Curating Quantitative Methods to Detect Long-term Trends in Phenological Species Monitoring

Client: Emily Kuzmick – Ohio Coastal Training Program Coordinator; ODNR Old Woman Creek National Estuarine Research Reserve

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Abstract:

Phenological species monitoring is crucial to determining the impacts of climate change on key indicator species (Diez et al. 2012, Ibáñez 2010). The Old Woman Creek National Estuarine Research Reserve (OWC NERR) is one of two reserves operating under the National Estuarine Research Reserve System (NERRS): a division of the Ohio Department of Natural Resources (ODNR) established in 1960 (Herdendorf et al. 2006). The OWC NERR runs a phenological program with 9 species monitoring initiatives including all-inclusive avian species, nest box monitoring with native cavity nesters such as tree swallows, bald eagle nesting data, and lungless salamander population data. The OWC NERR conducts research through citizen science by having volunteers make observations and collect data across initiatives over time. Using citizen science as a collection method may lead to the introduction of specific forms of biases and errors that must be overcome to draw meaningful conclusions. The OWC NERR asked our team to examine data from the selected initiatives and to attempt to answer the research questions they provided. To do this we made a Quality Assurance Quality Control plan for data collection and data entry for recommended adoption into OWC NERR's protocols and to make data clean-up for us and future research teams more manageable. Data clean-up consisted of a master R validation script that was adapted for the selected initiatives. We ran into common data entry errors (i.e., misspellings, inconsistencies, different name entries for the same observer) and flagged missing data or data that fell outside of the program's protocols. After the data clean-up, we created data analysis scripts for each selected initiative, all ran an "na_frac" table to determine what made up the missing data, most of which was weather entry data. We all set about answering the research questions provided through modeling and graphical analysis as well as determining the number of biases and errors there may be to continually keep new data entries up to protocol requirements without having to constantly change the clean-up validation script. After the analysis, we compiled a list of recommendations to present to OWC NERR to help develop a better Quality Assurance Quality Control protocol in which data collection and entry is consistent and to remove certain biases and errors. We also included recommendations for the individual initiative protocols and recommended to remove the need for volunteers to enter weather data and instead use the on-site weather station and water quality SWMP data collection that also runs out of OWC NERR. Also, to include detailed pictures or offer the use of an app like Canapeo to determine exact cloud cover and vegetation cover. Finally, we recommend overall that each initiative should implement key life stage observations to make it easier to go through the data for specific information that can lead to better educational material and volunteer training.

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Introduction:

The Old Woman Creek National Research Reserve (OWC NERR) is one of two reserves in the Great Lakes, of 30 in the nation, operating under the National Estuarine Research Reserve System (NERRS): a division of the Ohio Department of Natural Resources (ODNR) established in 1960 (Herdendorf et al. 2006). The reserve is located on a freshwater estuary (Herdendorf et al. 2006) usually defined as freshwater from rivers entering tributaries and mixing with salt water at high enough volumes to exclude high salt concentration but remaining more saline than freshwater (Bates and Jackson 1980). However, the reserve is unique as Old Woman Creek mixes with Lake Erie's freshwater which makes it chemically different from both with negligible salt concentration (Herdendorf et al. 2006). This unique ecosystem provides a specialized habitat for many keystone and indicator species, which can provide insight into overall ecosystem health (Herdendorf et al. 2006).

OWC NERR's Phenological Species Monitoring Program collects information on 9 different projects in which volunteer citizen scientists are trained to collect phenological data on keystone and indicator species within the freshwater estuary. Citizen science efforts enlist members of the public to collect large quantities of data over time and geographic space (Bonney et al. 2009). Citizen science is scientific research conducted by the public regardless of their educational, professional and/or personal background. The use of citizen science has grown exponentially within recent decades which can be primarily attributed to technological advancements (Adler et al. 2020). Citizen science has the ability to include people in research who may not have the background specific to the scientific community, making data collection more inclusive and efficient. However, there are certain biases and errors that accompany the implementation of citizen science. Biases and errors in citizen science data collection efforts can include but are not limited to, measurement errors, differing levels of skill in identification, and spatiotemporal clustering (Bird et. al 2014). There are ways to address and account for these ranging from statistical solutions to more structured data collection. For our group's research, we will address citizen science biases and errors in our recommendations and how OWC NERR can reduce these going forward.

OWC NERR's citizen science team collects phenological data on both indicators of ecosystem health (e.g., mole salamanders, great blue herons), and ecological keystone species (e.g., bald eagles, muskrats, beavers) within the estuary. Research in phenology - "the study of cyclic and seasonal natural phenomena, especially in relation to climate and plant and animal life" (Latteman 2018) - provides a time series establishing trends relative to national data and climate change. With over a decade of citizen science programmatic implementation, the reserve maintains a robust dataset. The citizen science phenological monitoring research will be used to develop an understanding of the impacts of climate trends on indicators and keystone species. It will also be used to inform Great Lakes coastal wetland resource management. According to the

OWC NERR's Climate Sensitivity Index, the reserve ranks highest in "Overall Ecological Stress" (Latteman 2018).

The OWC NERR's Phenological Species Monitoring Program follows guidelines outlined by NOAA (Herdendorf et al. 2006), and each initiative has individual protocols for data collection on observed species. However, the program lacks sound quality assurance and quality control (QA/QC) protocols, leading to potential observation/frequency bias and human error.

Phenological Species Monitoring Initiatives:

OWC's Phenological Species Monitoring Program focuses on different Keystone (K), Indicator (I), or Sensitive (S) species listed below

1. Bald Eagle Nesting Activity (K)
2. Tree Swallow Nest Boxes (S)
3. Lungless Salamanders (I)
4. Secretive Marsh Birds (S/I)
5. Frogs and Toads (I)
6. All Inclusive-Avian Species (S/I)
7. Muskrat Activity (I/K)
8. Beaver Activity (K)
9. Vernal Pool/Mole Salamanders (I)

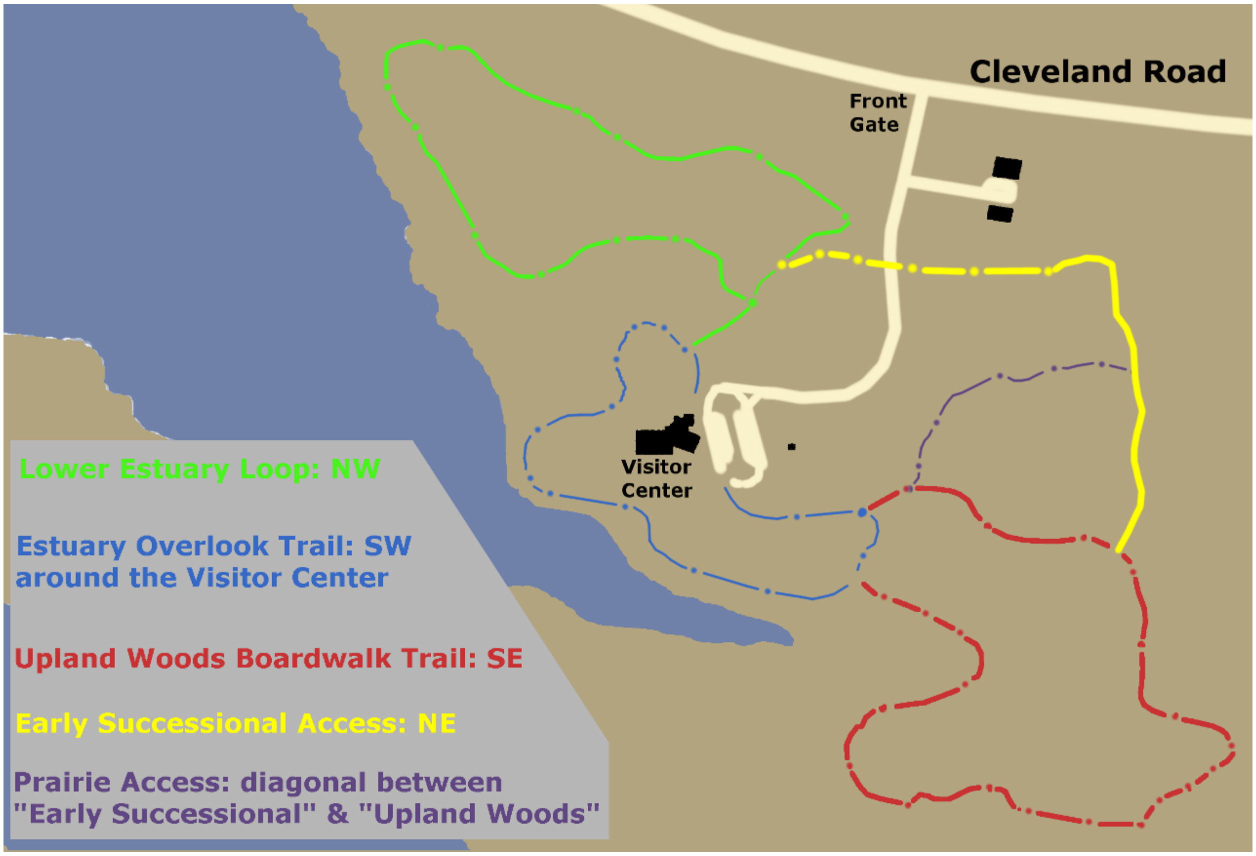

Figure 1. Old Woman Creek National Research Reserve trail map (Platt 2016).

Quality Assurance/Quality Control (QA/QC):

Quality Assurance/Quality Control (QA/QC) guidelines provide instruction on how to pre-emptively prevent introducing errors in a dataset (QA) and correct or flag errors that may be introduced or are from prior data entries in the dataset (QC) (Michener 2017). Errors can be introduced into a dataset through multiple pathways. Common errors are introduced through human error due to lack of training, experience, accidental oversight, or inaccurate, inconsistent, or malfunctioning tools/software used to collect variables (Barchard and Pace 2011; Michener 2017). A single error can notably change the outcome of a test from insignificant to significant or vice versa (Barchard and Pace 2011).

Sound QA/QC guidelines are necessary to utilize citizen science data better and establish trends applicable to ecological models (EPA 2019). Importantly, established QA/QC guidelines must be actionable and mindful of limitations faced by government agencies and citizen scientist initiatives. Limitations may include limited funding availability, restrictions on software authorization, and the time and resources available to spend on recruitment, retainment, and training of citizen scientists (ODNR 2022; GSA 2022; Adler et al. 2020). Our team worked with OWC NERR's Coastal Training Program coordinator to learn about her team's specific restrictions when conducting citizen science research. The coordinator suggested developing a citizen handbook and protocol training and also making tablets available to volunteers to use their Google forms.

Previous attempts by OWC NERR to design models and create infographics have seen varying degrees of success due to the lack of a more cohesive QA/QC on the data. To address the needs of OWC NERR, our team established research for a design protocol with an associated QA/QC to improve the usefulness of study outcomes and allow for inter-study comparison of data. Our QA/QC recommendations are listed in Figure 2. All recommendations are further explored in the *Recommendations* section of this report.

Quality Assurance (Preemptive)	Quality Control (Verify Quality)
Database Transfer from Excel to Microsoft Access (or other relational database software) Standardize Format of Data (Nominal data must be in the same format, e.g. Names: First Name, Middle Initial, Last Name) Standardize Forms (written forms must be consistent and match online forms) Standardize Terminology Used (e.g., what is a fledgling vs. a juvenile?) Include Image References to Explain Percent Coverage (Cloud Coverage, Vegetation Coverage) Better Documentation of Changes in the Data Format Documentation or Tagging of Important Life Cycle Events Coordinating Surveys to Reduce Sampling Bias Review/Training Sessions for Volunteers	Rare Species, first verify with eBird Compare Data to Local Sources (weather stations) Checking Dates and Hours of Observation (flagging observations that fall outside a reasonable time) Flagging Biological Impossibilities System Knowledge to Decide Reasonable Variable Ranges

Table 1. Developed Quality Assurance/Quality Control table from literature review research and dataset analysis.

Once these guidelines have been established, future research teams can identify datasets that lend themselves to long-term analyses which can aid future research, including developing adaptable ecological models.

Overview of Initiatives:

Monitoring Protocol Broadly:

OWC NERR generally asks its observers to record some of the same information for all monitoring initiatives. Important temporal and spatial covariates are asked for each initiative: when and where the observation took place, and who was making the observations. Also, weather conditions such as temperature, wind speed, precipitation, and others are asked for most of the initiatives. Some initiatives also record some environmental parameters and ask observers to estimate the percent cloud cover and percent foliage fill out.

For this project, our team validated the all inclusive-avian species, bald eagle nesting activity, tree swallow nest boxes, lungless salamanders, and muskrat activity datasets. We then analyzed all inclusive-avian species, bald eagle nesting activity, tree swallow nest boxes, and lungless salamanders. We did not have sufficient resources to analyze the muskrat activity dataset.

