck | 9029.00 | 4820.36 | 4697.01 | 41.67 |
| Pacific Flyway | Eurasian Wigeon | 511.16 | 536.64 | 535.30 | 42.52 |
| Pacific Flyway | Greater White-Fronted Goose | 78468.77 | 23919.04 | 21766.32 | 42.53 |
| Atlantic Flyway | Bufflehead | 75184.16 | 27754.43 | 26288.29 | 44.14 |
| Mississippi Flyway | Hooded Merganser | 47179.64 | 14715.96 | 13684.65 | 44.52 |
| Mississippi Flyway | Gadwall | 524090.34 | 185563.38 | 174012.47 | 45.27 |
| Pacific Flyway | Canada Goose | 278426.84 | 84939.42 | 84817.31 | 46.03 |
| Atlantic Flyway | Greater Scaup | 13418.63 | 4451.08 | 4427.38 | 48.43 |
| Pacific Flyway | Common Merganser | 4064.79 | 1612.13 | 1611.79 | 48.82 |
| Central Flyway | Snow Goose (blue) | 30553.42 | 11823.75 | 11058.15 | 51.42 |
| Pacific Flyway | Gadwall | 152665.62 | 51731.54 | 50692.18 | 51.76 |
| Central Flyway | Canvasback | 20299.29 | 7630.86 | 7364.11 | 53.79 |
| Pacific Flyway | Canvasback | 26583.82 | 9760.28 | 7651.52 | 53.87 |
| Atlantic Flyway | Red-Breasted Merganser | 8146.28 | 2973.83 | 2973.75 | 54.17 |
| Mississippi Flyway | Mallard (Domestic) | 2142.23 | 6292.54 | 5023.87 | 56.05 |
| Central Flyway | Common Merganser | 12.21 | 802.31 | 690.65 | 61.16 |
| Alaska | Bufflehead | 1322.33 | 594.11 | 587.35 | 66.62 |
| Mississippi Flyway | Greater Scaup | 18551.32 | 7951.61 | 7879.68 | 69.21 |
| Central Flyway | Northern Shoveler | 141775.44 | 60491.19 | 59663.59 | 75.04 |
| Atlantic Flyway | White-Winged Scoter | 3424.64 | 1553.26 | 1273.14 | 76.19 |
| Atlantic Flyway | Ruddy Duck | 6065.28 | 2941.16 | 2919.66 | 76.20 |
| Atlantic Flyway | Lesser Scaup | 39488.40 | 19603.64 | 19559.32 | 77.25 |
| Central Flyway | Gadwall | 498781.48 | 214345.10 | 211727.71 | 77.83 |
| Mississippi Flyway | Snow Goose (white) | 65400.48 | 25239.93 | 20923.88 | 81.63 |
| Central Flyway | Greater Scaup | 2303.19 | 1038.78 | 796.03 | 89.25 |
| Mississippi Flyway | Bufflehead | 95571.48 | 50616.55 | 50019.06 | 93.41 |
| Central Flyway | Snow Goose (white) | 118784.66 | 51573.83 | 47596.80 | 94.62 |
| Pacific Flyway | Blue-Winged/Cinnamon Teal | 41705.56 | 25905.49 | 25125.47 | 102.87 |
| Mississippi Flyway | Snow Goose (blue) | 28583.91 | 13097.93 | 10360.31 | 108.47 |
| Atlantic Flyway | Long-Tailed Duck | 22535.26 | 11562.79 | 8451.43 | 109.97 |
| Mississippi Flyway | Red-Breasted Merganser | 3802.95 | 2415.03 | 1932.86 | 111.86 |
| Mississippi Flyway | Common Merganser | 3651.49 | 2178.84 | 2086.91 | 112.47 |
| Atlantic Flyway | Redhead | 17615.73 | 9015.26 | 7993.98 | 114.91 |
| Alaska | Gadwall | 1170.69 | 578.77 | 416.84 | 117.56 |
| Atlantic Flyway | Black Scoter | 25521.82 | 12288.18 | 11954.04 | 118.13 |
| Mississippi Flyway | Redhead | 63672.02 | 32127.55 | 29630.54 | 118.26 |
| Pacific Flyway | Redhead | 22309.92 | 12300.13 | 12195.57 | 119.40 |
| Alaska | Common Goldeneye | 927.65 | 716.69 | 591.99 | 120.98 |
| Central Flyway | Lesser Scaup | 57519.38 | 31669.44 | 31650.33 | 124.42 |
| Pacific Flyway | Mallard (Domestic) | 1166.04 | 908.95 | 878.12 | 135.05 |
| Atlantic Flyway | Common Goldeneye | 9076.25 | 5396.62 | 4840.89 | 138.04 |
| Central Flyway | Greater White-Fronted Goose | 63612.07 | 35127.34 | 34834.62 | 170.62 |
| Mississippi Flyway | Mottled Duck | 16735.24 | 11677.21 | 11367.74 | 173.76 |
| Mississippi Flyway | Lesser Scaup | 144755.50 | 105755.27 | 104722.27 | 202.73 |
| Atlantic Flyway | Surf Scoter | 26704.43 | 17618.69 | 13581.02 | 205.32 |
| Central Flyway | Redhead | 118595.82 | 69942.61 | 62841.86 | 206.57 |
| Pacific Flyway | Greater Scaup | 18730.62 | 12223.21 | 11921.62 | 210.40 |
| Mississippi Flyway | Surf Scoter | 1463.74 | 878.31 | 795.76 | 222.67 |
| Central Flyway | Ruddy Duck | 9370.59 | 5720.11 | 5204.25 | 250.50 |
| Atlantic Flyway | Mallard (Domestic) | 3388.61 | 1888.24 | 1876.66 | 319.46 |
| Mississippi Flyway | Ruddy Duck | 12310.80 | 9303.30 | 9262.75 | 337.21 |
| Mississippi Flyway | Mallard X Black Duck Hybrid | 1820.19 | 1433.70 | 1378.12 | 341.79 |
| Central Flyway | Mottled Duck | 5908.28 | 7949.09 | 6556.81 | 366.54 |
| Atlantic Flyway | Common Eider | 12608.88 | 8711.30 | 8398.39 | 400.02 |
| Alaska | Canada Goose | 7042.51 | 4732.47 | 3621.99 | 731.10 |

The ARIMA model's harvest weight forecasts across various flyway regions and species indicate an assortment of prediction accuracies, as evidenced by the range in RMSE, MAE, and MAPE values. Certain forecasts, such as for the Ring-Necked Duck in the Mississippi Flyway and the American Green-Winged Teal in the Central Flyway, demonstrate high accuracy with relatively low RMSE and MAE, and exceptionally low MAPE values below 10%. This suggests a strong correlation between predicted and actual harvest weights, indicating that the model performs well for these specific flyway-region and species configurations.

Conversely, species like the Common Eider in the Atlantic Flyway and the Canada Goose in Alaska exhibit significantly higher RMSE and MAE values, coupled with MAPE values exceeding 400% in some cases. Such high errors suggest the model's predictions diverge considerably from the actual weights, highlighting potential challenges in capturing the dynamics of these species' populations or perhaps a lack of sufficient data for accurate modeling. These discrepancies across different flyway regions and species illuminate the complexity of accurately forecasting harvest weights, underscoring the need to perhaps tailor models more closely to regional ecological conditions and species-specific behaviors to enhance prediction precision.

Figure 17: Harvest Weight Forecasting by Species

| **Species** | **Prediction** | **RMSE** | **MAE** | **MAPE** |
| --- | --- | --- | --- | --- |
| Ring-Necked Duck | 379465.98 | 11311.90 | 10729.68 | 2.86 |
| Mottled Duck | 25796.70 | 1105.82 | 1088.91 | 5.77 |
| American Green-Winged Teal | 1275490.03 | 121326.66 | 91899.85 | 6.38 |
| Northern Pintail | 408661.56 | 33186.04 | 32050.29 | 10.39 |
| Canvasback | 71120.81 | 9259.77 | 9243.05 | 14.30 |
| Barrow's Goldeneye | 4100.39 | 740.69 | 531.53 | 17.34 |
| Common Goldeneye | 85627.03 | 12854.81 | 12748.49 | 17.47 |
| Northern Shoveler | 557353.99 | 80223.16 | 79933.81 | 17.85 |
| American Wigeon | 649966.96 | 105221.83 | 95946.51 | 18.50 |
| Common Merganser | 17251.23 | 2929.36 | 2765.89 | 19.68 |
| Snow Goose (white) | 297490.56 | 48428.37 | 41184.41 | 21.09 |
| Wood Duck | 1031776.16 | 208342.61 | 168487.96 | 21.17 |
| Mallard | 2845323.00 | 520145.56 | 486836.94 | 22.37 |
| Black Brant | 5472.75 | 1341.98 | 1298.93 | 23.12 |
| American Black Duck | 83966.49 | 17707.16 | 15413.12 | 23.30 |
| Eurasian Wigeon | 793.74 | 334.31 | 331.54 | 24.42 |
| Mallard X Black Duck Hybrid | 3720.93 | 1264.98 | 1027.97 | 25.37 |
| Blue-Winged/Cinnamon Teal | 1149036.14 | 252217.63 | 243968.78 | 28.94 |
| Hooded Merganser | 90406.62 | 21260.31 | 19536.84 | 29.12 |
| Canada Goose | 2056501.58 | 492997.63 | 456946.45 | 30.19 |
| Greater White-Fronted Goose | 235189.37 | 70193.10 | 49900.71 | 33.31 |
| White-Winged Scoter | 7987.84 | 1568.27 | 1373.67 | 35.74 |
| Mallard (Domestic) | 7277.57 | 4112.10 | 3669.21 | 39.64 |
| Red-Breasted Merganser | 13793.85 | 3964.90 | 3963.12 | 40.07 |
| Bufflehead | 254866.90 | 73526.50 | 73525.16 | 41.76 |
| Long-Tailed Duck | 35650.62 | 11171.93 | 8937.11 | 48.26 |
| Snow Goose (blue) | 58606.86 | 20442.23 | 18507.73 | 56.14 |
| Gadwall | 1274948.44 | 472342.79 | 471716.15 | 57.74 |
| Lesser Scaup | 214638.60 | 140267.59 | 131399.50 | 103.93 |
| Black Scoter | 27727.88 | 13046.10 | 12812.11 | 106.99 |
| Greater Scaup | 58761.32 | 32588.37 | 32242.05 | 108.42 |
| Redhead | 213736.43 | 105855.62 | 95128.62 | 115.80 |
| Ruddy Duck | 33627.77 | 18160.74 | 17806.61 | 116.74 |
| Surf Scoter | 32145.15 | 18330.05 | 15441.28 | 138.16 |
| Common Eider | 13485.93 | 9164.65 | 8947.01 | 414.00 |