All Inclusive-Avian Monitoring:

The avian monitoring initiative requires participants to remain at one of 4 locations for 15 minutes, and record every bird they are able to see or hear within that time frame within a 100m radius. Individuals record the time of observation of each individual of each species, and whether that individual was seen and/or heard. Unlike other data collected through the program which focuses on a very specific group of species, this initiative opportunistically collects data on over 100 species. This feature makes this data valuable for both individual species monitoring, but also the best-suited database for analyzing biodiversity within OWC NERR grounds.

Research Questions:

- **How is species diversity changing across habitats?**
- **How is species presence changing with temperature?**
- **Are there long-term shifts in seasonal timing when certain species are present?**

Bald Eagle Nest Monitoring:

The bald eagle monitoring initiative began in 1995 to measure population growth, two decades after bald eagles were listed as critically endangered (Bowerman et al 1998). In 1975, only 4 known nesting pairs were found in the state of Ohio. After the insecticide, Dichlorodiphenyltrichloroethane (DDT), was banned the population rose to just under 300 nesting pairs in the state of Ohio (Bowerman et al. 1998). Despite population increase, OWC NERR continues to monitor bald eagle nest sites due to concerns that climate change is expected to impact bald eagle populations, incubation times, and the growth of chicks (Schmidt et al. 2020; Cain 2012).

Each year bald eagles return to nesting sites located within Reserve property. Citizen scientists observe the nests on a multi-weekly basis (typically between February - June each year) at irregular time intervals during standard operating hours (9:00 am - 4:00 pm). All observations take place within a maximum of 2 hours with observations noted every 15 minutes or when there's new activity. Two nesting sites remain under observation, one on the west side of the green trail, and the other located off of the red trail (*Figure 1*). Observations take place from specified observation locations and the cartesian direction from the point of the observer to the observation nest is recorded. Citizen scientists also record local weather forecasts and conditions, the presence or absence of chicks, juveniles, and adults, and a series of qualitative observations on activity levels and behaviors.

Research Questions:

- **How is bald eagle nesting activity changing with temperature?**
- **How is nesting bald eagle pair presence changing with water quality?**

Nest Box Monitoring:

The nest box initiative has 18 nest boxes placed within a natural prairie ecosystem at Old Woman Creek to aid population growth in tree swallows (*Tachycineta bicolor*), a short-term native migrant bird that has had its population impacted by human factors such as logging and urbanization (Latteman 2018). In addition to human factors, the tree swallows population has been negatively impacted by invasive species such as the house sparrow (*Passer domesticus).* These 18 nest boxes at Old Woman Creek have been monitored bi-weekly since 2013, from the beginning through to the end of nesting periods. Activity within each nest box (nesting, eggs, empty, etc.) and any information about the habitant inside are recorded. If there is a clear indication that a house sparrow is nesting within one of the nest boxes, the nest is removed (Latteman 2018).

Research Questions:

1. **How is nest box activity changing with temperature?**
2. **How are native cavity nesters (e.g., tree swallows) faring over invasives (e.g., house sparrows) over time?**
3. **How does diet availability (i.e., mayfly arrival & population) impact tree swallow presence/abundance?**
4. **Are there long-term shifts in seasonal timing of when certain species are present?**

Lungless Salamander Monitoring:

The lungless salamander initiative has six monitoring areas; weekly year-round monitoring takes place and observers conduct unmarked capture-release surveys via cover object sampling. Of the six sites, the first two sites have natural vegetation (i.e., logs, woody debris) as cover objects, the next two are hybrid being made of both natural vegetation and artificial (i.e., tiles) cover objects, and the last two are entirely composed of artificial cover objects. The soil temperature is recorded as well as the weather, cloud cover, air temperature, precipitation, and humidity. As for the salamanders, the number of juveniles, adults, and eggs that were observed was recorded as well as the overall activity level, the site number the observer was at, and the description or number of the cover object. The initiative's goal is to identify any correlation between the Lungless Salamander's activity and presence with temperature (e.g., soil and air temperature) and precipitation. The client also wanted to identify any correlation between the activity and presence with the type of cover object (i.e., artificial or natural) to ensure consistency across sites.

Research Questions:

- **How is lungless salamander presence/activity composition changing with temperature?**
- **How is lungless salamander presence/activity composition changing with precipitation?**

Muskrat Monitoring:

The muskrat initiative monitors areas of the estuary where muskrats build huts; monitoring takes place spring-autumn and observers paddle out onto the estuary to eight designated zones. The monitoring records the exact location, the presence of a lodge (i.e., huts) as well as height, width, length, box, and dome approximation. The area of the estuary is broken up by zones and flag IDs, both are recorded during muskrat observations. The initiative's goal is to identify any correlation between the Muskrat's activity and presence with water attributes, the mouth of the estuary status is recorded as open or closed, and water quality and estuary water depth (m) are determined from OWC NERR's SWMP data, water depth (cm) at the lodge and overall observed estuary depth (m) is recorded, and the overall weather conditions. Activity level and vegetation cover around the lodge and surrounding area are both observed and recorded as well as the dominant vegetation species. The client's questions for the muskrat initiative involve the correlation between muskrat activity levels and water quality, also the change in hut composition with water levels, and the status of the estuary's mouth.

Research Questions:

- **How is muskrat hut composition changing with water levels/estuary mouth status?**
- **How is muskrat activity changing with water quality?**

Literature Review and Methodology:

Literature Review:

Our group's literature review focused on phenology monitoring broadly and species/initiative-specific literature. Considering the importance of temperature and weather, we specifically wanted to examine how this information is incorporated into species phenology in a diversity of contexts. We also examined what types of models and analyses are suited to citizen science data and phenology data. For each initiative, we searched for literature that used similar types of data and asked similar questions. We also looked for relevant biological information that could inform analysis and modeling.

General Methodology:

Temperature:

Temperature data is extremely important for phenology, although how it is applied is very different depending on the study system. For many species that have specific behaviors or temperature dependent emergence, degree-days are used to predict these traits. Degree-days is the amount of time that has reached a certain temperature, which is system-dependent (Richardson et al. 2006, Higley et al. 1986). This technique is generally applied to insects and plants but has been applied to some vertebrates (Hjernquist et al. 2012, Saino et al. 2011). Applying this concept to vertebrates comes with the problem of selecting a cutoff. There are often no clear cutoffs, ranges of cutoffs are explored for some species, and even ectotherms can modify their behavior somewhat to adjust to a given thermal environment (Saino et al. 2011, Sagonas et al. 2013). A similar approach that has been applied to a broader range of species is an averaging approach. Depending on the species you can pick a period over which the temperature is expected to matter, and find the average temperature over that time. This incorporates time and temperature like the degree-day, but rather than picking a specific temperature you only need to select a specific time range (Garcia-Tejera et al. 2022). Sometimes we favor aberrant temperatures, and this requires us to "detrend" the data and extract information on when temperature deviates from this trend. For this, you construct a simple model and look at how much temperature deviates from that model. For example, we can model temperature by time of year, and then look at when temperature deviates from the average for that time of year. This is useful for climate change since detrended data can tell us how much the deviation in temperature affects a given species (Iler et al. 2017). We also found a method that used a moving window over the time of year for each observation, and fit linear models within that window to discern phenological patterns (Daru et al. 2019). Depending on what exact questions are being asked about the system, and which species are being studied, some of these approaches may be better than others.

Sometimes temperature may not be affecting a species' behavior/distribution, but rather the probability of detecting that species. For this the current, or recent, temperature is much more important than the past temperature, and this can be more challenging. Most protocols ask for the current temperature, but sometimes this data is missing. To use local weather station data for this purpose one would need to create some kind of model for temperature and use that model to interpolate temperature between points of measurement. This can be done with several methods, but generally requires some kind of model. A common and effective method is called kriging, or gaussian process regression (Le Riche and Durrande 2019, Roberts et al. 2013, Frazier et al. 2016). There are a number of versions, but we will discuss the general application. This is often applied to geospatial data, in which kriging is conducted on a 2-dimensional surface, but can also be applied in a 1-dimensional context which is more often referred to as gaussian process regression. The underlying math assumes some covariance between observed points, which are drawn from a theoretical multinomial distribution. This method bases prediction for unsampled space based on proximity to nearby sampled points. Kriging makes a number of assumptions that may make it inappropriate in this case (for example, there should be no general trends in the data, and that data are normally distributed). Other models can accomplish similar results, and the Bayesian state space models have been applied for filling gaps in temperature data in similar citizen science contexts (Maguire and Mundle 2020). Many of these techniques are also likely appropriate for other types of weather variables although would require modification for data that were not normally distributed, such as cloud cover (beta-distributed) or precipitation (some strictly positive distribution).

Canopy Cover:

Many of the protocols ask surveyors to estimate plant cover, which is divided into percentage categories. We found several applications that can measure this more precisely and accurately than the estimates produced by disparate observers. Canopeo was a good candidate because that creates results consistent with professional image processing software and has free applications for both Apple and Android devices (Patrignani and Oschner 2015).

Species Presence:

Most if not all of the monitoring initiatives can be interpreted in a presence-absence framework. For this purpose, it is important to expand the information in the data to include implicit absences. For the avian monitoring protocol, this would mean including implicit zeros in each observation event on which that species was not seen. This also helps to account for survey effort, if you plot data on a per-survey basis (percent of time it is seen on a given survey) then you automatically would not over-represent presence just because a certain time period has more observations. When plotting this type of data, it is important to look at averages over a specified period or variable range, since graphing raw 1s and 0s is difficult to visualize.

In terms of analyzing this type of data, there are several analyses and modeling techniques that are catered to this type of data. Depending on what type of questions are being asked, different techniques would be appropriate. When trying to determine simply how often a given species is seen, using a Generalized Linear Model with a binomial distribution for the likelihood can predict basic patterns in species observation. It is also possible to include observers as a random effect in a linear mixed model, which has been shown to help account for observer experience in citizen science applications. This can be further extended to non-linear models or a Generalized Additive model. This class of models can fit smoothed, nonlinear curves to data. This can be extremely useful for nonlinear relationships, like seasonal sinusoidal relationships.

If the only thing that matters is the predictive effect of the model, and not the relationship between variables, then random forests and neural networks can work as purely predictive models. These are generally applied to species distribution models and are unlikely to be particularly valuable to OWC NERR.

When trying to determine how often a species is occupying a space, whether it is observed or not, occupation models are necessary. These are more complex models that attempt to model both species occupancy patterns, and factors that affect the observation of a species given its presence. Various multivariate methods can handle binary data, like clustering analysis.

Species Abundance:

Species abundance data share several similar problems with presence data. Generally, abundance data should incorporate information about when species are absent as well as abundant so zero filling the data is usually necessary. Similarly, when plotting abundance, it is usually beneficial to plot average abundance over some variable since this is easier to visualize than a cloud of zeros, ones, twos, etc. Unlike with presence/absence data, it is easy to misinterpret and create poorly specified models for count data. In an ideal world, this data follows a Poisson distribution, but it is often over/under-dispersed and is often filled with many more zeros than would be expected based on an idealized model. To account for this a negative binomial distribution is often used, or if the data is zero-filled then a zero-filled Poisson or zero-filled negative binomial is used. There is also an R package “vegan” which has many prebuilt functions for analyzing species community data and are designed to handle data in this form (Oksanen et al. 2013). For some of the relevant functions from this package (like “rarefy”), zero-filling may not be necessary, although other types of reformatting often are.

Data Cleanup:

Background:

Real-world datasets in their original form are rarely ready for analysis (Alasadi and Bhaya 2017). Most often they contain inconsistencies and errors that must be addressed before performing robust analysis. Failure to rectify inconsistencies and errors in a dataset precludes our ability to draw meaningful conclusions leading to erroneous results (Chu et al. 2016). Data cleaning and wrangling are both necessary multistep processes utilized for real-world datasets to ensure data quality. Data cleaning is the process by which observations that don't meet collection-determined criteria are flagged, missing data is reconciled, outliers are managed, and structural errors are corrected (Chu et al. 2016). Data Wrangling is a subsequent process that entails converting the format of the data into a usable structure for data analysis (Endel and Piringer 2015). The datasets we received from OWC NERR underwent a multistep data cleaning and wrangling process before we were able to conduct analysis.

General:

Our team received 9 datasets from OWC NERR - each dataset corresponding to one of the citizen science initiatives. We were given access to the excel spreadsheets on the OWC NERR Microsoft Teams drive. We started by reviewing the data to determine the data structure and the robustness of each dataset and find common errors and inconsistencies. After the initial review process, a team member developed a master R script using the avian dataset as a template. This dataset was chosen as the primary dataset to create the Master Script and to use for future analysis because it was the most robust of the 9 initiatives: containing the most data points and requiring the most complex processing steps. The Master Script was designed to perform both cleaning and wrangling objectives. Each script performed similar cleaning objectives which included: creating a robust flagging system that highlights missing data variables, variables that fall outside of program protocols (e.g. data collection time falls outside of standard operating hours or falls outside of allotted collection period), misspellings, and general inconsistencies. Data wrangling objectives included restructuring the dataset by changing the format of data structure to conduct modeling, analysis, and visualization, and pulling data (temperature and precipitation) from the local weather station into the dataset. Team members then copied and tailored the Master Script to accommodate the differences in observation requirements and the specific attributes of each dataset.

We encountered several problems (errors/inconsistencies) in the data and tried to create robust protocols for filtering and cleaning the data for analysis. We also wanted to ensure that the original data was preserved relatively unaltered and that there was a record of where adjustments needed to be made. To address this, we created an R script for each initiative that could read the data, make alterations to a new copy (or copies), and then find discrepancies in the new and original datasheet and record those in a new field in the original copy stored in R. This served both purposes without compromising the needs of either. It allowed us to be particularly restrictive of the data that were included in the analysis, ensuring high data quality from a quality control perspective. It also allowed us to preserve the original data in R so that alterations could be made where there are easily fixed problems. For most of the variables, we took the most reasonable conservative data inclusion approach. We will not go into detail about what values were excluded for each variable in each initiative, since this will be documented in the R code that we will provide to OWC NERR. We do include several sections on particular problems that require unique solutions or that require some further attention by the Species Phenology Team. We also include tables of the missing data fraction after validation using our methods in the appendix of this document.

Observer Variables:

Converting the names of each observer into a standard format required a significant amount of code. The naming system for this variable lacked consistency. Names were written in multiple formats; sometimes including initials, nicknames, and only last names. Because this variable is categorical and nominal, R reads it as a character vector. R software is extremely specific about how it reads “character” information. Capital letters, extra spaces, and different name orders create inordinate complexity. This had to be converted into a standard format for names to have consistent meaning on the software's end. This required us to try to interpret names and coerce names into a set standard. We selected a standard that worked for us, but we had to reduce information to do so and made some assumptions about which names were intended to refer to the same individual. This is likely suboptimal from an organizational standpoint, which we will discuss in the *Recommendations* section.

Rare Species:

In the avian monitoring initiative we found some species that were observed at OWC NERR, but were extremely rare within the eBird database of the region. Since eBird’s protocol is much less restrictive than OWC NERR’s, and their sampling is much denser, we believe these observations are highly suspect. We created a filter that removed them from the validated “good data” and flagged them in the original R datasheet. We also designed this code to flag any new species that occur in the database. This will need to be reviewed and altered if new species invade the region and become common, or if the initiative is expanded into new habitats (such as the beach) where other species are common.

Methodology Applied to Initiatives:

All-Inclusive Avian Species:

To work with this type of data we compared data and used eBird which also provides a rich set of models and observation data. The website, eBird, is a semistructured citizen science platform that allows observers to record observations of birds in several different forms. Contributors select a protocol (incomplete, stationary, traveling, historic, area, etc.), set a location and duration, and then record all the species seen and their abundances during that time. The dataset is extremely large, and global in scope. It is also less restrictive than OWC NERR’s protocol generally, although the area protocol can be specified to be equivalent. For the sake of comparison, there are not sufficient area surveys so we examined all complete checklists from any protocol. Authors have used anything from linear models to neural networks and random forests to analyze this data for different applications.

We adapted methods from the literature to build a Generalized Additive Model predicting the total number of species observed during a given observation event (Johnston et al., 2018, Johnston et al., 2021, Urquhart et al., 2023). The model was built using a negative binomial likelihood family for the response variable, and predicted the total number of species as a function of the year (as a fixed effect factor), observer (as a random effect), wind speed, time of year (as a cyclic smoothed term), start time (as a smoothed term), route (as a fixed effect), and temperature at the time of observation (as a smoothed term). In the R package MGCV it follows the form : total_species ~ s(day_of_year, bs = "cc") + year + s(Start.Time..24.00.) + Route + s(correct_names, bs = "re") + s(Wind.Speed...mph.) + s(Temperature..F.) + Sound.Intensity. We conducted a bi-directional AIC selection on this model, leaving only the AIC optimal terms in the final model used for the rest of the analysis. We also compared the inclusion of year and route in different ways. We fit the optimal model with the route by variables on the day of year spline, to see if different routes may produce different numbers of species at different times of the year. We also tested if including the year as a smooth parameter itself (just as a spline over date) would more parsimoniously explain the data. You can also modify the term k for each smooth which modifies how many control points each spline uses, allowing it to have more peaks and valleys. We did not explore that since it increases computation time, and most of the variance seems well explained by the best models.

We also compared the model results for each year to the average temperature for that year to see if there are trends with annual temperature. We plotted model predictions from the model that included year as a factor, and also constructed a separate model with identical specification but including annual temperature as a predictor in place of the annual factor.

An author examining eBird data found that indices created from a random effect fit from the total number of species observed were also useful as an overall index of observer skill, and could help improve models of individual species that were difficult to observe (Johnston et al. 2018). We extracted the equivalent observer skill measures from this model for use in future single-species models.

To examine the change in biodiversity across the different habitats sampled at the reserve, we used the “rarefy” function from the “vegan” package to determine the species richness of each route. Rarefaction is a common tool for community ecologists that uses the total number of each species observed to create simulated subsamples of individuals from the community. These subsamples can then be used to estimate the expected number of species observed after observing a set number of individuals. This is used so that we can compare the expected number of species observed across different routes with different levels of surveying effort.

In order to compare this data with regional bird observations, we downloaded eBird observations from a 60x60 mile grid centered on OWC NERR’s property. We then looked at complete checklists from this region and compared eBird species observation frequencies to OWC observed frequencies. We also compared which species were mutually exclusive to either database. This tells us if some species are missed by OWC’s sampling protocol, and if there are species observed at OWC that are not present in the eBird database.

Nest Box:

To effectively address the research question “How are nest boxes changing with temperature?” our group performed a linear regression that essentially tests the relationship between the day of year of the first egg observed in the nest box and the date of observation, across years (Bates et al., 2023). We first created a time series of the observation of eggs in nest boxes over the decimal date. We then applied a linear filtering to that time series and number of eggs observed in the nest boxes and plotted it in a linear model with Decimal Date (x) over Decimal Date divided by one (y). We divided our y variable by one in order to look at the decimal part of the year after the year has been cut off. From this linear regression we were able to deduce that Tree Swallow eggs are being observed earlier in the year, each year. This finding can possibly be attributed to long-term shifts in Temperature affecting nesting patterns in Tree Swallows, but without further data this can not be statistically supported.
In order to make a definitive statement that Tree Swallow eggs are being observed earlier in the year, each year we looked at the R-Squared, P-Value and Slope of the linear model. Our R-Squared was valued at 0.01073 with a P-Value of 0.1172 and the slope 0.0161332. We then

multiplied the slope by 365, to account for the days in the year (Bates et al., 2023), and transformed the units to ~5.88. This shows, preliminarily, that there is about a 5 day shift per year in the number of eggs being observed in nest boxes at OWC.

Lungless Salamander:

We found some good examples of models used for lungless salamander cover object modeling (Luymes and Chow-Fraser 2019; Kleeberger and Werner 1982; Bailey et al 2004). In particular, complex occupancy models have been developed for this group of species. We constructed a Bayesian model using JAGS in R, that modeled probability of presence and probability of observation based on whether a salamander was or was not observed (Bolker 2008; Plummer at al. 2022). Lungless salamanders can live inside the soil and are more likely to come closer to the surface when temperature and precipitation conditions are conducive for emergence into the forest duff layer (Luymes and Chow-Fraser 2019). We have opted to use a Bernoulli (presence absence) distribution rather than using information from counts to simplify the analysis somewhat. Because of model convergence issues we also fit a simpler model that included only site, daily precipitation, and daily temperature.

Description of complex model:

y_i~bernoulli(p_i*z_i)

logit(p_i)=α1*daily precipitation$_i$ + α2*daily-temperature$_i$ + observer_effect[observer$_i$]+ cover_effect[cover object type$_i$]

logit(z_i)=β1*annual precipitation$_i$ + β2*annual temperature$_i$ + β3*year$_i$ + site_effect[site$_i$]

Description of simple model:

y_i~bernoulli(p_i)

logit(p_i) <- site_effect(site$_i$) + α1*daily_precip$_i$ + α2*daily_temp$_i$

P_i is the probability of observation for each observation within the dataset i, and z_i is the probability of salamanders being present at the site. α1 and α2 are both linear slopes on daily precipitation and daily temperature respectively. β1, β2, and β3 are linear slopes on the annual precipitation, temperature, and the trend over years. Priors for all betas,alphas, and fixed effects were drawn from a normal distribution with mean of zero and variance of 1000. Year, site, and observer are random effects, with the site random effect having a hyper-parameter for habitat at the site as well. For the simpler model site was modeled with a fixed effect. All models were burned in for 5000 iterations on three chains before parameters were tracked for another 5000 iterations for testing hypothesis and convergence. There are only two cover object types so this was included as fixed effect. We could not use a more traditional formulation of an occupancy model because the study design violates some of the assumptions of the technique. Occupancy models assume occupancy is consistent within a site (i.e. each cover object is drawing from the same salamander population), which seems reasonable based on the literature surrounding lungless salamander home ranges (Kleeberger and Werner 1982). However, this is almost certainly violated by the use of artificial and natural cover objects, which each likely produce a different probability of observation given that salamanders are present at the site (Hesed 2012). Some natural cover objects are also different sizes, which seems like it would bias observation by allowing more salamanders to hide under larger objects and creating novel microhabitats (Hesed 2012).

In order to test whether artificial cover objects exhibited similar characteristics to the inferior plywood boards described by Hesed (2012), we ran some statistical tests on the soil temperature under the two types of cover objects. We tested whether the means, and variances were the same across the two types. We also plotted the temperature for a visual comparison.

Results:

Each team member ran similar analyses on the selected datasets. The most robust results were found for the Avian monitoring program.

Avian Monitoring:

The AIC optimal model for total number of species observed during each event was able to explain 60.4% of the variance in the data. Most of this comes from the observer effect, suggesting that accounting for the effect of observer skill through models is critical for this dataset. Through AIC selection, we determined that the most likely model was formulated as follows: total_species ~ s(day_of_year, bs = "cc") + Route + year + s(Start.Time..24.00.) + s(correct_names, bs = "re") + s(Wind.Speed...mph.). A full list of AIC for each term from the stepwise selection can be found in the Supplement 1 and the summary of the AIC selected model in Supplement 2. Diagnostic QQ plots and residual plots can be found in Supplement 4. The omitted sound intensity and temperature at the time of observation, which suggests that these are either not as significant or are explained by other covariates. With more data that may change however, especially for sound intensity which was slightly worse in terms of AIC. It seems likely that most of the variation from temperature is better explained by the time of year. We also found that using date as a smooth spline, and fitting a different day of year spline to each route was not as parsimonious, although the date smooth was only slightly worse in terms of AIC.

The number of species observed tended to increase into April, and then slowly decline after June into the winter. This also happens to be when the most surveys are conducted (*Figure 2*). This model also showed a good ability to account for observer skill through a random effect. A table was produced to show the average number of species observed by each observer in an average checklist, which is the metric used by eBird to account for observer skill (Appendix 5). This can be used in individual species models to attempt to account for differences in overall skill. After constructing a general model that accounted for the year as a factor (allowed each year to vary independently), we plotted the predictions from the model for each year against annual temperature and found a clear positive and linear relationship (*Figure 3*). When we included annual temperature in the model as a linear predictor, that predictor was highly significant ($p < .05$) and positive (Appendix 3). We also cannot ascribe this to a change in species composition necessarily. It could be that observers are more accurate or more present in warm weather, or that birds tend to be out in the open more when it is warm. Regardless, this is definitely worth looking into in the future, and maybe looking into whether it is the entire year or a more specific time frame (i.e. 2 months leading up to an observation, springtime temperatures) that is contributing to this phenomenon. Brian Weeks (An ornithologist at the University of Michigan) suggested that the increase in abundance could be the result of available plant biomass in warmer weather, which could be measured through NDVI (Personal Conversation). Because we are using model predicted averages, we can conclude that this is not the result of oversampling at a given time of year or any other covariate included in the model. We suggest using caution when using this to extrapolate to future years, since less than 10 years were sampled at the time of this analysis.

The results of the Rarefaction analysis show that Red and Green routes likely host the most biodiversity based on simulation (Appendix 7). The Blue and Purple Routes are more heavily sampled than the Red and Green Routes so their total biodiversity is higher, which biases the raw data. The Species accumulation curves for Purple and Blue also cross, which means that depending on sampling density either route may be expected to host more species (*Figure 4).* It is possible that the Green and Red routes also cross at some point, but more sampling would be required to determine if that occurs.

When compared to regional eBird data, there are some distinct differences. For most species, the observed frequencies are extremely similar. However, many species that are located in the region are observed far more often at OWC NERR than throughout the region (*Figure 5*). There are fewer species which are observed less often. This is surprising considering that eBird has a more lenient observation protocol, allowing observers to walk around and observe species at any distance over any period of time, while OWC requires observers to limit observations to 100 meters and to 15 minute intervals. This suggests that either the observers at OWC are more skilled than eBird users writ large, or that many species are simply more abundant or active at the OWC. Either way this data suggests that the data collected at the OWC may be uniquely valuable to avian monitoring.