The ARIMA model's forecasts for harvest weight by species present a spectrum of accuracy levels. For some species like the Ring-Necked Duck, the model shows excellent accuracy with an exceptionally low MAPE of 2.86%, suggesting a strong fit between the model's predictions and the actual data. In contrast, forecasts for species such as the Common Eider exhibit a MAPE of 414.00%, indicating substantial prediction errors that could be due to complex behaviors and ecological interactions not fully captured by the model.

Key species like the American Green-Winged Teal and Northern Pintail have moderately low MAPE values, indicating that the model predictions for these species are relatively reliable and may be used confidently for management decisions. However, high MAPE values for species such as the Greater Scaup, Redhead, and Ruddy Duck reflect less reliable predictions, possibly necessitating further model refinement or additional data inputs to enhance forecast precision. Overall, these results suggest that while the model performs well for certain species, there is variability in its effectiveness across different species, which highlights the need for species-specific considerations in harvest weight forecasting models.

| **State** | **Species** | **Prediction** | **RMSE** | **MAE** | **MAPE** |
| --- | --- | --- | --- | --- | --- |
| MF | geese | 231464.68 | 1705.02 | 1511.93 | 0.65 |
| NV | ducks | 3870.52 | 46.99 | 46.02 | 1.24 |
| MF | ducks | 391539.48 | 5567.80 | 5565.69 | 1.45 |
| MN | geese | 41617.29 | 1150.24 | 960.55 | 2.38 |
| US | geese | 563807.47 | 17784.37 | 15909.24 | 2.77 |
| CF | geese | 129514.96 | 3600.41 | 3598.75 | 2.81 |
| MO | geese | 11025.22 | 418.65 | 373.22 | 2.98 |
| GA | geese | 8108.24 | 324.94 | 301.30 | 2.99 |
| UT | geese | 8966.54 | 324.70 | 256.41 | 3.03 |
| NE | ducks | 11539.91 | 403.52 | 375.25 | 3.12 |
| ND | ducks | 31832.14 | 1274.82 | 1274.24 | 4.13 |
| WI | geese | 37836.40 | 1690.72 | 1627.25 | 4.35 |
| WA | sea ducks | 651.67 | 35.45 | 30.53 | 4.45 |
| VT | ducks | 3153.91 | 126.16 | 122.53 | 4.64 |
| IL | geese | 17132.25 | 1112.51 | 959.44 | 4.88 |
| VA | brant | 1022.40 | 60.79 | 45.26 | 4.93 |
| CO | mourning dove | 10458.12 | 735.84 | 617.33 | 5.04 |
| MT | geese | 10625.21 | 913.77 | 656.49 | 5.31 |
| AF | geese | 97759.62 | 6601.62 | 6042.79 | 5.49 |
| US | ducks | 941968.90 | 52677.22 | 48643.40 | 5.51 |
| NJ | brant | 1653.59 | 93.61 | 93.30 | 5.52 |
| TX | white-winged dove | 127690.49 | 8528.45 | 6867.59 | 5.64 |
| KS | mourning dove | 24550.14 | 1602.24 | 1306.83 | 5.84 |
| CM | white-winged dove | 143123.53 | 7992.26 | 7957.29 | 5.93 |
| NC | geese | 15330.38 | 1294.06 | 1023.84 | 5.96 |
| CM | mourning dove | 349406.79 | 24544.89 | 22203.71 | 6.17 |
| TX | mourning dove | 203130.12 | 13601.38 | 13594.58 | 6.29 |
| AK | geese | 1738.07 | 113.90 | 110.31 | 6.47 |
| FL | Wilson's snipe | 3213.61 | 322.25 | 235.44 | 6.49 |
| PA | geese | 19132.81 | 1425.85 | 1240.11 | 6.65 |
| OH | ducks | 15538.20 | 1041.62 | 906.70 | 6.66 |
| EM | mourning dove | 250776.90 | 22044.89 | 19264.08 | 6.87 |
| ND | geese | 24435.84 | 1752.70 | 1610.92 | 7.07 |
| OR | ducks | 19126.11 | 1461.01 | 1367.32 | 7.23 |
| CA | ducks | 52053.24 | 4610.08 | 3351.99 | 7.35 |
| US | white-winged dove | 134981.09 | 16259.92 | 11774.23 | 7.45 |
| MO | Wilson's snipe | 595.68 | 69.17 | 51.83 | 7.50 |
| MA | ducks | 2911.74 | 426.00 | 307.59 | 7.55 |
| CF | ducks | 202442.02 | 17662.69 | 14427.63 | 8.00 |
| FL | ducks | 15158.35 | 1160.25 | 1159.76 | 8.14 |
| PF | ducks | 157718.33 | 12693.06 | 11866.20 | 8.26 |
| MN | ducks | 55967.80 | 4427.44 | 4363.94 | 8.29 |
| UT | ducks | 14695.59 | 1472.70 | 1388.57 | 8.29 |
| GA | mourning dove | 35330.78 | 3333.91 | 3107.39 | 8.32 |
| UT | American coot | 1357.65 | 160.58 | 129.01 | 8.40 |
| NH | American woodcock | 1855.65 | 203.99 | 185.75 | 8.45 |
| WM | white-winged dove | 21185.22 | 1779.94 | 1638.91 | 8.47 |
| MA | Wilson's snipe | 57.88 | 5.43 | 5.03 | 8.67 |
| NE | geese | 10875.39 | 1090.93 | 1080.16 | 8.73 |
| TN | geese | 9141.81 | 1102.61 | 811.44 | 8.84 |
| IA | geese | 9298.58 | 817.16 | 761.55 | 8.92 |
| NY | geese | 12651.89 | 1132.68 | 1030.55 | 8.93 |
| PF | geese | 100719.60 | 9303.76 | 8038.26 | 8.96 |
| CA | mourning dove | 51436.13 | 5066.88 | 4310.04 | 9.56 |
| FL | mourning dove | 8498.29 | 812.67 | 753.79 | 9.69 |
| AK | sea ducks | 1459.91 | 239.75 | 173.74 | 9.79 |
| US | mourning dove | 736241.69 | 68958.97 | 68812.68 | 9.84 |
| TX | ducks | 80073.22 | 8135.03 | 7052.24 | 9.92 |
| VA | geese | 12067.45 | 1656.96 | 1315.79 | 10.07 |
| RI | geese | 756.11 | 76.08 | 67.07 | 10.15 |
| AK | ducks | 4393.26 | 439.76 | 438.96 | 10.20 |
| ME | geese | 2959.91 | 296.85 | 290.42 | 10.29 |
| DE | ducks | 3282.62 | 561.36 | 439.90 | 10.95 |
| MF | Wilson's snipe | 8509.85 | 1236.28 | 1230.70 | 10.97 |
| AL | ducks | 12360.10 | 1346.03 | 1231.79 | 11.02 |
| AR | mourning dove | 13088.11 | 2134.57 | 1969.98 | 11.03 |
| OK | mourning dove | 15701.81 | 2251.51 | 1974.63 | 11.06 |
| US | rails | 7048.21 | 901.69 | 722.25 | 11.12 |
| NJ | ducks | 6260.58 | 687.46 | 665.49 | 11.70 |
| GA | ducks | 17172.49 | 2198.07 | 2119.72 | 11.72 |
| KY | geese | 6970.89 | 1157.15 | 923.83 | 11.87 |
| US | Wilson's snipe | 18394.13 | 2725.65 | 2719.34 | 11.87 |
| UT | white-winged dove | 1026.12 | 120.78 | 116.35 | 12.26 |
| NE | mourning dove | 12584.08 | 1457.57 | 1379.58 | 12.29 |
| WI | ducks | 46991.54 | 6649.08 | 6220.51 | 12.31 |
| CO | ducks | 12831.13 | 1412.01 | 1381.93 | 12.31 |
| NY | brant | 1433.04 | 142.97 | 140.09 | 12.36 |
| LA | ducks | 37482.73 | 8827.59 | 6324.61 | 12.71 |
| EM | American woodcock | 28984.96 | 3727.77 | 3724.73 | 12.92 |
| MO | mourning dove | 24851.85 | 3009.90 | 2891.80 | 13.05 |
| RI | ducks | 745.19 | 139.53 | 124.12 | 13.11 |
| OH | geese | 15286.54 | 2154.92 | 1622.11 | 13.17 |
| IL | ducks | 23217.14 | 3878.88 | 3347.73 | 13.30 |
| OK | ducks | 20090.91 | 3835.79 | 3083.98 | 13.37 |
| WA | ducks | 23019.19 | 4306.33 | 3664.91 | 13.38 |
| ME | ducks | 4743.41 | 595.30 | 594.75 | 13.48 |
| CA | geese | 38576.15 | 4884.05 | 4627.76 | 13.63 |
| VA | mourning dove | 14887.31 | 2257.57 | 2099.25 | 13.69 |
| AL | white-winged dove | 967.51 | 191.22 | 177.60 | 13.71 |
| MD | ducks | 18223.24 | 2252.26 | 2242.22 | 13.73 |
| ND | mourning dove | 4932.26 | 646.66 | 569.96 | 13.74 |
| CA | band-tailed pigeon | 1955.80 | 477.07 | 357.89 | 13.80 |
| OR | geese | 10946.47 | 1521.82 | 1324.10 | 14.26 |
| US | sea ducks | 18264.34 | 2930.23 | 2192.68 | 14.31 |
| WA | brant | 198.42 | 67.77 | 53.82 | 14.36 |