There are 3 birds which are present in the OWC dataset, but absent from the eBird set. These are Bullock's Oriole, Gray Flycatcher, and Sprague's Pipit. These birds are all found farther west of us, although there have been a few very rare observations in the east. These checklists would normally be flagged for review by eBird, and observations confirmed by local eBird users. Without this verification process, we can safely assume that these observations are the result of incorrect identification or data entry. We flagged these species as part of the data validation code, and created a list of acceptable species that can be updated to ensure data quality into the future. The eBird dataset did have 202 species which are absent in the OWC set. We can look more specifically at this by examining eBird checklists which were submitted at Old Woman Creek, but were not necessarily part of the OWC phenological program. This data shows us there are 60 species observed at the park that were not observed during the OWC program. Many of these are rare species which are present in low numbers, and which are unlikely to be captured by OWC's more restrictive protocols and lower sampling effort (e.g. American Pipit, Common Redpoll, and Prothonotary Warbler). Others tend to avoid humans, and are very skittish (e.g. Wild turkey and Sora). Some are missing because their preferred habitat is not present (e.g. Horned Lark and Sanderling). This latter one can be easily remedied by including the beach area as an observation site. In fact, eBird has a separate location for the beach area of OWC, which has 40 species recorded that are missing from OWC set, and many of which are obligate beachgoers, diving birds, and other waterbirds. Anecdotally, we observed Red Breasted Mergansers every day during our first visit at the beach, which are absent from OWC's main reserve dataset.

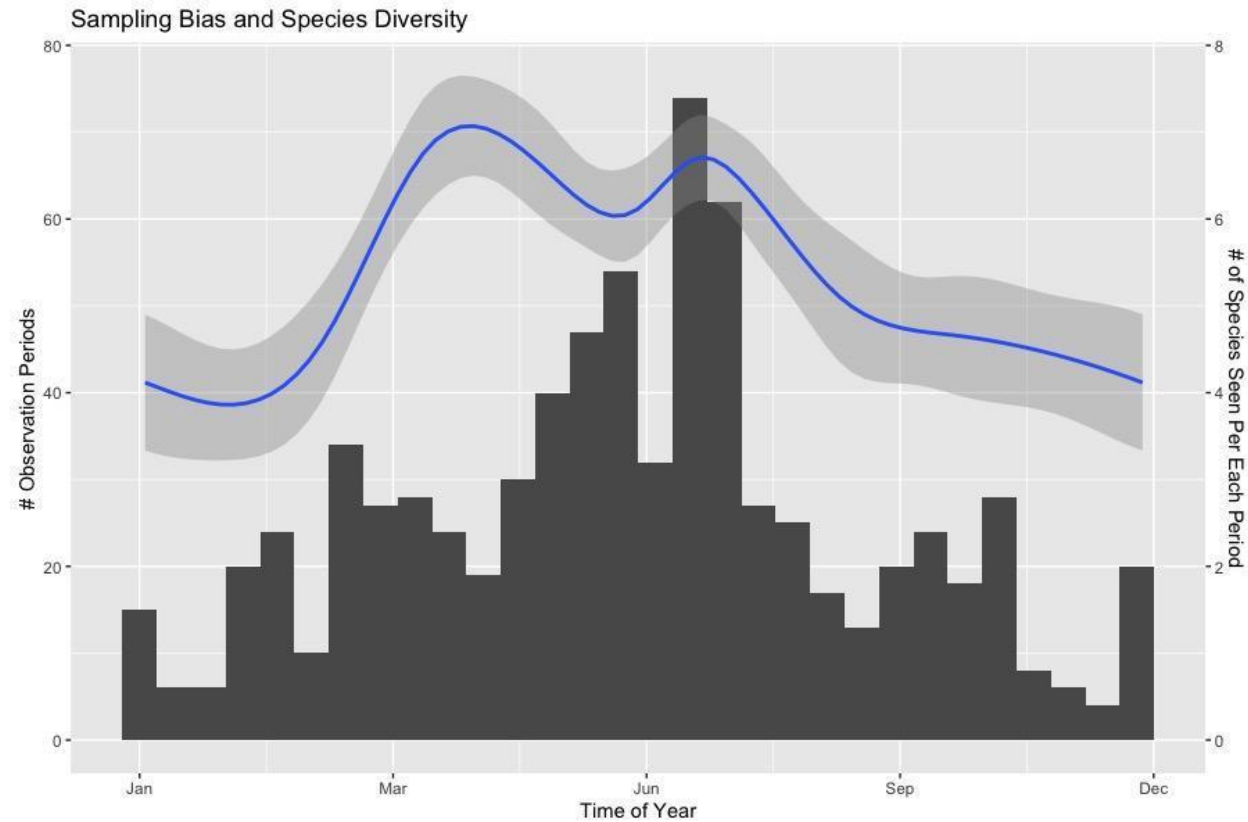

Figure 2. Graphical representation of Sampling Bias and Species Diversity for All-Inclusive Avian dataset. Number of observation periods and the number of species observed during each period compared with time of year to show any possible bias that may exist with seasonal changes.

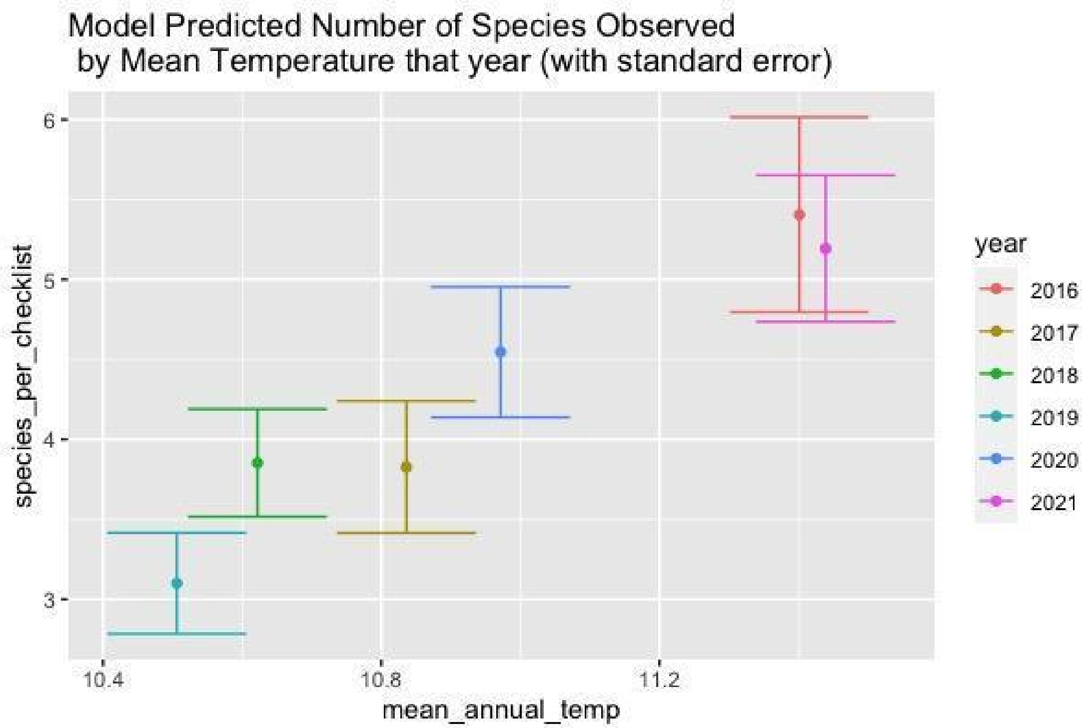

Figure 3. Model ran to determine the possible predicted number of Avian species observed with the mean temperature for each year (standard error is included).

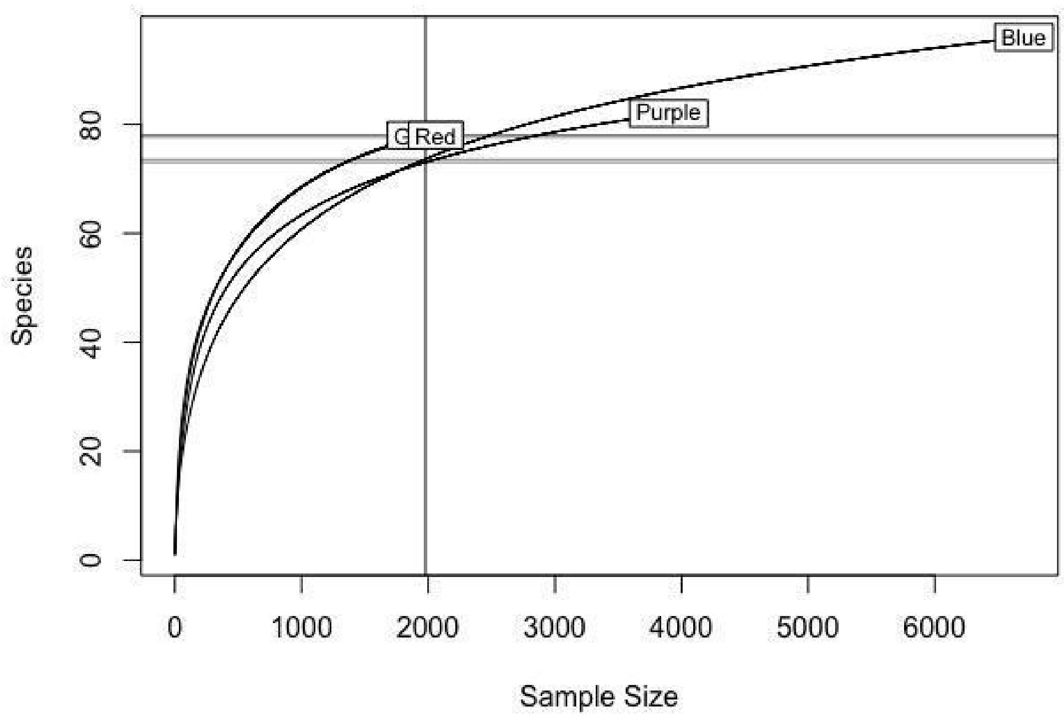

Figure 4. Number of Observations done for each trail route and the amount of Avian species observed.

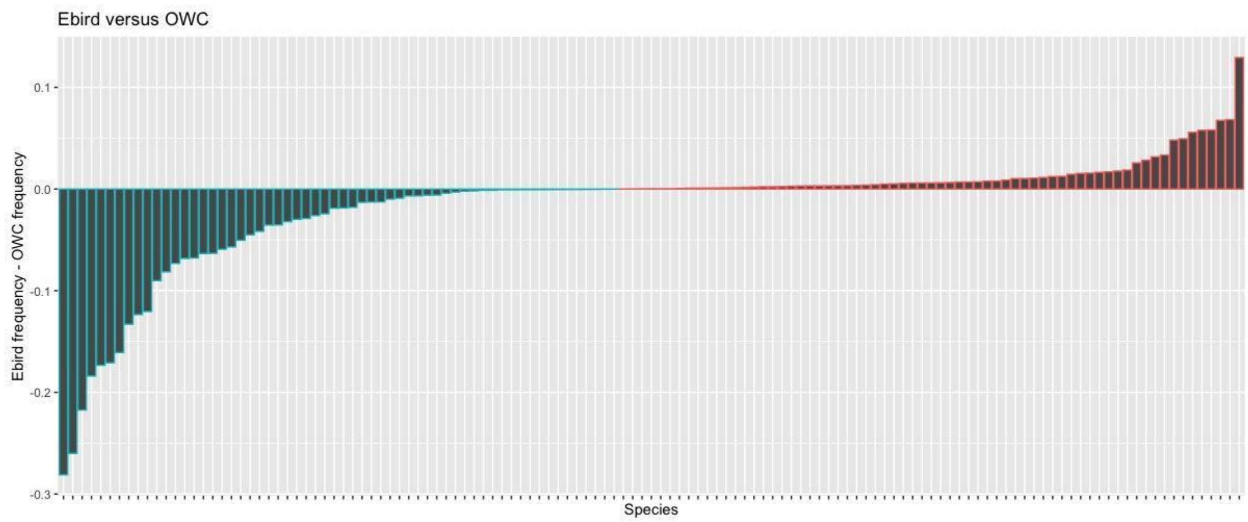

Figure 5. Comparison model of Avian species observed with OWC NERR's volunteers and eBird volunteers.

Bald Eagle:

The Bald Eagle dataset does not lend itself easily to any form of statistical analysis. The available data contains large sections of missing values, biological inconsistencies, and is missing key information that could help explain the phenomena expressed by the data.