| VT | American woodcock | 1480.11 | 184.34 | 171.85 | 14.48 |
| AR | ducks | 60734.37 | 11026.95 | 10016.18 | 14.50 |
| NM | sandhill crane | 423.56 | 91.75 | 78.90 | 14.62 |
| AF | ducks | 192180.76 | 26075.22 | 25965.90 | 15.23 |
| NJ | geese | 4493.68 | 659.93 | 557.52 | 15.25 |
| WY | geese | 3852.01 | 526.44 | 521.32 | 15.26 |
| MI | ducks | 35472.42 | 4956.82 | 4519.31 | 15.37 |
| PA | mourning dove | 10625.01 | 2105.20 | 2050.83 | 15.46 |
| MT | ducks | 13171.56 | 3628.78 | 2692.25 | 15.47 |
| MT | mourning dove | 1517.10 | 389.27 | 328.19 | 15.80 |
| IL | mourning dove | 9892.53 | 2190.23 | 2080.15 | 15.89 |
| MS | geese | 4263.96 | 1169.71 | 951.43 | 15.93 |
| WA | geese | 14118.12 | 2329.22 | 2255.55 | 16.11 |
| WM | mourning dove | 99901.97 | 13878.04 | 13454.21 | 16.16 |
| MI | geese | 34430.94 | 4769.99 | 4623.29 | 16.40 |
| CA | white-winged dove | 11135.37 | 1593.97 | 1559.98 | 16.45 |
| TN | ducks | 21012.41 | 3166.75 | 2949.65 | 16.95 |
| CO | geese | 11815.44 | 1999.56 | 1946.71 | 17.00 |
| MN | American woodcock | 11073.70 | 1769.77 | 1621.18 | 17.13 |
| NM | mourning dove | 9102.82 | 1972.65 | 1719.85 | 17.20 |
| MS | ducks | 12005.64 | 2629.28 | 2594.19 | 17.29 |
| ID | ducks | 17020.66 | 2611.23 | 2510.29 | 17.58 |
| ME | Wilson's snipe | 463.21 | 113.47 | 94.86 | 17.95 |
| VT | geese | 2355.57 | 386.00 | 340.55 | 17.97 |
| SC | ducks | 15746.88 | 4056.71 | 3842.99 | 18.10 |
| NJ | American woodcock | 1296.54 | 184.72 | 183.28 | 18.25 |
| AR | geese | 25688.54 | 4670.03 | 4659.96 | 18.28 |
| IA | American woodcock | 462.00 | 104.40 | 79.34 | 19.41 |
| VA | ducks | 19012.82 | 3278.59 | 3228.38 | 19.44 |
| WY | mourning dove | 1534.75 | 232.38 | 226.71 | 19.46 |
| SD | mourning dove | 5462.00 | 1112.96 | 1071.57 | 19.66 |
| CT | brant | 296.89 | 57.14 | 44.11 | 19.98 |
| MN | sandhill crane | 387.04 | 89.94 | 84.52 | 20.06 |
| IA | rails | 1011.64 | 207.10 | 206.98 | 20.14 |
| OR | band-tailed pigeon | 562.14 | 92.06 | 84.08 | 20.16 |
| US | American woodcock | 97634.80 | 17571.74 | 17428.42 | 20.21 |
| SD | ducks | 15312.63 | 2638.82 | 2410.74 | 20.25 |
| AL | mourning dove | 36942.43 | 6588.73 | 6259.64 | 20.33 |
| CT | American woodcock | 525.96 | 163.62 | 139.02 | 20.44 |
| CF | Wilson's snipe | 4743.32 | 1461.01 | 1114.10 | 20.53 |
| TX | Wilson's snipe | 3943.04 | 767.11 | 596.23 | 20.70 |
| OH | mourning dove | 10050.62 | 2932.60 | 2169.57 | 20.72 |
| IN | ducks | 8689.24 | 2160.93 | 2159.52 | 20.74 |
| CT | ducks | 1449.91 | 400.00 | 392.20 | 20.82 |
| PC | band-tailed pigeon | 2112.06 | 768.65 | 658.23 | 21.59 |
| LA | Wilson's snipe | 1264.92 | 225.35 | 172.21 | 21.66 |
| KS | geese | 13025.23 | 2552.26 | 2325.37 | 21.76 |
| SC | geese | 4955.95 | 1208.08 | 1183.81 | 21.87 |
| NC | ducks | 36736.16 | 6557.81 | 6479.14 | 22.09 |
| NM | geese | 2311.17 | 694.91 | 645.17 | 22.35 |
| MF | rails | 2388.78 | 1022.78 | 735.28 | 22.71 |
| MT | sandhill crane | 138.53 | 59.84 | 48.66 | 22.73 |
| MA | geese | 3013.69 | 962.46 | 919.58 | 22.78 |
| MD | mourning dove | 4323.86 | 1458.52 | 1378.12 | 22.89 |
| CM | American woodcock | 69032.19 | 13518.58 | 13086.77 | 22.90 |
| LA | American coot | 2079.88 | 1069.78 | 795.11 | 22.94 |
| SC | mourning dove | 24022.64 | 5976.43 | 4965.37 | 22.99 |
| NM | white-winged dove | 5299.22 | 1505.36 | 1337.44 | 23.25 |
| MS | mourning dove | 16758.38 | 3287.94 | 3170.66 | 23.40 |
| AZ | band-tailed pigeon | 414.96 | 98.36 | 95.68 | 23.50 |
| IN | mourning dove | 7505.70 | 2860.31 | 2503.08 | 23.60 |
| MA | American woodcock | 1141.08 | 370.70 | 370.67 | 23.72 |
| DE | mourning dove | 1481.16 | 346.89 | 342.06 | 23.90 |
| TN | mourning dove | 24322.34 | 5213.62 | 4340.36 | 23.93 |
| OR | sea ducks | 100.19 | 21.44 | 21.24 | 24.41 |
| CA | sea ducks | 85.50 | 41.57 | 34.67 | 25.09 |
| CT | Wilson's snipe | 73.54 | 24.91 | 24.70 | 25.34 |
| MD | geese | 20261.05 | 4107.50 | 4107.01 | 25.42 |
| DE | geese | 2702.05 | 851.39 | 763.07 | 25.70 |
| CO | sandhill crane | 211.87 | 52.85 | 51.19 | 25.85 |
| NM | ducks | 2622.35 | 925.56 | 912.99 | 25.87 |
| AK | sandhill crane | 978.20 | 215.67 | 212.96 | 26.30 |
| WI | American woodcock | 11685.21 | 3968.02 | 3666.65 | 26.32 |
| AF | sea ducks | 17410.16 | 4094.51 | 3423.64 | 26.45 |
| KS | ducks | 19531.95 | 4392.02 | 4090.96 | 26.78 |
| NY | ducks | 20160.29 | 4269.95 | 4266.94 | 26.80 |
| AZ | white-winged dove | 11336.78 | 2456.28 | 2318.93 | 26.95 |
| EM | white-winged dove | 5040.75 | 1622.08 | 1583.75 | 26.99 |
| CF | sandhill crane | 13013.51 | 10503.35 | 7488.62 | 27.12 |
| US | band-tailed pigeon | 4104.92 | 1061.83 | 892.57 | 27.17 |
| NC | mourning dove | 45898.95 | 10231.96 | 9875.21 | 27.32 |
| AF | gallinules | 1273.01 | 293.83 | 275.05 | 27.47 |
| CA | brant | 620.24 | 147.62 | 146.09 | 27.49 |
| WY | American coot | 157.92 | 36.87 | 29.75 | 27.56 |
| TX | geese | 49474.45 | 10350.39 | 10349.77 | 27.64 |
| KS | sandhill crane | 456.75 | 208.16 | 187.47 | 27.67 |
| WY | ducks | 3982.42 | 924.34 | 797.99 | 27.79 |
| WV | ducks | 714.02 | 333.34 | 322.62 | 27.91 |
| AZ | mourning dove | 19936.15 | 4831.77 | 3764.11 | 27.95 |
| KY | ducks | 10913.46 | 2587.35 | 2234.64 | 28.12 |
| WV | mourning dove | 806.47 | 303.01 | 300.63 | 28.20 |
| TX | American coot | 2159.47 | 843.40 | 802.35 | 28.49 |
| US | American coot | 41209.63 | 9719.78 | 8129.46 | 29.34 |
| NH | geese | 1069.79 | 578.92 | 532.59 | 29.52 |
| SD | geese | 15567.51 | 3553.03 | 3478.71 | 29.97 |
| NJ | sea ducks | 1051.42 | 520.52 | 489.10 | 30.26 |
| NV | geese | 1233.00 | 848.22 | 682.58 | 30.26 |
| WA | mourning dove | 5732.58 | 1429.44 | 1365.20 | 30.35 |
| MD | brant | 118.77 | 90.77 | 70.95 | 30.37 |
| FL | geese | 1224.14 | 325.45 | 325.45 | 30.80 |
| NC | American coot | 581.06 | 577.85 | 436.37 | 31.19 |
| AK | brant | 477.05 | 136.44 | 136.44 | 31.53 |
| WV | geese | 714.09 | 372.13 | 369.05 | 31.71 |
| NH | ducks | 2741.52 | 724.76 | 561.34 | 31.77 |
| IN | geese | 7580.84 | 3652.91 | 3595.29 | 32.37 |
| MO | ducks | 35274.48 | 8717.17 | 8716.77 | 32.57 |
| TX | sandhill crane | 9483.65 | 8569.26 | 6346.25 | 33.18 |
| ID | geese | 14220.69 | 3569.84 | 3454.10 | 33.44 |
| ND | American coot | 353.12 | 197.09 | 197.01 | 33.50 |
| CO | white-winged dove | 1108.31 | 672.51 | 572.93 | 33.56 |
| MD | sea ducks | 4501.39 | 1673.36 | 1657.27 | 33.63 |
| NH | Wilson's snipe | 70.17 | 61.52 | 54.09 | 33.96 |
| OK | geese | 8424.45 | 4605.71 | 4519.88 | 34.90 |
| US | brant | 10085.15 | 2841.67 | 2805.18 | 35.13 |
| US | sandhill crane | 12391.74 | 12074.72 | 9275.53 | 35.19 |
| ME | American woodcock | 2727.75 | 2100.23 | 1748.85 | 35.22 |
| MI | Wilson's snipe | 1469.76 | 2671.48 | 1920.09 | 35.41 |
| UT | mourning dove | 5119.93 | 2449.58 | 2449.03 | 35.57 |
| MO | white-winged dove | 1520.39 | 722.05 | 717.70 | 35.62 |
| NJ | rails | 169.12 | 110.98 | 90.38 | 36.18 |
| MA | sea ducks | 1026.24 | 603.55 | 597.99 | 36.34 |
| ME | sea ducks | 508.49 | 390.27 | 389.51 | 36.36 |
| RI | American woodcock | 127.05 | 138.61 | 100.59 | 36.84 |
| KY | mourning dove | 17593.23 | 4837.74 | 4434.80 | 37.75 |
| NY | sea ducks | 1798.36 | 475.15 | 440.71 | 38.45 |
| OK | American coot | 679.45 | 291.14 | 251.87 | 38.50 |
| NV | white-winged dove | 334.47 | 141.83 | 131.82 | 39.24 |
| WY | sandhill crane | 93.89 | 66.50 | 63.63 | 39.48 |
| RI | brant | 207.85 | 136.54 | 122.27 | 40.02 |
| CT | geese | 1479.24 | 715.93 | 615.50 | 40.62 |
| CT | sea ducks | 395.13 | 191.36 | 175.45 | 40.72 |
| IN | Wilson's snipe | 214.54 | 253.80 | 230.09 | 40.77 |
| AL | American coot | 1331.65 | 1093.48 | 1082.40 | 40.93 |
| CF | American coot | 4492.83 | 2530.24 | 1949.48 | 41.20 |
| OK | white-winged dove | 1247.07 | 1048.83 | 957.29 | 41.21 |
| RI | sea ducks | 289.07 | 221.50 | 214.45 | 41.36 |
| PF | brant | 1136.82 | 358.43 | 302.24 | 43.05 |
| MA | brant | 265.81 | 339.30 | 291.40 | 43.73 |
| NV | Wilson's snipe | 35.68 | 111.79 | 82.28 | 44.42 |
| DE | brant | 284.23 | 74.56 | 71.39 | 45.09 |
| FL | white-winged dove | 2516.06 | 818.96 | 646.24 | 45.35 |
| NV | American coot | 131.27 | 89.91 | 84.33 | 46.19 |
| AF | brant | 9219.44 | 3193.78 | 3125.41 | 47.98 |
| MF | American coot | 13521.36 | 9382.19 | 7541.00 | 49.37 |
| IA | ducks | 16118.25 | 5385.88 | 5362.05 | 49.81 |
| PF | sea ducks | 569.27 | 512.53 | 462.98 | 50.60 |
| NC | brant | 1257.85 | 668.77 | 642.23 | 50.79 |
| SC | American coot | 890.18 | 787.20 | 727.40 | 50.89 |
| NC | American woodcock | 3214.97 | 2892.05 | 2451.54 | 50.94 |
| NY | American woodcock | 4801.14 | 1580.00 | 1489.68 | 51.16 |
| PA | ducks | 21424.11 | 7533.64 | 7533.62 | 51.43 |
| DE | American coot | 35.82 | 45.10 | 43.88 | 52.28 |
| MI | American woodcock | 26986.18 | 10383.88 | 10131.97 | 54.15 |
| DE | sea ducks | 131.22 | 230.20 | 230.14 | 54.47 |
| CT | American coot | 44.03 | 35.64 | 27.49 | 54.52 |
| NM | band-tailed pigeon | 81.73 | 74.72 | 59.24 | 57.97 |
| CF | rails | 1832.24 | 926.31 | 846.52 | 58.19 |
| SC | rails | 249.72 | 627.06 | 621.74 | 58.39 |
| FC | band-tailed pigeon | 772.99 | 383.50 | 336.56 | 60.03 |
| MS | American coot | 95.89 | 740.45 | 692.38 | 61.47 |
| AL | geese | 4298.16 | 1649.15 | 1547.09 | 61.85 |
| ND | Wilson's snipe | 751.75 | 366.59 | 351.80 | 63.08 |
| PA | American woodcock | 2118.47 | 2703.17 | 2623.09 | 63.38 |
| GA | white-winged dove | 1297.16 | 373.48 | 370.95 | 64.29 |
| CO | American coot | 580.71 | 238.89 | 237.79 | 64.83 |
| OR | mourning dove | 4754.71 | 2164.24 | 2074.57 | 65.00 |
| MS | American woodcock | 178.36 | 797.56 | 597.67 | 67.28 |
| LA | geese | 15561.56 | 6320.47 | 5704.58 | 67.80 |
| LA | mourning dove | 13779.49 | 5552.08 | 4564.93 | 70.83 |
| MA | American coot | 17.91 | 39.11 | 38.79 | 71.80 |
| WV | American woodcock | 419.71 | 186.08 | 182.68 | 73.48 |
| SC | Wilson's snipe | 284.94 | 1045.97 | 1045.88 | 74.94 |
| WI | American coot | 2331.75 | 939.92 | 891.66 | 75.60 |
| AF | rails | 3057.05 | 1320.12 | 1257.50 | 75.98 |
| VA | American coot | 125.52 | 182.25 | 164.57 | 77.27 |
| WI | Wilson's snipe | 867.27 | 3494.56 | 3493.41 | 77.89 |
| OR | American coot | 846.91 | 344.17 | 325.44 | 77.93 |
| WV | American coot | 10.69 | 21.37 | 21.06 | 78.82 |
| VA | sea ducks | 3558.75 | 1645.55 | 1558.08 | 79.32 |
| AZ | geese | 1758.38 | 754.39 | 556.93 | 79.79 |
| AZ | ducks | 3730.82 | 1463.62 | 1383.19 | 80.28 |
| IL | American woodcock | 151.93 | 1811.99 | 1777.79 | 85.45 |
| TN | American coot | 223.62 | 2406.88 | 2400.84 | 90.87 |
| PF | American coot | 5963.67 | 2988.98 | 2984.82 | 93.25 |
| CO | Wilson's snipe | 234.48 | 224.68 | 179.14 | 93.94 |
| MN | Wilson's snipe | 1176.74 | 758.08 | 718.52 | 99.00 |
| AF | American coot | 0.00 | 4295.56 | 4295.54 | 100.00 |
| AF | Wilson's snipe | 0.00 | 5631.16 | 5619.60 | 100.00 |
| ND | sandhill crane | 0.00 | 1471.91 | 1438.07 | 100.00 |
| NE | rails | 0.00 | 320.52 | 251.36 | 100.00 |
| RI | gallinules | 0.00 | 3.01 | 2.13 | 100.00 |
| SD | sandhill crane | 98.94 | 46.21 | 43.92 | 100.11 |
| UT | Wilson's snipe | 237.29 | 125.69 | 125.64 | 103.43 |
| IA | American coot | 285.22 | 972.75 | 955.46 | 103.92 |
| NJ | American coot | 38.88 | 89.77 | 66.25 | 103.93 |
| OH | American woodcock | 2311.49 | 1673.49 | 1621.31 | 105.17 |
| MD | American woodcock | 499.30 | 421.07 | 409.79 | 112.58 |
| WA | American coot | 56.45 | 222.83 | 205.02 | 112.69 |
| MN | American coot | 1387.74 | 827.60 | 817.40 | 113.18 |
| IN | American woodcock | 1262.12 | 824.56 | 822.67 | 115.65 |
| VA | American woodcock | 2604.93 | 1300.77 | 1142.52 | 115.91 |
| KS | Wilson's snipe | 830.90 | 872.72 | 800.05 | 117.30 |
| US | gallinules | 7138.00 | 3530.06 | 2630.97 | 117.83 |
| MI | American coot | -877.92 | 3701.15 | 3688.38 | 123.67 |
| RI | American coot | -4.01 | 15.81 | 15.76 | 124.85 |
| LA | American woodcock | 3610.11 | 2208.41 | 2206.13 | 125.19 |
| RI | mourning dove | 216.17 | 159.85 | 150.09 | 125.39 |
| IA | Wilson's snipe | 978.23 | 335.87 | 283.16 | 127.97 |
| ME | rails | 29.45 | 57.13 | 50.21 | 129.76 |
| FL | American coot | 3126.80 | 1519.31 | 1265.14 | 131.59 |
| AR | American woodcock | 4408.43 | 2903.81 | 2888.03 | 134.41 |
| RI | Wilson's snipe | 13.59 | 8.57 | 8.57 | 137.09 |
| ID | mourning dove | 12826.23 | 6661.10 | 6638.04 | 139.65 |
| NE | white-winged dove | 768.06 | 478.96 | 478.39 | 148.30 |
| MF | gallinules | 4386.75 | 2813.69 | 2793.78 | 154.60 |
| VA | rails | 352.68 | 207.82 | 198.82 | 159.40 |
| CA | Wilson's snipe | -404.57 | 570.19 | 537.57 | 167.22 |
| NV | mourning dove | 2929.55 | 1836.99 | 1328.27 | 173.16 |
| NE | Wilson's snipe | 1384.65 | 927.85 | 926.61 | 176.13 |
| UT | band-tailed pigeon | 86.56 | 60.32 | 60.21 | 181.28 |
| WA | Wilson's snipe | 528.17 | 301.57 | 285.90 | 191.51 |
| LA | gallinules | -914.07 | 1586.28 | 1407.13 | 202.34 |
| NH | sea ducks | 139.22 | 79.96 | 65.06 | 206.80 |
| WA | band-tailed pigeon | 463.88 | 338.06 | 336.76 | 285.81 |
| PF | Wilson's snipe | 3312.38 | 2489.97 | 2489.17 | 290.46 |
| WY | Wilson's snipe | 303.39 | 207.57 | 204.03 | 307.14 |
| VT | American coot | 1.88 | 41.94 | 33.44 | 313.17 |
| CA | American coot | 4369.36 | 2886.33 | 2798.71 | 320.14 |
| FL | American woodcock | -423.04 | 2397.75 | 1938.34 | 323.69 |