We found that the major cause for missing data is due to a sixteen-year gap between collection periods from the year 2000 to 2016. The gap in the data is due to a discontinuation of the Bald Eagle project followed by the reestablishment a decade later. When the program was re-established new variables were added to the survey for citizen scientists to collect. OWC NERR continued to use the original data collection spreadsheet and added new collection variables to the already existing dataset. New variables were added to the excel file without previous equivalents to fill in missing data values. The lack of consistency between the original program and the relaunch of the program yielded a high percentage of missing values.

In addition to the program missing data, our findings showed multiple biological inconsistencies. The major concern we found was that the number of eggs present and chicks present are rarely consistent over the course of a calendar year. When the number of eggs in a given year outnumbers the number of chicks (see year 2017 in *Figure 6*), we could assume that the inconsistency is due to a loss of egg(s) that did not survive to the chick stage. When the number of chicks outnumbers the number of eggs in a given year (see years 2018 and 2020 in *Figure 6*), we could assume that there was a data entry error that needs to be addressed. The inconsistencies are shown in the presence and absence of chicks and eggs in *Figure 6*. Without clear notes indicating major changes in the presence or absence of chicks and eggs, it's difficult to determine the reasons for inconsistencies without relying on post hoc interpretation, searching through inconsistent notes, and institutional knowledge from participants who were present when the events took place.

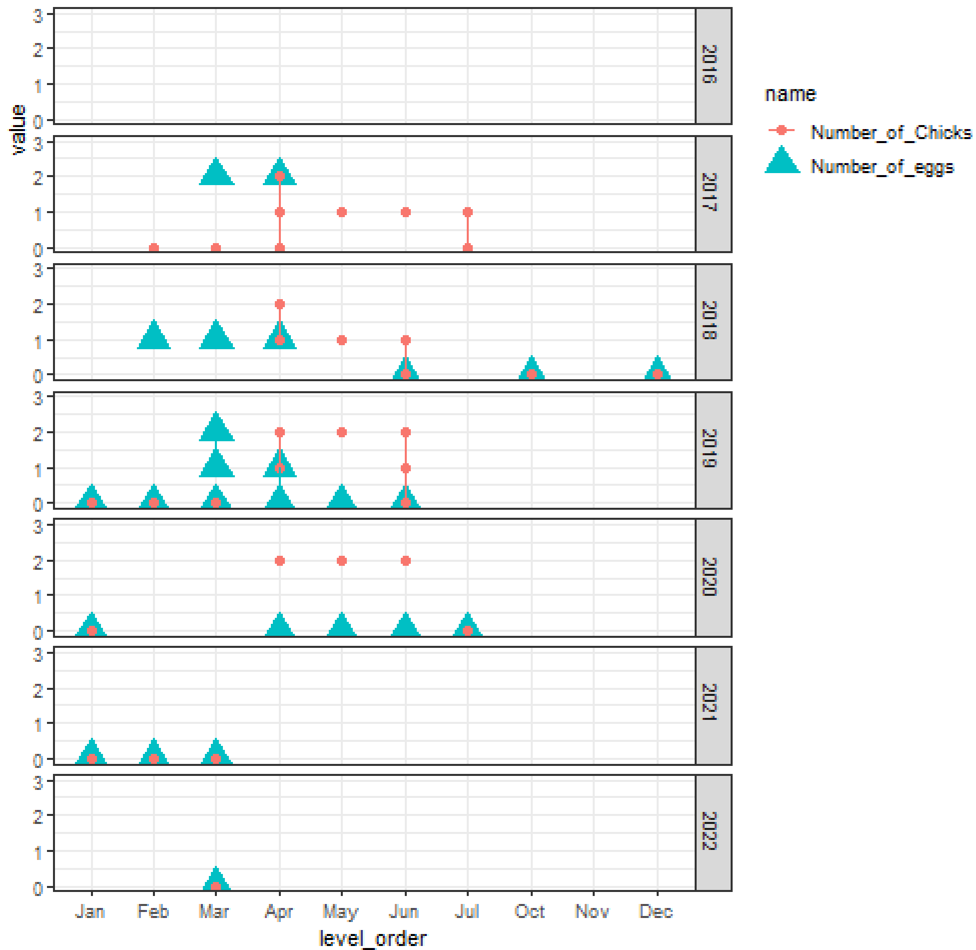

Figure 6. Comparison of number of eggs present and chicks present over the course of a calendar year.

The question identified by the OWC NERR addresses the relationship between nesting activity and temperature and the relationships between nesting pairs and water quality. The data provided was not robust enough to sufficiently answer the questions posed by OWC NERR. Due to the following concerns: there is no data provided under the “Activity Level of Chicks” level, as mentioned previously, the counts of eggs and chicks don’t appear to be accurately accounted. The inconsistencies in counts preclude our ability to draw meaningful conclusions from the data.

Nest Box:

The Nest Box data had sufficient data to address the research questions posed by OWC NERR. This is not to say that the data was robust enough to hold statistical significance in its analysis, but it was at a minimum able to show some trends over time. Data analysis to address the first research question "How are nest boxes changing with temperature?" is described previously in the section *Methodology Applied to Initiatives*. Before running the linear regression, we did look at the relationship between Bird Frequency per observation and Temperature in Fahrenheit (*Figure 7*) where black dots represented Tree Swallows and red dots represented House Sparrows, but this graph didn't show a definitive relationship between the two variables. We then decided to run the linear regression to address this question by looking at different variables provided in the Nest Box dataset.

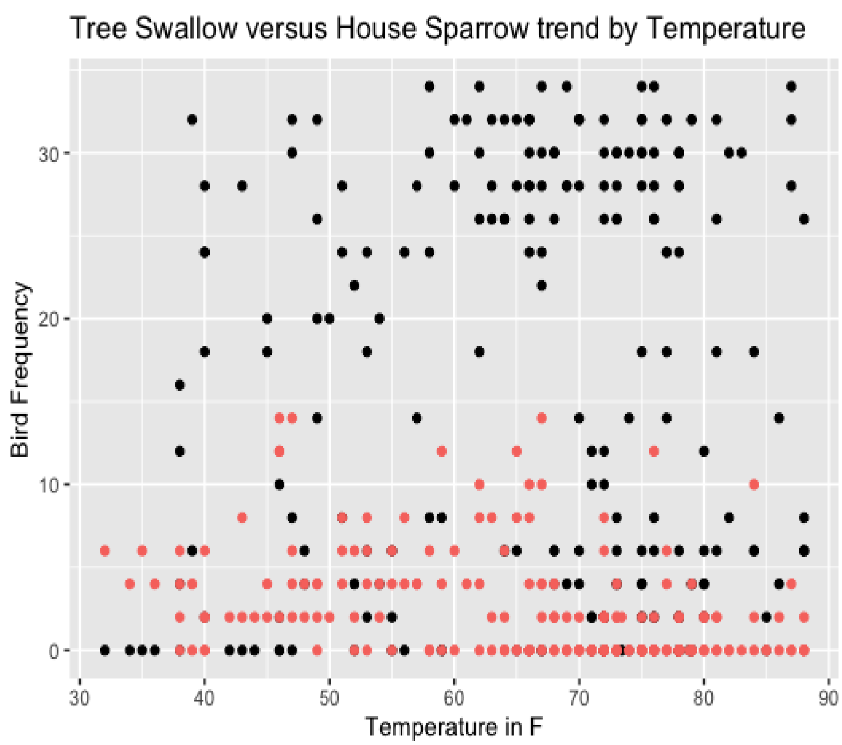

Figure 7. This shows the relationship of Tree Swallow and House Sparrow nest numbers and population with temperature.

Next, we wanted to address the second research question "How are native cavity nesters faring over invasives over time" by looking at Bird Frequency over Years but more data is needed in order to see distinct trends. We then looked at Bird Frequency trends over Months (*Figure 8)*, where the blue line represents Tree Swallow observations, and the red line represents House Sparrow observations. From this graph we were able to see a distinct trend that Tree Swallows are observed more over months than House Sparrows. From what you can see in our graph, there is a slight decrease in House Sparrows over time, which can possibly be attributed to nest removal by observers. This trend is what you would expect to see because of efforts to aid growth in Tree Swallow populations, but additional data would support this.

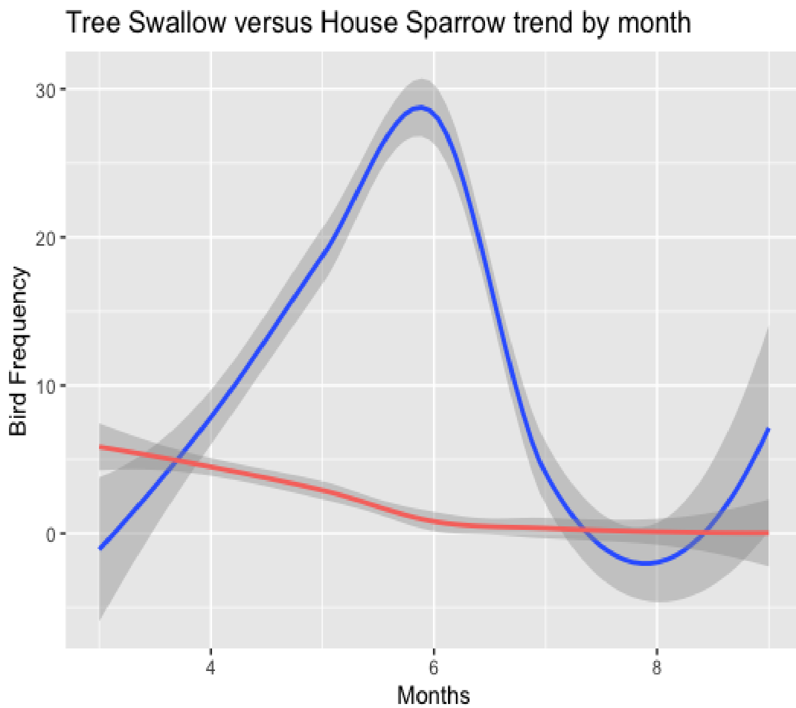

Figure 8. Comparison of Avian population of Tree Swallows and House Sparrows over the course of a year by month. The blue line represents Tree Swallow frequency and the red line represents House Sparrow frequency.

Lastly, we looked at the relationship between Number of Eggs observed in nest boxes and time of year to address the research question "Are there long-term shifts in seasonal timing of when certain species are present?". We additionally looked at the relationship between Number of Babies and Time of Year, as well as Number of Fledglings and Time of Year to ensure the observations were consistent amongst all groups. Number of eggs, babies and fledglings slightly increased over time and could be attributed to nesting patterns of Tree Swallows, but looking at these variables didn't quite answer the question. It should also be noted that it's not definite that the eggs observed in the dataset are from Tree Swallows, but we make this assumption due to the efforts of removing nests made by House Sparrows. Furthermore, our team was able to use the methods applied to the first research question to answer the question of long-term shifts in seasonal timing of when certain species are present. As shown in *Figure 9,* Tree Swallow eggs are being observed earlier in the year, each year. This means that the seasonal timing of when Tree Swallows are present may be shifting to earlier in the year than in previous years, but more data is needed in order to make any definitive statements with statistical significance.

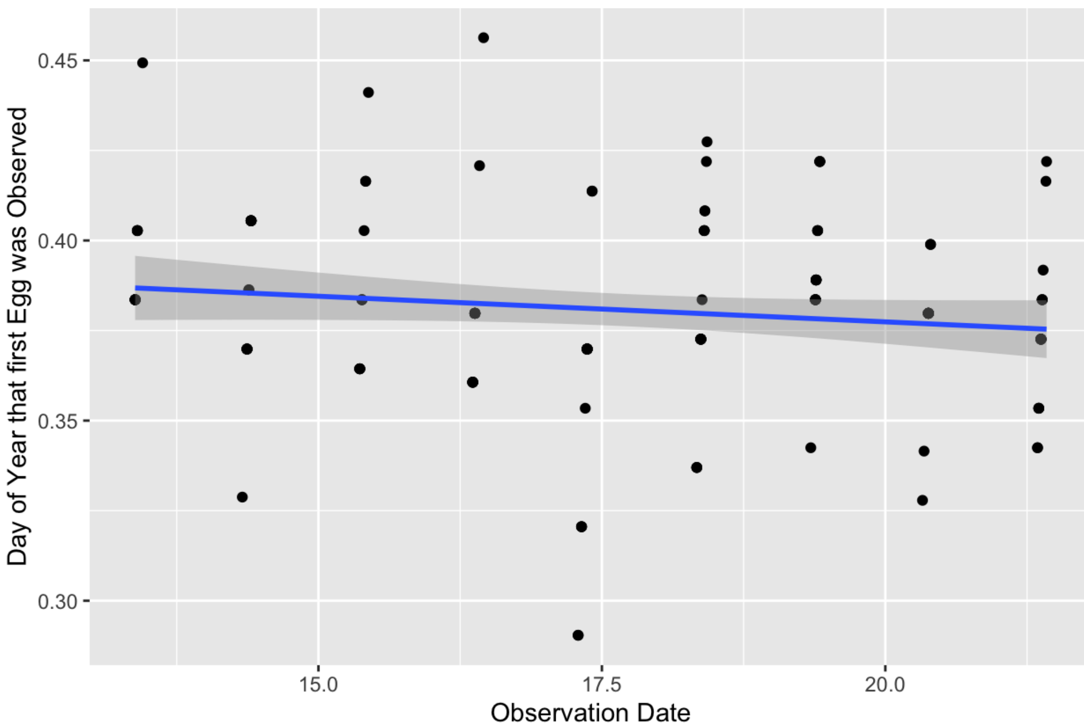

Figure 9. Comparison graph of the relationship between the day of year of the first egg observed in the nest box and the date of observation, across years.