| MT | American coot | 71.27 | 200.99 | 161.21 | 328.32 |
| FL | gallinules | 111.17 | 561.82 | 510.44 | 329.92 |
| KY | white-winged dove | 206.15 | 410.13 | 366.00 | 330.39 |
| TX | rails | 1947.69 | 482.91 | 451.69 | 358.00 |
| NM | Wilson's snipe | -11.64 | 79.62 | 67.69 | 400.62 |
| OR | brant | 28.37 | 18.55 | 16.23 | 404.12 |
| DE | American woodcock | 233.86 | 221.57 | 221.24 | 451.70 |
| OK | Wilson's snipe | -191.65 | 202.58 | 199.50 | 456.30 |
| NM | American coot | -92.20 | 78.97 | 70.24 | 472.67 |
| GA | Wilson's snipe | 424.04 | 393.52 | 390.54 | 481.31 |
| KY | American woodcock | 819.26 | 1205.73 | 1136.83 | 501.13 |
| MA | rails | 56.34 | 188.04 | 155.96 | 509.62 |
| GA | American woodcock | 2781.75 | 2461.33 | 2425.03 | 520.15 |
| MS | Wilson's snipe | 364.46 | 700.69 | 602.00 | 549.46 |
| SD | American coot | 165.69 | 131.17 | 130.32 | 589.88 |
| NY | Wilson's snipe | 343.78 | 207.27 | 177.70 | 594.51 |
| MO | American woodcock | 1799.60 | 1181.61 | 852.49 | 650.06 |
| MT | Wilson's snipe | -127.94 | 212.85 | 205.06 | 732.16 |
| SC | American woodcock | 2307.86 | 1607.51 | 1503.79 | 739.10 |
| IN | American coot | 627.08 | 425.75 | 369.85 | 743.46 |
| VT | Wilson's snipe | 114.56 | 81.24 | 76.09 | 743.75 |
| CO | band-tailed pigeon | 238.59 | 258.74 | 243.16 | 782.88 |
| OR | Wilson's snipe | 1108.02 | 755.98 | 643.74 | 914.30 |
| GA | rails | 735.81 | 652.51 | 652.50 | 992.38 |
| SD | Wilson's snipe | 188.37 | 140.38 | 133.89 | 1028.09 |
| MD | American coot | 182.81 | 162.04 | 162.03 | 1039.13 |
| GA | American coot | 74.18 | 648.38 | 474.80 | 1177.79 |
| MD | Wilson's snipe | 338.98 | 241.64 | 219.87 | 1299.88 |
| AZ | Wilson's snipe | 129.10 | 297.85 | 257.94 | 1341.94 |
| AL | American woodcock | 914.56 | 960.44 | 954.84 | 1471.33 |
| PA | American coot | 620.86 | 440.49 | 382.56 | 1936.17 |
| CT | rails | 106.22 | 78.54 | 71.65 | 2207.75 |
| AZ | American coot | 491.83 | 440.37 | 439.16 | 2243.70 |
| TX | American woodcock | 12084.10 | 8608.53 | 7370.29 | 2251.35 |
| IN | rails | 379.59 | 400.85 | 399.50 | 2547.89 |
| PA | Wilson's snipe | 942.27 | 663.28 | 546.60 | 2759.52 |
| NY | American coot | 465.07 | 532.64 | 525.04 | 6880.05 |
| AK | Wilson's snipe | -25.41 | 186.76 | 144.15 | inf |
| AL | Wilson's snipe | -66.19 | 651.92 | 492.88 | inf |
| AL | gallinules | 94.92 | 774.80 | 593.27 | inf |
| AL | rails | 317.76 | 293.79 | 292.72 | inf |
| AR | American coot | 314.55 | 502.35 | 475.77 | inf |
| AR | Wilson's snipe | 239.89 | 321.05 | 312.68 | inf |
| AR | gallinules | 171.52 | 1236.10 | 955.60 | inf |
| AR | rails | 106.90 | 1111.27 | 837.41 | inf |
| AZ | gallinules | 91.51 | 99.38 | 99.09 | inf |
| CA | gallinules | 521.77 | 450.16 | 443.26 | inf |
| CF | gallinules | 871.95 | 995.58 | 988.71 | inf |
| CO | rails | 29.32 | 26.20 | 26.06 | inf |
| DE | Wilson's snipe | 44.32 | 32.30 | 27.69 | inf |
| DE | gallinules | -15.76 | 39.43 | 34.62 | inf |
| DE | rails | -7.08 | 24.22 | 20.30 | inf |
| FL | rails | 115.28 | 220.07 | 177.63 | inf |
| GA | gallinules | 135.53 | 915.52 | 711.58 | inf |
| ID | American coot | 572.32 | 599.20 | 598.63 | inf |
| ID | Wilson's snipe | 529.40 | 381.95 | 318.33 | inf |
| ID | gallinules | 108.33 | 76.65 | 56.26 | inf |
| IL | American coot | 728.51 | 705.79 | 705.41 | inf |
| IL | Wilson's snipe | 485.46 | 448.26 | 446.57 | inf |
| IL | gallinules | 1.60 | 1.41 | 1.40 | inf |
| IL | rails | 301.71 | 245.51 | 236.76 | inf |
| IN | gallinules | -148605.09 | 157032.18 | 156817.30 | inf |
| KS | American coot | 177.09 | 232.80 | 187.68 | inf |
| KS | rails | 150.83 | 161.69 | 114.99 | inf |
| KY | Wilson's snipe | 422.94 | 299.18 | 217.57 | inf |
| KY | gallinules | 45.22 | 89.22 | 81.51 | inf |
| KY | rails | 33.18 | 49.46 | 47.38 | inf |
| LA | rails | -522.52 | 916.13 | 896.70 | inf |
| MD | rails | 181.94 | 188.58 | 187.21 | inf |
| ME | American coot | 144.65 | 139.65 | 139.55 | inf |
| ME | gallinules | -1.70 | 20.11 | 16.69 | inf |
| MI | gallinules | -183.15 | 186.19 | 186.17 | inf |
| MI | rails | 380.27 | 294.06 | 274.30 | inf |
| MN | gallinules | 211.84 | 276.49 | 270.25 | inf |
| MN | rails | 845.88 | 814.77 | 814.15 | inf |
| MO | American coot | 320.36 | 241.01 | 218.37 | inf |
| MO | gallinules | 86.68 | 85.03 | 85.01 | inf |
| MO | rails | -44.37 | 95.57 | 95.12 | inf |
| MS | gallinules | 448.73 | 317.93 | 238.49 | inf |
| MS | rails | 46.40 | 182.74 | 150.31 | inf |
| MT | gallinules | 61.74 | 44.49 | 36.94 | inf |
| NC | Wilson's snipe | 618.00 | 754.35 | 743.79 | inf |
| NC | gallinules | 0.00 | 0.00 | 0.00 | inf |
| NC | rails | 356.69 | 369.22 | 369.01 | inf |
| ND | rails | 114.68 | 100.75 | 99.62 | inf |
| NE | American coot | 209.01 | 163.05 | 153.21 | inf |
| NH | American coot | 49.16 | 49.63 | 49.62 | inf |
| NJ | Wilson's snipe | 149.25 | 183.77 | 181.01 | inf |
| NJ | gallinules | 15.19 | 9.78 | 9.54 | inf |
| NM | gallinules | 38.35 | 44.34 | 43.98 | inf |
| NM | rails | 51.89 | 57.04 | 56.83 | inf |
| NV | gallinules | -24.87 | 27.95 | 27.80 | inf |
| NY | gallinules | 254.05 | 216.96 | 213.05 | inf |
| NY | rails | 511.82 | 394.82 | 367.50 | inf |
| OH | American coot | 854.01 | 668.32 | 629.48 | inf |
| OH | Wilson's snipe | -140.92 | 126.76 | 125.86 | inf |
| OH | gallinules | -14.17 | 13.54 | 13.53 | inf |
| OH | rails | 131.20 | 92.77 | 65.60 | inf |
| OK | gallinules | 505.04 | 381.67 | 347.75 | inf |
| OK | rails | 279.35 | 228.89 | 221.44 | inf |
| OK | sandhill crane | 302.67 | 2455.82 | 1881.26 | inf |
| OR | gallinules | 30.88 | 27.25 | 26.96 | inf |
| PA | gallinules | 248.76 | 208.13 | 203.04 | inf |
| PA | rails | 481.14 | 341.15 | 258.36 | inf |
| PF | gallinules | 935.28 | 729.18 | 684.82 | inf |
| RI | rails | 11.60 | 8.21 | 5.93 | inf |
| SC | gallinules | 104.57 | 75.20 | 61.97 | inf |
| TN | Wilson's snipe | 247.47 | 347.93 | 336.38 | inf |
| TN | gallinules | 262.93 | 258.40 | 258.36 | inf |
| TN | rails | 11.47 | 9.16 | 8.75 | inf |
| TX | gallinules | 1521.11 | 1216.90 | 1163.02 | inf |
| VA | gallinules | 97.82 | 110.18 | 109.55 | inf |
| WA | gallinules | 106.10 | 94.41 | 93.57 | inf |
| WI | gallinules | 540.40 | 410.80 | 395.37 | inf |
| WI | rails | 386.01 | 803.16 | 778.42 | inf |
| WV | Wilson's snipe | 21.07 | 16.64 | 15.77 | inf |
| WV | gallinules | 1.15 | 2.55 | 2.29 | inf |
| WV | rails | -1.19 | 38.25 | 27.63 | inf |
| WY | rails | 19.86 | 33.57 | 31.49 | inf |
| AK | American coot | 0.00 | 0.00 | 0.00 |  |
| AK | gallinules | 0.00 | 0.00 | 0.00 |  |
| KY | American coot | 0.00 | 0.00 | 0.00 |  |
| NE | gallinules | 0.00 | 0.00 | 0.00 |  |
| VA | Wilson's snipe | 0.00 | 0.00 | 0.00 |  |

Figure 18: Active Hunter Forecasting by State and Species

The forecasting data presents predictions on active hunter numbers by state and species with varying degrees of accuracy as indicated by the Mean Absolute Percentage Error (MAPE). For certain states and species, the predictions are exceptionally precise, with MAPE values as low as 0.65%, suggesting a strong predictive performance of the model. For example, forecasts for geese in MF (presumably Mississippi Flyway) and ducks in MF and NV show MAPE values below 2%, pointing towards highly reliable forecasts that could potentially inform wildlife management and hunting regulations with considerable confidence.

Conversely, there are instances where the MAPE values are significantly higher, even reaching the extreme of "inf", which may indicate an absence of hunters or discrepancies so vast that the model cannot provide a meaningful prediction. This level of inaccuracy necessitates caution in utilizing these predictions for any practical application without further analysis or data collection. Overall, the model appears to exhibit a broad spectrum of prediction quality across different states and species, reflecting the inherent variability in hunter activities and the complex factors that influence such behaviors. These results underscore the importance of understanding the limitations of forecasting models and the necessity for ongoing data refinement and model adjustment to enhance prediction accuracy for active hunter forecasting.

| **Species** | **Prediction** | **RMSE** | **MAE** | **MAPE** |
| --- | --- | --- | --- | --- |
| American coot | 31792.73 | 67560.22 | 65981.96 | 79.67 |
| American woodcock | 293296.22 | 52987.51 | 52542.39 | 20.31 |
| Wilson's snipe | 53338.86 | 7541.91 | 6036.24 | 9.27 |
| band-tailed pigeon | 9966.91 | 1038.42 | 926.34 | 8.53 |
| brant | 30222.60 | 7508.29 | 7506.88 | 32.08 |
| ducks | 2804844.16 | 142567.83 | 129178.86 | 4.89 |
| gallinules | 20134.01 | 9670.02 | 6948.57 | 106.39 |
| geese | 1706654.60 | 31146.03 | 28761.51 | 1.70 |
| mourning dove | 2210499.81 | 205511.11 | 204818.12 | 9.77 |
| rails | 10117.23 | 8013.79 | 7396.99 | 36.59 |
| sandhill crane | 46159.88 | 31148.58 | 24449.07 | 31.94 |
| sea ducks | 53263.31 | 7535.80 | 5717.21 | 12.90 |
| white-winged dove | 508735.24 | 40231.10 | 39908.90 | 8.38 |

The data indicates a significant spread in the predictive accuracy for active hunter forecasting across different species. Geese are forecasted with exceptional precision, boasting the lowest MAPE and suggesting the predictability of their hunting patterns. Ducks also show promising forecast accuracy, indicating that their hunting numbers are well-tracked and exhibit regular patterns. On the other end of the spectrum, gallinules present a high level of uncertainty in their forecasts, which may hint at irregular hunting patterns or possibly less data availability for precise predictions.

Species such as American coots, rails, and sandhill cranes have relatively high MAPE values, signaling less confidence in the model's predictions for these birds, perhaps due to variable hunter interest or environmental factors that affect their populations. In contrast, band-tailed pigeons and white-winged doves are predicted with more certainty, as reflected by their low MAPE values. This distinction in forecast accuracy highlights the complexities inherent in hunter activity modeling, where various species are subject to different degrees of predictability.

# Section 6: Summary

### 6.1 Machine Learning Summary

The series of results tables collectively convey predictive insights into wildlife harvest weights and hunter activity across different geographical regions and species. The data suggests an overarching improvement in forecast accuracy when predictions are made at the species level rather than broader categories.

Starting with harvest weight forecasts by flyway region and species, the models seem to perform with varying degrees of accuracy, with some species such as the Ring-Necked Duck and the American Green-Winged Teal having lower errors and thus higher predictive accuracy. The granularity of data at the species level appears to facilitate more accurate modeling, likely due to the distinct behavioral patterns and environmental factors affecting each species.

In the second set of results focusing solely on species, the models exhibit a clear enhancement in forecasting precision. This improvement is evident in the lower error metrics across various species, underscoring the benefit of species-specific approaches. Such targeted predictions likely benefit from more refined data and the ability to account for unique variables pertinent to each species.

When considering active hunter forecasting by state and species, the models demonstrate an ability to handle complex patterns of hunter activities, which vary greatly from state to state and species to species. Although the accuracy differs among the species and states, with some forecasts exhibiting higher MAPE values, the overall trend suggests that focusing on the species level enables the models to leverage more specific behavioral and migratory patterns, which in turn sharpens accuracy.

The predictive capability is further evidenced in the subsequent tables, which continue to reflect the trend of improved accuracy at the species level. Lower RMSE, MAE, and MAPE values for certain species like geese and ducks are indicative of the robustness of species-specific models. Meanwhile, higher error metrics for species with less predictable patterns hint at the challenges still present in forecasting wildlife-related activities.

Overall, the datasets suggest a significant stride in forecasting precision at the species level. The data-driven approach, refined by incorporating species-specific behaviors and patterns, proves to be a powerful tool in enhancing the accuracy of predictions in wildlife management and conservation efforts. The ability to accurately predict at this level can assist in more efficient resource allocation, better wildlife management policies, and enhanced conservation strategies.

### 6.1 Project Summary

The Fish & Wildlife Service’s (FWS) Division of Migratory Bird Management (DMBM) is tasked with safeguarding migratory bird populations. To support this mission, they collect and report bird harvest and hunter data – the data is used by federal and state agencies to set wildlife management policies. Thus, reporting is time consuming and prone to human error, technical/nontechnical end users do not use the data, and insights that could inform policymaking are less likely to surface. This research explored three associated opportunities: (1) automate report creation; (2) enable self-service data access and analysis; and (3) apply novel analysis and visualization techniques. The section below discusses each opportunity, including what the team discovered and proved/disproved.

1. Automate report creation

The FWS’s processes to generate Flyway Data Books are ripe for automation. Using open-source tools, like Python, the team was able to automate all data tables for each Flyway. In addition to reducing the time to create and report Flyway Data Books, automation also reduces the likelihood of human errors. Though the team did not find errors in existing Flyway Data Books, automation adds as an extra ‘validation’ step and reduces the likelihood of errors in the future. We also learned that automation provides the FWS with a transparency benefit – outside of a one-page document that lists the variables and descriptions of the data, the team learned that there is not any documentation that defines calculations, aggregations, and other aspects of the data.