Lungless Salamander:

The salamander initiative has changed sites and cover objects throughout the run of the program and has minor discrepancies when running models as the site numbers are not recorded similarly and only in excel validation is it changed. While modeling the extra sites that did not match to the current 6 sites were grouped into the N/A section and flagged. The Description/Number of Cover object also gave us problems as anything without a number had to be grouped into a N/A category due to us not being able to determine which matched to the numbers.

While we explored the more complex models outlined in the methods, there was not sufficient data and time to resolve these complex models using the interpretation of the data we used (example plots of converged and unconverged model parameters in supplement 9 and 10). More specifically, there was not enough information to simultaneously resolve cover object and site effects. This suggests these variables are too correlated to differentiate the effects from them. There are only two sites with both types of cover objects, and the sites with the most observations have only natural cover objects (Bayman and Dexter 2021). This is a problem with study design and could be resolved in the future. We were also unable to resolve year effects simultaneously with site effects, which may be fixed in the future as more years are sampled across all sites. We were not able to resolve any models specified with two different probabilities based on observation probability and probability of presence. This could be due to lack of data, or could be due to an error in model specification. We were unable to find examples of this exact specification in the literature, but Dr. Inés Ibáñez recommended we try this specification (personal conversation). This can occur for many reasons but we suspect that for this data it is likely due to insufficient data. It is also likely that these models would resolve if we ran them for many more iterations, however we did not have sufficient time while conducting this analysis to explore this option. Even if they did converge, the high level of correlation between many of the variables would still make interpretation difficult. We still include the above specification because we wrote code to implement it, and it may be relevant for the future when there is more data or for other initiatives (i.e. for single species within the avian initiative). Especially relevant is the ability for models of this nature to separately model "is a species observed given that it is actually there" and "is a species actually present" effects, which is extremely helpful depending on the questions being asked.

We did explore some simpler models that incorporate some of the components from this more complex model. The simpler model we tested had an R-square of .08, indicating it did not account for the majority of the variance in the dataset. There was not a significant trend in the relationship between the predicted and actual values so the model shows minimal bias (Supplement 11) . The simpler model also showed that site 1 and 2 both had a statistically significant higher probability of observing salamanders than the other sites, and site two had a statistically significant higher probability than site 1. Daily temperature had a significant negative effect on salamander observation, and daily precipitation had a significant positive effect (full list of parameter values in Supplement 8). Unfortunately, we cannot distinguish whether this effect is the result of salamanders being more observable or actually more abundant. Previous research suggests that precipitation during certain times of year (spring and fall) have an impact on salamanders occupying a site, while daily temperature and precipitation has a greater impact on whether salamanders come closer to the surface where they can be observed (Luymes and Chow-Fraser 2019). We were not able to include year effects in our models and have them still converge. Using a frequentist rather than bayesian model framework may allow for a model to converge, but the correlation that resulted in the lack of convergence in the bayesian context should still be addressed (Alin 2010).

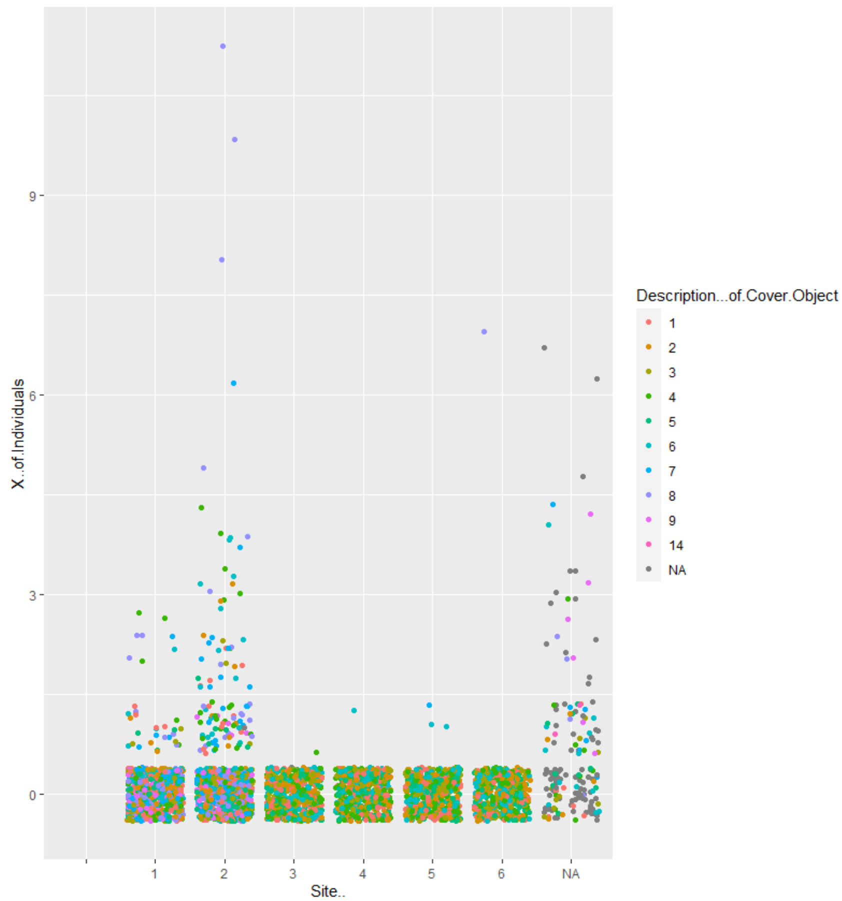

Figure 10. Population of salamanders observed at each site for each cover object.

We looked at the number of individual salamanders to qualitatively examine population observations per site and for each cover object (*Figure 10*). Sites 1 and 2 reported the highest population numbers, sites 3 through 6 are virtually indistinguishable from each other due to similar observations of salamanders. The N/A site category includes the previously mentioned sites that either don't match with the current site numbers or had a description for it. The N/A for Description of Cover Objects included all verbally described objects. It is important to note that despite differences in observed salamanders, we cannot ascribe this difference to a real difference in abundance. This information is also confounded by the use of different cover object types at each site. Sites 1 and 2 both consist of only natural objects,

When examining the temperature underneath each cover object, we found that artificial cover objects were warmer than natural objects by about 2 degrees Fahrenheit ($p < .05$). There was no significant difference in the variation in temperature between the two object types. Although the effect was only a few degrees Fahrenheit, the difference could still have a large impact on cover object use (*Figure 11*). Based on our reading of Hesed (2012), this would suggest that there is insufficient moisture reaching under the artificial objects to cool the dirt below the ceramic plates. This difference in temperature would suggest that these places are very dry, and would thus not support salamanders. It is possible that during particularly wet events salamanders may venture under the tiles, but it seems improbable that these tiles are a suitable long term home for salamanders.

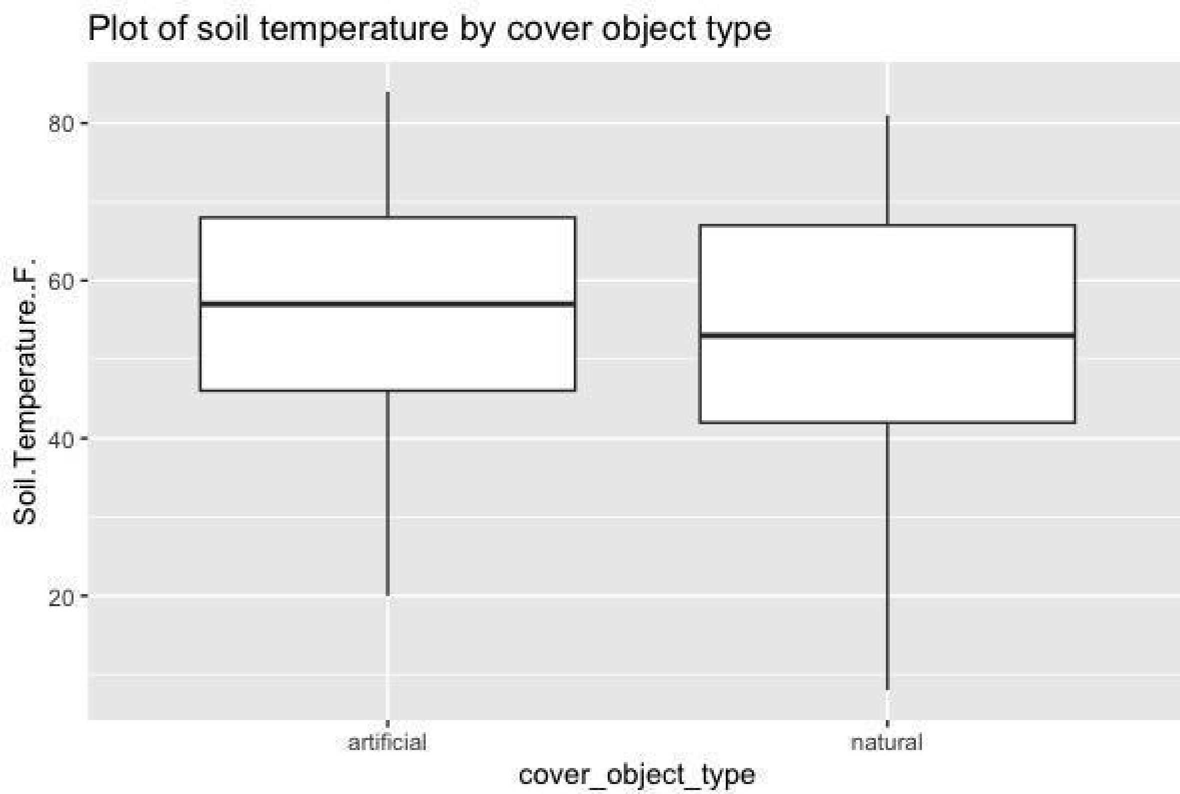

Figure 11. Soil temperature recorded for the different types of cover object.

Recommendations:

Visualizing and Exploring Data:

The bias in sampling effort through time and space needs to be accounted for when exploring these datasets. There are a number of ways to account for this that we have already discussed above. The easiest way to do this is to not look at pure counts of organisms, since this data is strongly influenced by the number of surveys taken. Instead, we advise using metrics like "Number seen per observation event" or similar ratios that can control for some of this bias. For educational material or for simple tracking of individual species phenology, we also advise using some kind of flagging system similar to what is outlined for the bald eagle initiative. This allows key life events to be tracked without having to scan through an abundance of data each time.

Collecting Weather Covariates:

Based on conversations with volunteers, on our literature review and data analysis, we strongly recommend simplifying the data sheets to exclude weather data at the time of collection. This data is already just coming from local weather stations through a website, and it takes valuable time and mental effort to fill in that information. As the team at the citizen science platform Zooniverse say, “Don’t waste volunteers' time with work that can be done by a machine” (Trouille 2023). The data from the weather station is more consistent, with less missing entries. Another critical aspect is that the weather station data is not biased by the times people choose to sample, so when constructing averages throughout a year or season they are more accurate than internal data from observers. It is difficult to extract the exact temperature at the precise time of observation, but we found this is unnecessary for the majority of cases. Using the daily temperature or using means over reasonable time frames is sufficient for most applications. The averaging approach also requires modelers and researchers to think through the exact temperature mechanisms they wish to examine, instead of just naively imputing the exact current temperature which is not relevant for most phenology. When it is necessary to have exact measurements, you could apply similar kriging techniques that were used to produce the observer recorded data or use some other model to fill in gaps (Frazier et al. 2016, Maguire and Mundle 2020). This recommendation applies to cloud cover (replaced by light level measurements), air temperature, precipitation, humidity, wind speed, wind direction, and barometric pressure.

Vegetation Cover:

This data has a number of ways it can be improved. As it currently stands, the protocol asks for vague categories without reference photos. This means that the records from different observers are likely quite different. There are apps for taking an image of canopy or plant material and an algorithm will systematically determine how much greenery there is in the picture. This gives a more precise percentage, and would be more standardized than the current measurement used by the phenology program protocol. This could be set up as its own volunteer project, using the app to take a picture and report the foliage cover. OWC could also hold onto these images and keep them as a historical record of foliage throughout the year. Based on discussions with the team it seems that plant phenology is a potential growing area independent of the vertebrate phenology programs already implemented, so splitting this initiative off and creating a new protocol just to collect this data would simplify the existing protocols while allowing volunteers to collect higher quality data at more relevant intervals. This data would likely only need to be collected a few times a week during certain times of year when foliage is actively changing, whereas right now it is incidentally captured every time someone collects data for an unrelated program. As previously stated, “do not waste volunteers' time when you can avoid it”.

Entry Forms and Data storage:

Using entry forms, as opposed to typing information into excel, is a possible way forward for this protocol. This restricts the information to types that make sense (i.e., no coercion of a number to a date, or excel incrementing a number that is dragged down). However, the Google forms already in use have some issues. Some are quite complicated to navigate, and as we have discussed, ask for lots of extraneous information. They also do not provide reference photos for many types of information that it could benefit from (e.g., difference between chick and fledgling). Finally, these forms connect to a Google sheet, which then has to be read into the Excel file through code. All of this could be simplified for both users and managers.

We would recommend switching from Google sheets to some type of direct-to-database form. The most common for an organization like OWC NERR would be Microsoft Access. This allows users to create forms that enter data into a relational database, which connects different information/datasets through related tables. This would allow OWC to avoid using code to connect the form to the final data repository, and use other valuable tools. In a relational database, for example, you could host a list of surveyor names that volunteer at OWC NERR. Then when inputting an observer name, the recorder would be limited to known persons in a consistent format. This would completely eliminate the issues we ran into with converting names by hand. There is an enormous amount of potential here, even opening the door for connecting data throughout OWC NERR’s other monitoring and initiatives (e.g. phonological initiatives and SWMP data). Setting up a system like this on OWC NERR’s scale would require a lot of buy-in and work, so we advocate more for managers to look into the possibilities of a database like Microsoft Access or some type of SQL server. There are likely some low-hanging fruit that could be used as a gateway to larger improvements. As part of this process, we strongly recommend working with volunteers to ensure that online forms are clear and effective. In our discussions with some of the volunteers they had some great thoughts on including reference images and knew which parts of the data recording process were most arduous. Using some iterative process where forms are modified, feedback is gotten from some of the experienced volunteers, and then adjusted to accommodate feedback seems like it would produce optimal results for both OWC and volunteers.

Avian Species:

Modeling:

Since avian is in some ways the most data-rich protocol, we created some very complicated and advanced models for it. However, we only did this for the total number of species observed. For some of the more common species it is possible to build on this work and develop individual species models if there are particular questions you want to ask from the data.

Comparisons with eBird:

We recommend some small changes to how OWC and eBird data are combined, both for the sake of eBird's data integrity and OWC's. Currently, data is submitted as stationary checklists. This is not the most accurate protocol available from eBird, since OWC protocol only samples a small portion of the area that eBird allows. In the browser submission, you can submit an "Area" checklist, which allows you to specify the area being surveyed. This is more accurate and will help ensure that the surveys taken as part of the phenology program are distinct in the eBird database from the casual birders. You could also ask eBird to create a special survey type, with OWC NERR's name on it. There are a number of these specialty types already in eBird, and this would give even more control and ease of use for volunteers. There are also a number of advantages to using eBird, such as the internal data validation that eBird uses. As we discussed, there are several species which are extremely rare but that observers claim to have seen at the preserve. When observers submit an observation of this type to eBird, it gets flagged and the checklist data enterer is notified. This is an extremely valuable service to OWC because it helps with validation while the observation is still fresh in someone's mind, allowing them to make adjustments to better reflect what they actually saw. We created an internal flag but this would require review if the types of birds being observed changes in the future.

Beach Area:

The beach area provides opportunity and challenge for the OWC NERR's Avian All-Species monitoring program. There are a number of species that are rare through the rest of the reserve, but common at the beach. Setting up an observation station there would grant access to a number of species which would be valuable to monitor. The constantly shifting sands pose a challenge. There may need to be a sign farther up (where the land is stable) with instructions to walk to a certain spot for monitoring. Additionally, without landmarks it would be difficult to maintain the 100m radius that is asked for at the other locations. Installing a buoy could facilitate this observation, allowing observers to position themselves consistently. This addition would also improve accessibility for some volunteers, since the beach is often more accessible than many of the trails.

Data Collection Simplification:

Currently, observers will record when they observe each individual bird during a 15-minute period. Because the time periods are so short, it seems unlikely that this data provides any meaning. We would recommend preserving the heard/seen parameter, but simply applying this to each species generally rather than to individuals within the time frame. As mentioned previously, we also recommend removing the weather collection requirement.

Bald Eagles:

Tagging Life Cycle Events:

Tagging major life events is a method used in medical data collection to provide new dimensions to understanding and interpreting data without relying on post hoc interpretation (Jeddah et al. 2021; Bigdely-Shamlo et al. 2016). In the case of the bald eagle dataset, it was difficult to discern between erroneous data entry and expected shifts in life cycle events. OWC NERR already has markers to track behaviors associated with the nest such as “guarding”, “building”, “abandoned”. These create an easy way to search and reference data. Adding tags at major life events (e.g. egg is laid, egg hatches into chick, chick becomes a juvenile, and juvenile leaves the nest) would allow for easier search parameters and would give new insight into how changes in activities emerge over time.

Lungless Salamander:

Cover Objects:

Observers have the option to describe the cover object instead of putting the number down which may cause problems when modeling as they may not be descriptive enough to assign a number to. The other problem was that some of the cover objects weren’t being sampled. We observed the same problems when collecting data that many of the cover objects were either missing an identifier or it was too hard to find on the object. We would recommend putting a more visible token or identifier on the cover objects as well as listing the number of cover objects at the site at the time of observation to ensure full sampling of all objects.

Of greater concern is the choice of cover object type. In the review of cover object study design that we found, we did not find any description of ceramic cover objects. It is thus difficult to say how ceramic cover objects compare to natural (Hesed 2012). There were statements about other cover objects that can inform us about some potential problems. Large plywood cover objects tend to prevent water from permeating, leading to warm dry zones under the boards. Since ceramic objects are completely impermeable, we suspect this same problem exists for this study.

We also anecdotally found the ceramic boards to be much drier underneath than the wooden boards. When we were thinking about how to model observations, we also realized that variation in the size of natural cover objects would likely affect observations as well. Larger cover objects will naturally have more area for salamanders to occupy, so observations at differently sized objects are not directly comparable. Based on the results of our exploratory modeling and the existing literature, we strongly recommend at a minimum replacing all ceramic cover objects with something more permeable. Based on the literature, it seems that choosing some untreated solid wood (not plywood) for the boards works well for other study sites and other *Plethodon* species. Pine boards ranging from 24cm*24cm to 106.7 × 17.8 cm worked well for *P. cinereus*. This change would reduce the usability of the existing salamander data since the new and old cover objects would not be as comparable. However, there are so few observations under artificial cover objects that the reserve would not lose very much in terms of understanding of the system. The difference between cover objects can seriously bias results and as we saw in our modeling and in the literature (Hesed 2012). In our view, this is not a choice between maintaining an imperfect study design and throwing out the old data and replacing it. OWC NERR's study design already requires an accounting of different cover objects before a scientist can get at the other variables the reserve cares about. We would also suggest placing some of these new objects at sites 1 and 2, allowing for better differentiation between site effects and cover object effects. In the long term, we believe it may be even better to replace the variably sized natural objects with identically sized wooden boards. This would reduce concerns about comparability between different objects even further. It may be wise to test if better boards are effective before taking this measure since finding salamanders provides some benefit from an engagement perspective with volunteers and visitors.

Conclusion:

Engaging citizen scientists in the collection of environmental data has been shown to benefit communities and further scientific research (Walker et al. 2020; Aczel et al. 2022). The OWC NERR team maintains a team of motivated citizen scientists, and it is our intention to prepare collected data for analysis and set the program up for future success. After reviewing and cleaning the Phenological Species Monitoring data, conducting data analyses and formulating recommendations, our team expects that OWC NERR can use the protocols we created as a stepping stone to strengthen further research with their initiatives.

Each initiative contained a unique set of obstacles to overcome; however, we found consistent obstacles across all the datasets. Although our team focused our efforts primarily on 4 initiatives, the methodology and analysis we applied to the 4 initiatives can be applied more broadly across all the initiative datasets. Broadly, we believe OWC NERR can benefit greatly from leveraging existing infrastructure and data to improve the experience of volunteers and conduct more rigorous analyses. Inviting students and researchers to continue to build on this work and sharing this with collaborators will ensure that high-quality science continues to be feasible with this data. Continuing to build on, disseminate, and reference this document and the code provided in tandem will help to improve the continuity and quality of analysis done with this data.

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Appendix

1:AIC selection results for Avian Total Species Models:

#Optimal Model AIC: 2989.225
#AIC with terms removed -----
#day of year smooth:3078.123
#year: 3060.596
#Route Factor variable: 3025.401
#wind speed: 2999.783
#Sound intensity: NA (2991.425 with sound included)
#Start time: 2995.691
#correct_names: 3191.058
#Temperature: NA (2993.967 when included)

#alternative formulations:
#with date as smooth term instead of factor: 2992.262
#Route as by variable on day of year smooth: 3037.918

2:R summary of AIC optimal Avian Total Species Model:

```
Family: Negative Binomial(985731.902)
Link function: log

Formula:
total_species ~ s(day_of_year, bs = "cc") + Route + year + s(Start.Time..24.00.) +
    s(correct_names, bs = "re") + s(Wind.Speed...mph.)

Parametric coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  1.92418    0.10212  18.842  < 2e-16 ***
RouteGreen  -0.22175    0.04551  -4.872 1.10e-06 ***
RoutePurple -0.07774    0.04344  -1.789  0.07356 .
RouteRed    -0.25134    0.04556  -5.517 3.45e-08 ***
year2017    -0.34513    0.11240  -3.071  0.00214 **
year2018    -0.33847    0.11415  -2.965  0.00303 **
year2019    -0.55586    0.11405  -4.874 1.09e-06 ***
year2020    -0.17313    0.11247  -1.539  0.12371
year2021    -0.03995    0.11505  -0.347  0.72839
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Approximate significance of smooth terms:
                      edf Ref.df Chi.sq p-value
s(day_of_year)        5.972  8.000 141.28 < 2e-16 ***
s(Start.Time..24.00.)  2.954  3.733  14.66 0.00501 **
s(correct_names)      21.083 37.000 231.57 < 2e-16 ***
s(Wind.Speed...mph.)   3.159  3.947  16.30 0.00275 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.604   Deviance explained = 60.6%
-REML = 1526.4  Scale est. = 1         n = 688
```

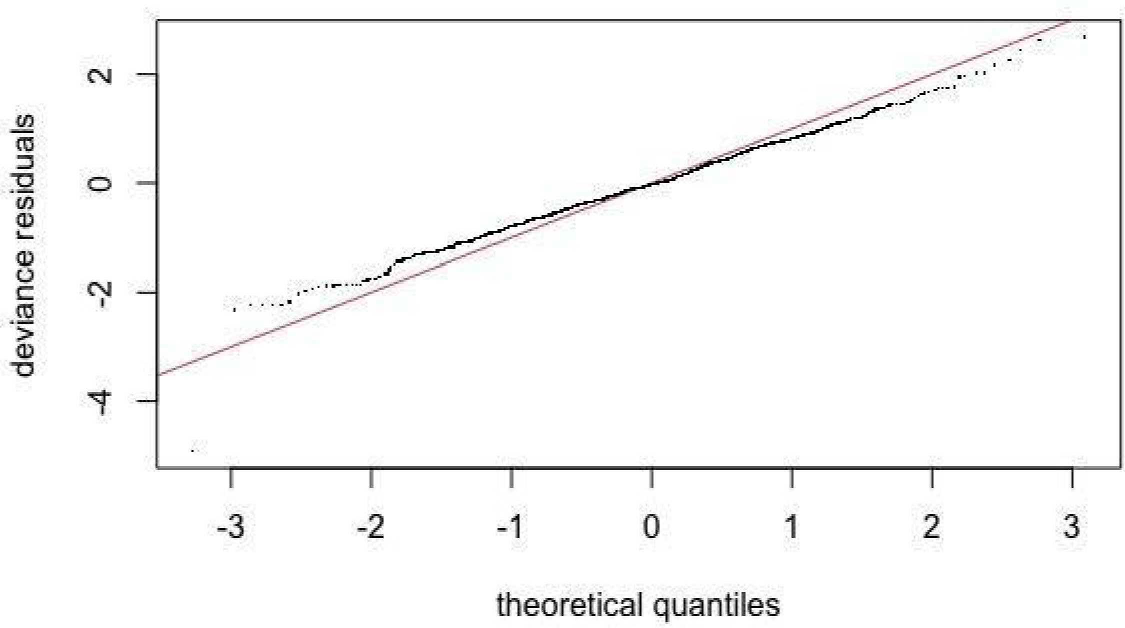
NOTE: Routes were tested with regards to their difference from the Blue Route, and years were tested against 2016. To test if any given pair is statistically different you would look to see if the 95% confidence intervals for the two parameters overlap.