2. Enable self-service data access and analysis

As-is, the data reported in Flyway Data Books is static, limited to PDF tables. This makes it challenging for end-users to access and use the data. Through the requirements solicitation, the team learned about ad hoc data visualizations FWS produced and some common use cases in terms of how end-users use the data. The team used Tableau to replicate these common, high-value data points and visualizations. When creating a protype dashboard, the team also discovered additional data and data visualization use cases. However, as noted in prior sections, the team discovered that FWS has only limited knowledge of how end-users are actually using the data. Stakeholder surveys or interviews are highly recommended to add clarity to existing requirements and use cases and even surface new ones.

3. Apply novel analysis and visualizations

Over the past decades, the FWS has amassed ‘big data’ from its multiple surveys and collection efforts, but the data has yet to be thoroughly explored. The reported data includes basic count and averages by flyway (region), state, and year, but only limited visualization had been developed. This led the team to discover three opportunities to boost the utility of the data, including new descriptive statistics (e.g., different types of moving averages), predictive analytics (e.g., time series forecasting), and new visualizations (e.g., choropleth maps). Through these efforts, we explored the value of the data for forecasting – however, the datasets provided do not include variables that are likely to drive models. The team hypothesizes that integrating novel datasets with variables more correlated to outcomes, based on SME input, would likely provide more valuable insights.

# Section 7: Future Work

This project represents GMU’s and FWS’s first collaboration. Though a big step forward, the team has identified several future work opportunities that build on this project.

A major sponsor requirement was automating FWS’s ability to create the data tables published in their Flyway Data Books. To do this, FWS sent data pulled from their SQL databases via email. Future work could include connecting the solutions of this project (e.g., auto table creation and Tableau dashboards) directly to FWS data sources. This could enable further automation opportunities, reducing file sharing and enabling more frequent, real-time dashboard updates. Further, the data entered into FWS’s databases are sourced from dozens, if not hundreds, of partner surveys – additional work could be done to collect, preprocess, and integrate these survey results into FWS data sources.

Future work could also include additional analysis. Prior to this project, little analysis had been applied to the data. One may argue that the FWS is sitting on a goldmine of unexplored data, there are likely untold insights that can be extracted from the data and novel questions that can be answered. To-date, analysis has been mostly limited to aggregate values (e.g., annual sums and averages), so additional opportunities to apply descriptive, inferential, and predictive statistics are ripe. With regard to the latter, initial attempts (notably, ARIMA time series forecasting) were tried but inconclusive – i.e., error rates were too high to be useful. The team attributed this to the lack of data that could be used as drivers, so future work should include integrating datasets that based on SME are likely to explain outcomes being forecasted.

Historically, FWS and its stakeholders rely on the data books and ad hoc data requests to access and use the data to answer questions. To make the data more friendly, a prototype dashboard was created to enable broader self-service and democratize data analysis. Though a step forward, this still requires a degree of technical familiarity – e.g., how to apply filters in Tableau or use its drag-and-drop features. Nontechnical end-users represent a significant proportion of FWS stakeholders, so future work could include requirements or technology to make the dashboard more user friendly. There are free/low-cost opportunities to embed natural language generation or conversational AI capabilities in Tableau. Like Google Search, these would enable natural language queries, allowing nontechnical users to ask more questions of the data or conduct more in-depth analysis.

The last future work opportunity is less technical. When gathering business and technical requirements from FWS, it was evident that there is a knowledge gap in terms of how their stakeholders use the data. Perspectives on the types of questions they use the data to currently answer, the types of questions they want to answer in the future, how they present the data, and what policy decisions the data is used for were often unknown or ambiguous. Future work could apply customer journey analysis to answer these questions – this could be done through stakeholder interviews or surveys. Better knowledge of these end users could surface new requirements, boosting the value of FWS data and associated data services.

Appendix

Appendix A: Glossary

|  |  |
| --- | --- |
| Term | Definition |
| Flyway | Major routes used by migratory birds, divided into four main corridors in the United States. |
| Flyway Data Books | Publications containing yearly data about bird populations and harvests, specific to each Flyway. |
| Time-Series Data | Data points collected or recorded at regular time intervals, offering insights into trends and changes over time. |
| Harvest Information Program (HIP) | All registered hunters in US must provide their name, address, and hunting activity from the past season when they register for a hunting license. |
| Migratory Bird Hunter Survey (Diary Survey) | A sample of hunters from the HIP are selected to complete a hunting diary form with the date, county, and number of birds taken for every hunt. |
| Migratory Bird Parts Collection Survey (Wing Survey) | US-FWS annual survey in which a sample of hunters from around the U.S. send in one wing from each duck, dove/pigeon, and woodcock/rail that they shoot, and the wing tips and tail feathers from each goose. |
| Migratory Game Birds | Bird species that migrate across regions and are hunted for sport or food (eg. ducks, geese, swans, and other webless species including doves, sandhill cranes, rails, coots, gallinules, snipe, and woodcock) |
| Population and Harvest Estimates | Statistical data representing the number of birds and the count of birds hunted, respectively. |
| Ducks | Any of the following 19 species: 'Mallard', 'American Black Duck', 'Gadwall', 'American Wigeon', 'American Green-Winged Teal', 'Northern Shoveler', 'Northern Pintail',  'Redhead', 'Canvasback' ,'Greater Scaup', 'Lesser Scaup', 'Ring-Necked Duck',  'Common Goldeneye', 'Bufflehead', 'Ruddy Duck' , or "Barrow's Goldeneye" |
| Wingbee | Annual event at which state and federal biologists examine the wing or tail feathers contributed by hunters to collect data for the Migratory Bird Parts Collection Survey |
|  |  |
|  |  |

Figure 19: Glossary Table

Appendix B: GitHub Repository

Overview

**REPORT SECTION INSTRUCTIONS**

Provide a GitHub Link and the README.MD content. Do not just provide a link to the GitHub repository but provide a narrative paragraph which introduces the project. This section should mirror the look and feel of a well-documented professional GitHub site.

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GitHub Repository Link

<https://github.com/gjrsas/DAEN690>

**Problem Description:**

Annually, the Division of Migratory Bird Management (DMBM) collects population and harvest data on migratory game birds, principally ducks, geese, swans, and other webless species including doves, sandhill cranes, rails, coots, gallinules, snipe, and woodcock. These data are collected and analyzed within DMBM programs and estimates are reported out to the public in annual reports. Also, these data are made available to the States, public, and other stakeholders in the form of time-series tables by Flyway, known as “Flyway Data Books” to help inform State and Federal decisions about appropriate annual hunting regulations and other management programs. Each of the four Flyways has a separate Data Book and set of data tables. Annually, a practitioner (generally one for each Flyway) receives the current year estimates from our monitoring programs and manually appends the estimates to Flyway-specific excel time-series tables that go back as far as the 1950s (about 75–100 tables per Flyway) and produces an updated Data Book, generally in a PDF format (see attached example). The annual task of appending data to time series tables and producing Data Books is time and labor intensive and can result in data reporting errors and inconsistencies among Flyways for national data that is reported in all four Flyways.

**Project Goals:**

Ideally there would be a well-engineered automated, data pipeline from our game bird monitoring programs that produce annual demographic estimates to a single time-series repository (database) where data can be viewed and queried digitally or online with control over special and temporal extent depending on the applicable management scenario. This could be an especially large project considering multiple species, years, geographic reference areas (e.g., State, Flyway), types of data (e.g., harvest, population abundance), and types of estimates (e.g., point estimate, variance) from our monitoring programs. We would like to start with a limited set of data and develop a proof in concept that can later be expanded and applied to all of our available monitoring data. A suggested starting point is to consider only mallards. There are two types of data, annual harvest estimates and annual abundance estimates, each from a different monitoring program. Both of these types of data include examples of the temporal and spatial scales of interest and also the variance that may be available with point estimates for each year/area. Another possible partition of the project is to consider: 1) flow of data from monitoring programs to a single repository where Flyway-specific Data Books may be produced as PDF documents, and 2) digital or online database where data can be viewed and queried with control over special and temporal extent depending on the applicable management scenario. For the later portion, consideration of a dashboard that displays the time-series data of interest (point estimates and variance where available) and some basic summary statistics (e.g., long-term average; 3-, 5-, and 10-year moving averages) would be of interest.

GitHub Repository Contents

A screenshot of a computer program

Description automatically generated

Appendix C: Risks

Sprint 1 Risks

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Risk | Description | Probability | Impact | Mitigation |
| Project Scope & Complexity | Ability to complete all project goals within 5 sprints | medium | high | Clearly define project scope with the team and stakeholders at the start of the project. |
| Availability of Datasets | Able to access and evaluate datasets and data definition timely in Sprint 1 to prepare for Sprint 2 requirements | medium | medium | Reach out to partner POC for status. |
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Figure 20: Sprint 1 Risks

In Sprint 1, as requirements and vision for the final product are being formed, the team raised a concern about the extent of the project scope. Due to the course's fixed time constraint, there is inherent risk in the team's ability to fully deliver a complete solution for our partner. To mitigate this risk, the team must work closely with our partner to clearly define the scope, requirements, and expectations for the project in the early phase.

Since students are not given access to the agency’s environment and database, the team must only rely on the data made available by our partner. At this point, the team does not have a comprehensive understanding of the data and data fields. If the dataset is delayed, this can impact our Sprint 2 planning and execution.

Sprint 2 Risks

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Risk | Description | Probability | Impact | Mitigation |
| Less defined requirements for final product​ | Partner described their general vision for the final product but details still lacking. It is up to the team's expertise and creative effort.​ | medium | high | Regularly communicate with partner during the duration of project development to gather feedback.​ |
| Project Scope & Complexity | Ability to complete all project goals within 5 sprints | medium | high | Clearly define project scope with the team and stakeholders at the start of the project. |
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Figure 21: Sprint 2 Risks

In Sprint 2, partner requirements for the final products are still very vague. The team does not have a concrete vision of what visualizations or data reports. Partner leaves it up to the team’s expertise and creativity to determine what to produce, thus requirements are still locked down. The team most communicate regularly with partner to ensure our effort always align with their business needs. This poses a risk for the team.

Sprint 3 Risks

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Risk | Description | Probability | Impact | Mitigation |
| Lack of well-defined visualization requirements for final product​ | Partner described their general vision for the final product but details still lacking. It is up to the team's expertise and creative effort.​ | medium | high | Regularly communicate with partner during the duration of project development to gather feedback.​ |
| Lack of understanding of how end customers use this data. | Though we know what data is being published in the current Data Books, we do not know how data is used by end customers so we can build targeted visualizations. | medium | high | Reach out to Partner POC to perform customer surveys or establish direct communication with end customers of the data. |
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Figure 22: Sprint 3 Risks

Sprint 4 Risks

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Risk | Description | Probability | Impact | Mitigation |
| Lack of well-defined visualization requirements for final product​ | Partner described their general vision for the final product but details still lacking. It is up to the team's expertise and creative effort.​ | medium | high | Regularly communicate with partner during the duration of project development to gather feedback.​ |
| Lack of understanding of how end customers use this data. | Though we know what data is being published in the current Data Books, we do not know how data is used by end customers so we can build targeted visualizations. | medium | high | Reach out to Partner POC to perform customer surveys or establish direct communication with end customers of the data. |
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Table 5:

Sprint 5 Risks

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| --- | --- | --- | --- | --- |
| Risk | Description | Probability | Impact | Mitigation |
| There are no identified risks |  |  |  |  |
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Figure 23: Sprint 5 Risks

Appendix D: Agile Development

Scrum Methodology

A diagram of a timeline

Description automatically generated

Figure 24: Sprint project dates

The team uses the Agile methodology to plan, execute, and track concurrent project tasks across the development team. The project timeline is broken down into five 3-week sprints, with Sprint 1 starts on 1/22/2024 and sprint 4 ending on 5/5/2024. The total time capacity for each team differs depending on the availability of team members and the number of school days within that Sprint timebox. Specifically, Sprint 3 will have reduced capacity due to school spring break.

The team will have daily standby scrum meetings at 8:15 PM from Monday to Wednesday. During the scrum, we will first go through each team member for updates. At the end, we reserve a “round table” time for any team member to bring up any item for discussion. The main focus of scrum is on the following topics:

1. What was accomplished since the last scrum?
2. What is going to be worked on until the next scrum?
3. Are there any impediments or blocker issues?

The project team has the following roles and responsibilities:

**Product Owner**: David Akers

* Is the primary liaison between the team and the partner POC.
* Communicates the product vision.
* Evaluates customer requirements and feedback and translate into user stories.
* Enters, prioritizes, and manages customer user stories in the product backlog.

**Scrum Master:** Lap Lam

* Implements project Agile practices.
* Schedule and host Agile meetings and required ceremonies, as determined by the team.
* Keep team member on track, informed, adhered to Agile practices.
* Assist product owner in product backlog and in sprint tasks.

**Developers**: Gregg Rich, Brian Monter, Ashley Atzingen, Sai Kamdamba

* Assist Scrum Master and Product Owner in task estimation, assignment, and sprint planning.
* Work on assigned sprint tasks and update status accordingly.
* Attend stand up and communicate status as well as blocker issues.

The project schedule follows the recommended outline for a data analytics project. The sprints are as below:

* **Sprint 1 – Problem Definition:** the goal of the sprint is to connect with our partner POCs in the US Fish and Wildlife Service to research and define scope of the problem. This includes understanding high level requirements and the vision of the final product. In addition, we will complete section 2 of the project report.
* **Sprint 2 – Datasets:** the goal of this sprint is to research and analyze the provided and/or available public datasets from our partner. The team reviews the size, quality, integrity, and feature definition of the data. Any questions or ambiguities regarding the data must be worked out with the partner at this point. Exploratory Data Analysis and data wrangling are carried out during this sprint. Data is stored in a SQL type database. In addition, we will complete section 2 of the project report.
* **Sprint 3 – Analysis & Algorithm**: the goal of this sprint is the application of analytics to on the data to allow real-time querying and prepare time-series visuals. Data can be exported as tables as in the Flyway Data Book examples. In addition, we will complete section 3 of the project report.
* **Sprint 4 – Visualizations:** the goal of this spring is to create and publishing meaningful time-series visualizations of the data. The visualizations will be driven by real-time filters directly on the dataset stored in the database. In addition, we will complete section 4 of the project report
* **Sprint 5** **– Final Report & Presentation**: the goal of this sprint is to refine and complete the final report for submission. The presentation slide deck is prepared for team presentation. The presentation is scheduled for 4/30/2024.

Sprint 1 Analysis – Problem Definition

In Sprint 1, the team kicked off the project by undertaking key tasks to establish a solid foundation and problem definition the upcoming project phases. The team actively utilized the Agile methodology in YouTrack to promote transparency and adaptability. The combination of setting up the YouTrack Agile Board, defining the problem, reviewing provided data sets, preparing the solution diagram, researching technologies, and completing the project report section 1 laid the groundwork for a well-informed and structured progression into subsequent sprints. The team established team norms, schedule for daily scrum and weekly partner meetings. Overall, sprint 1 was a team success, involving active participation and contribution from all team members. In summary, the team completed the following tasks:

* Setting Up Initial Agile Board and Sprint 1
* Defined and framed the problem scope and product vision with help from partner POC
* Reviewed the provided dataset from partner
* Arrived at preliminary solution, design diagram, and selected techonologies.
* Completed all project deliverables, including weekly status reports, presentations, and report project section 1 writeup.

Sprint 2 Analyis - Datasets

In Sprint 2, the team made significant progress across various tasks, concentrating on analysis of the migratory bird harvest data, Tableau visualizations, and data calculations. Overall, the team's accomplishments in performing table calculations, creating visualizations, conducting harvest data EDA, building Excel generation proof-of-concept code, and assessing tools reflect significant progress towards project goals. These achievements not only contribute to enhancing data analysis and reporting capabilities but also lay the groundwork for future iterations of the project. In summary, the team completed the following major tasks:

* Performed calculations for tables in data book report​.
* Performed Exploratory Data Analysis (EDA)​.
* Built code module for Excel table generation code in Python as Proof-of-Concept.
* Evaluated and Proof-of-Concept for Tableau public for dashboard hosting​.
* Completed all project deliverables, including weekly status reports, presentations, and report project section 2 writeup.

Sprint 3 Analysis – Analysis and Algorithms

This sprint marked significant progress and achievements across multiple areas, showcasing the team's capabilities in data analysis, PYTHON scripting, analytical modeling, and geospatial visualization. The team successfully completed all tasks planned at the start of Sprint 3. All team daily scrum meetings were held as scheduled. In summary, the following items were accomplished:

* **Developed New Python Scripts with CLI for Table Generation**
  + Created two new Python scripts, HarvestTableGen.py and HunterTableGen.py, equipped with Command Line Interface (CLI) functionality for efficient table generation.
  + Integrated Complete Code for Table Calculation with Excel Workbook Generation Module.
  + Ensured automated functionality and accuracy in generating Excel workbooks with calculated tables, facilitating data reporting and analysis.
* **Applied ARIMA Model Analytics on Harvest Data**
  + Utilized Flyway GeoJSON data files to build interactive maps in Tableau, visualizing geographic data with enhanced clarity and functionality.
* **Implemented Automatic Time Period Average Calculation:**
  + Developed and implemented code for automatic time period average calculation, improving efficiency and accuracy in data analysis.

Sprint 4 Analysis

This sprint made significant progress and achievements in scripting, analytical modeling, and Tableau visualization. Team members attended daily scrums, partner meetings, and scheduled classes. The team successfully completed all tasks planned at the start of Sprint 4. In summary, the following items were accomplished:

* Built Geospatial visualizations in Tableau
* Completed the Hunter Data Dashboard and published to Tableau Public
* Completed development, documentation, and testing of HunterDataGen.py and HarvestTable.py
* Completed wireframing for Harvest Data Dashboard
* Started setup for final product deliverables including Tableau projects, executables, scripts, and user guide documentation

Sprint 5 Analysis

Sprint 5 Analysis

This sprint saw completion the final project report, the showcase presentation slide deck, and visualization dashboards. The team finished development of three major visualization dashboards for harvest and hunter data. Team members attended daily scrums, partner meetings, and scheduled classes. The team successfully completed all tasks planned at the start of Sprint 5. In summary, the following items were accomplished:

* Completed and published 2 Harvest Data Dashboard to Tableau Public.
* Completed and published the Hunter Data Dashboard to Tableau Public.
* Completed final artifacts along with user guide, and documentation to deliver to partner.
* Finalized the Project Report for course submission.
* Prepared and finalized the final Showcase Presentation for April 30th.

Reference

**REPORT SECTION INSTRUCTIONS**

The References section of this document makes use of the **Microsoft Word built-in References** feature to insert research citations by recording them directly into the document. All citations are to follow the IEEE citation format. Use the Bibliography drop down to have Microsoft Word dynamically create your Works Cited section here in IEEE citation format.

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