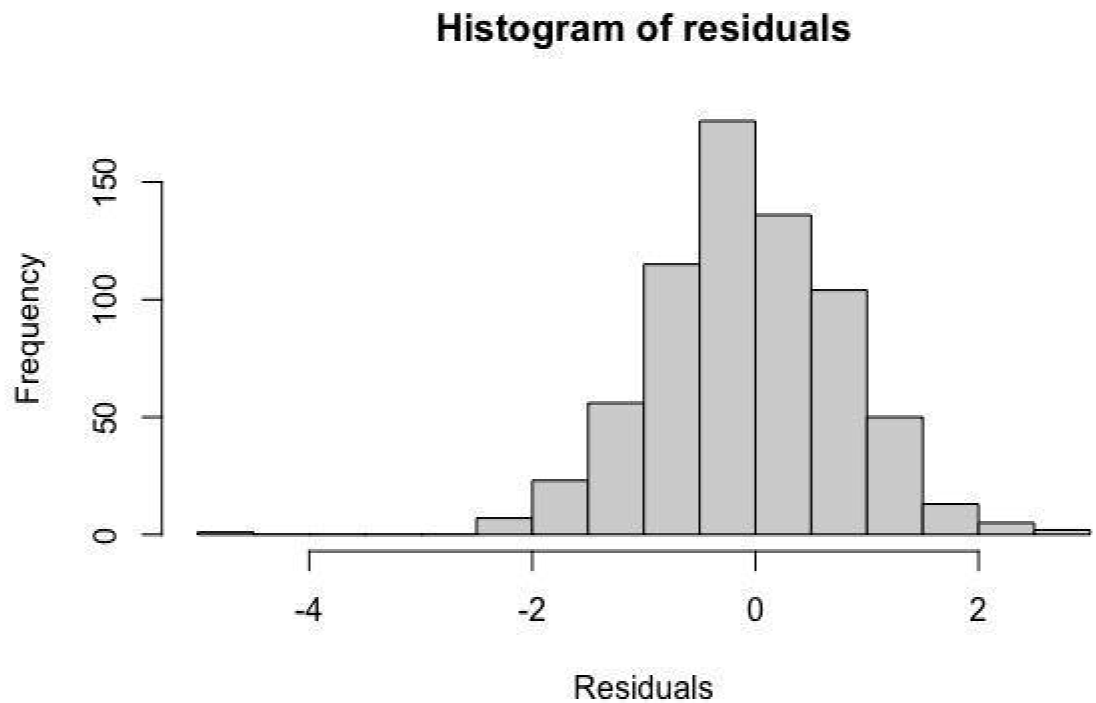
3:R summary of Annual Temperature Model:

```
Family: Negative Binomial(579253.064)
Link function: log

Formula:
total_species ~ s(day_of_year, bs = "cc") + Route + mean_annual_temp +
    s(Start.Time..24.00.) + s(correct_names, bs = "re") + s(Wind.Speed...mph.)

Parametric coefficients:
                 Estimate Std. Error z value Pr(>|z|)
(Intercept)      -4.15174    0.65344  -6.354 2.10e-10 ***
RouteGreen       -0.21594    0.04545  -4.751 2.03e-06 ***
RoutePurple      -0.07719    0.04335  -1.781    0.075 .
RouteRed         -0.24896    0.04549  -5.473 4.43e-08 ***
mean_annual_temp  0.53164    0.05989   8.878  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                      edf Ref.df Chi.sq  p-value
s(day_of_year)        5.817  8.000 154.43 3.57e-05 ***
s(Start.Time..24.00.)  3.065  3.868  16.09  0.00298 **
s(correct_names)      21.276 37.000 238.25  < 2e-16 ***
s(Wind.Speed...mph.)   3.141  3.925  16.43  0.00262 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

R-sq.(adj) = 0.595   Deviance explained = 59.8%
-REML = 1524.5 Scale est. = 1   n = 688

4:Diagnostic plots for Avian Model all species model(QQplot and residuals histogram):





5:Modeled Observer Skill:

	corrected_name	Skill_metric (Average number of species seen on average checklist)
1	R Kovacs	5.404613
2	C Arnstein	6.249170
3	J Reising/R Reising	10.974305
4	C Johnson	6.527692
5	Oberlin	5.169193

6	P Keller	6.146454
7	E Kuzmick	6.584366
8	M Gast/P Keller	5.722882
9	G Rhoades	4.770509
10	R Wood	5.899352
11	Z Hecht	5.729606
12	S Kuenzer	6.014287
13	M Donnelly	7.196948
14	G Nosanchuk/R Ort	5.133907
15	K/L	4.725420
16	Z Hecht/C King-Clements	4.470957
17	C King-Clements/Q Meckley	5.275672
18	Bock-Wright	9.601350
19	H Latteman	9.400510

20	Z Hecht/Q Meckley	7.579533
21	L Faulstich	7.485327
22	O Drake	7.733318
23	A Gurfinkel	5.758325
24	K Keleher	4.861750
25	K Bolenger	6.515989
26	A Didion	8.558069
27	G Roberts	5.844288
28	M Gast	6.667484
29	M Boppel	8.346571
30	Duckie	5.945418
31	B Baker/D Baker	5.143782
32	M Boppel/ Bolinger/N Maynard	6.081183
33	C Edwards/R Kovacs	6.734324

34	Training Group	6.796954
35	M Bolinger	6.484692
36	R Kovacs/H Latteman	5.961499
37	C Edwards	5.871208
38	A McCleary	5.803416

6:Missing data fraction from Avian All Species:

■

Variable	Fraction missing after validation
Route	0.0072530864
Date..m.d.y.	0.0774691358
Observer	0.0000000000
Temperature..F.	0.0000000000
Cloud.Cover....	0.0154320988
Wind.Speed...mph.	0.0070987654

Direction	0.0291666667
Humidity....	0.3330246914
Pressure..Hg.	0.3924382716
Precipitation	0.0074074074
Vegetation.Range	0.0634259259
Equipment	0.0000000000
Time.Period	0.0029320988
Start.Time..24.00.	0.0682098765
End.Time..24.00.	0.0682098765
Sound.Distractions	0.0000000000
Sound.Intensity	0.0007716049
eBird	0.0070987654
Time..24.00.	0.0035493827
Species	0.0771604938

H.S	0.0001543210
Individuals	0.0007716049
Additional.Notes	0.0000000000

7:Rarefaction and Avian Biodiversity For each Route:

Table of total number of species observed, rarefied totals, and diversity indices

	Blue	Green	Purple	Red
Count	96	78	82	78
Rarefied Count	73.6	78.0	73.0	77.6
Shannon	3.038901	3.333346	3.062095	3.500523
Simpson	0.9194473	0.9413201	0.9056577	0.9573123

8:Summary table for parameters from Simple Salamander Model:

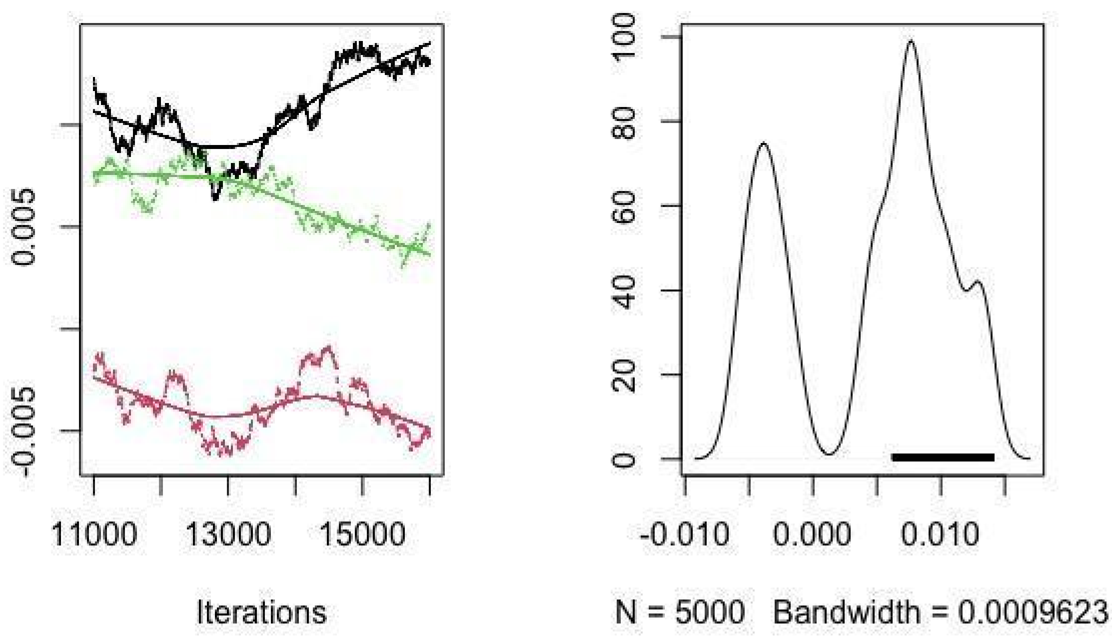
```
Iterations = 6001:11000
Thinning interval = 1
Number of chains = 3
Sample size per chain = 5000

1. Empirical mean and standard deviation for each variable,
   plus standard error of the mean:

                  Mean      SD  Naive SE Time-series SE
beta[1]         0.07452 0.01858 1.517e-04      0.0002470
beta[2]        -0.03505 0.01109 9.052e-05      0.0002294
site_effect[1] -2.92377 0.22851 1.866e-03      0.0037916
site_effect[2] -1.60299 0.17553 1.433e-03      0.0035724
site_effect[3] -6.44203 1.25245 1.023e-02      0.0153174
site_effect[4] -6.43863 1.28175 1.047e-02      0.0160459
site_effect[5] -4.85035 0.65875 5.379e-03      0.0082895
```

site_effect[6]	-6.37851	1.26903	1.036e-02	0.0163147

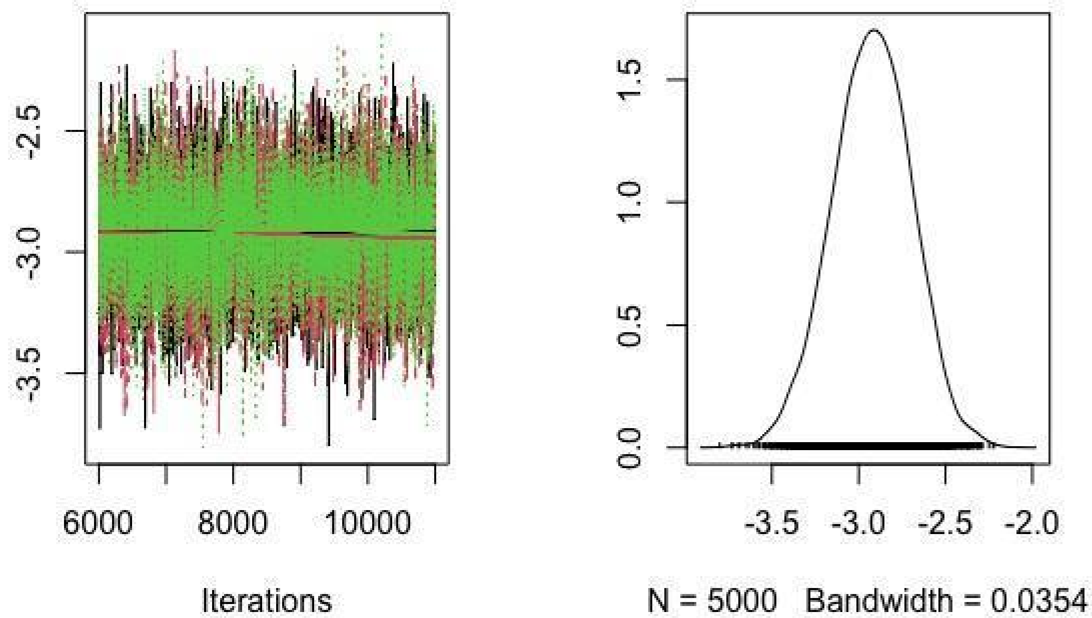
2. Quantiles for each variable:

	2.5%	25%	50%	75%	97.5%
beta[1]	0.0384	0.06185	0.07461	0.08711	0.11018
beta[2]	-0.0571	-0.04253	-0.03497	-0.02736	-0.01382
site_effect[1]	-3.3832	-3.07605	-2.92018	-2.76699	-2.48760
site_effect[2]	-1.9514	-1.72234	-1.60029	-1.48462	-1.25867
site_effect[3]	-9.4061	-7.10267	-6.26615	-5.56271	-4.53821
site_effect[4]	-9.5150	-7.12008	-6.22989	-5.51626	-4.53277
site_effect[5]	-6.2813	-5.24491	-4.79489	-4.39594	-3.69911
site_effect[6]	-9.4157	-7.05258	-6.19284	-5.47631	-4.47657

9:Example plot of unconverged parameter from complex model:



10:Plot of well converged parameter:



11:Diagnostic plot for Simple Salamander Model: