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Science, Community, and Culture: A Holistic Approach to Ecological Research and Education

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SCIENCE, COMMUNITY, AND CULTURE: A HOLISTIC APPROACH TO ECOLOIGCAL RESEARCH AND EDUCATION

By

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Science, Community, and Culture: A Holistic Approach to Ecological Research and Education

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ABSTRACT

SCIENCE, COMMUNITY, AND CULTURE: A HOLISTIC APPROACH TO ECOLOIGCAL RESEARCH AND EDUCATION

By

Laura Susan Whipple

Global biodiversity has declined at an alarming rate over the past century as a result of many complex human-induced environmental changes. Standardized surveys have historically been used to identify drivers of species declines, but such studies are often resource-intensive, resulting in significant spatial and temporal data gaps when researchers lack the resources necessary to maintain such studies. One promising solution for overcoming gaps in standardized studies is the integration of species observations by community members (e.g., community science). Along with improving modeling techniques to address biodiversity declines, the education of future ecologists on the importance of Indigenous ecological knowledge, robust scientific research, and community engagement in addressing myriad environmental problems is also imperative in addressing ecological challenges. Thus, my goals are 1) determine the efficacy of integrating standardized survey data with community-sourced observations to create species distribution models (SDMs) for species with varying responses to human-mediated environmental change and 2) create a curriculum that synergizes Indigenous ecological knowledge, scientific research techniques, and community science to establish a more holistic learning experience. I used data from Snapshot USA, a standardized nation-wide camera trap survey, and iNaturalist, an online community science platform, to create species distribution models and hands-on ecology lessons. My results demonstrate that integrated SDMs do produce informative predictions of the environmental factors that influence species distributions and provide a scaffolded framework for creating a more holistic approach to ecological education.

DEDICATIONS

I dedicate my master's thesis work to my family and friends. This work would not have been possible without your endless support and encouragement. Mom and Dad, thank you for inspiring and encouraging my love for the outdoors and all of the creatures that inhabit it, and for supporting all of my cross-country moves so I could pursue my wildlife research dreams. A very special thank you to Bolt for being the best feline support a master's student could ever ask for.

I also dedicate my master's thesis to my incredible thesis advisor, Dr. Diana Lafferty, who has supported my research and ecology education goals endlessly over the past two years. I am grateful that I had the opportunity to work with such an amazing mentor and researcher on such an exciting project. This work would not have been possible without you, and it has been a pleasure working with you.

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INTRODUCTION

Today, ecologists and ecology students alike are confronted with the challenges of global climate change, human-mediated landscape degradation, and rapid biodiversity loss [1–3]. To better understand key drivers that threaten species populations, ecologists rely on large-scale ecological models to estimate the current environmental factors that affect species distribution and abundance and to predict how future changes in landscape use and climate may alter species distributions [4]. However, such surveys are often resource-intensive to maintain over long periods of time, with a lack of funding and time often resulting in significant spatial and temporal data and knowledge gaps [5]. Such knowledge gaps are often further exacerbated by the exclusion of diverse points of view from conservation plans, particularly from Indigenous communities that have long histories of successful conservation efforts [6]. Therefore, ecologists must develop new ways to address issues with standardized survey data and broaden the diversity of people informed on and participating in ecological conservation to implement successful conservation plans.

One opportunity for simultaneously overcoming data gaps in standardized surveys and including diverse groups of people in conservation efforts is community science. For example, the integration of wildlife observations by the public with standardized survey datasets in wildlife population and distribution models can compensate for low quantities of survey data [5]. Online community science platforms such as Zooniverse, eBird, and iNaturalist have also increased public engagement with conservation efforts by enabling researchers to communicate with millions of diverse people around the world [7]. Yet community-sourced wildlife observations are often underutilized by researchers due to concerns over data quality [5,6].

Despite challenges, community-sourced wildlife data are abundant and may be a powerful tool for wildlife conservation research and educational outreach [8,9].

As ecologists seek to improve the inclusion of diverse groups and to increase community participation in ecological research, it is of ever-increasing importance that ecology students are provided with the necessary tools and knowledge to act as effective ecologists, ecosystem managers, and advocates for change in addressing global ecological issues. Thus, it is imperative for modern ecology students to learn about the role of Indigenous communities in ecological conservation, develop scientific research skills, and understand the value of community science initiatives in addressing ecological issues [10–12]. University undergraduate courses offer a unique opportunity to provide large groups of students with such skills by incorporating Indigenous ecological knowledge, scientific research techniques, and community science initiatives into a single course, thus allowing students to gain a more holistic understanding of the many interacting components of ecology [10–12].

In my first chapter, I used Snapshot USA camera trap data and iNaturalist community observations to test the efficacy of integrating robust scientific wildlife surveys with abundant community-sourced wildlife observations into a single dataset to develop a novel approach to species distribution modeling. In my second chapter, I translated my integrated species distribution modeling research into a culturally competent hands-on ecology curriculum for undergraduate college students to teach students about the importance of Indigenous ecological knowledge to better understand how ecosystems function, ecological research techniques, and ecological community science initiatives.

1. CHAPTER ONE: INTEGRATING STANDARDIZED SURVEY DATA WITH COMMUNITY OBSERVATIONS TO CREATE ROBUST SPECIES DISTRIBUTION MODELS

1. Introduction

Globally, nearly 20% of vertebrate species are classified as vulnerable or endangered, with 30% of species having demonstrated population declines since 1970 [1,2]. Such significant declines in global biodiversity are troubling because high genetic and species diversity are critical for maintaining key ecosystem functions such as nutrient cycling, soil formation, water purification, and climate regulation [3]. To better understand drivers of biodiversity loss, ecologists rely on complex ecological models to predict the environmental factors that affect species distribution and abundance [4]. Such models can also be used to predict how future changes in land use and climate may alter species distributions, which may prove critical in developing proactive species management plans based on predicted changes in climate [5]. However, these ecological models require robust species occurrence data to accurately predict species responses to current and future environmental conditions.

Large-scale and long-term standardized surveys have historically been the gold standard for modeling the environmental factors that influence species distributions, as these datasets allow the comparison of ecological data across space and time directly without concerns over methodological differences [6]. However, such surveys can be expensive, time-consuming, and difficult to coordinate across jurisdictions, often resulting in significant spatial and temporal data gaps when researchers lack the resources necessary to maintain long-term, large-scale standardized studies [7]. One potential method for overcoming such gaps in standardized survey data is the integration of species observations by the public (e.g., community science) with standardized survey datasets [4,6,7]. Community observations are often abundant, publicly available, and free to use, making these data easy for ecologists to obtain. However, community-sourced wildlife observations are often underutilized by researchers because such data are opportunistic, often contain no measure of sampling effort, and carry increased risk of misidentification [6,8]. Despite such challenges, community-sourced wildlife data may be a powerful tool for biodiversity conservation, especially as online community science platforms, such as eBird and iNaturalist, are increasingly being used by the general public [9,10].

Methods for integrating standardized survey data with community observations in ecological models already exist, but these methods have only emerged in the past couple of years and are not yet regularly used by ecologists and wildlife managers due to a lack of accessible modeling tools and data acquisition information [4,11]. As a result, many currently available studies on the use of integrated models focus on a limited range of taxa (e.g., birds) that have easily accessible and widely used standardized survey (e.g., Breeding Bird Survey) and community observation datasets (e.g., eBird) [4,6,7]. Thus, little is known about the efficacy of using integrated models for species in other taxonomic groups (e.g., mammals, insects, amphibians, fish) with different responses to specific environmental factors (e.g., human-tolerant species vs old growth forest dependent species). This lack of information on the efficacy of integrated models for species with varying responses to environmental factors is concerning, as the efficacy of including community observations in integrated models may differ between species because community observers are more likely to detect species that are abundant and associated with human-dominated landscapes [12]. Yet little guidance is available on how variability in species ecology may affect the efficacy of integrated models. Despite such challenges, integrated models are rapidly growing in popularity among quantitative ecologists and will likely become standard tools for wildlife managers in the future [4,11].

Species Distribution Models (SDMs) are one type of large-scale ecological model widely used to predict environmental factors associated with a given species' presence and are often used by wildlife managers to inform decisions on land acquisition for endangered species habitat conservation [4,6,7]. Historically, SDMs have only used one data source due to the complexity of integrating data that originate from different sampling processes, but recent developments in modeling techniques allow for the integration of many data sources into a single integrated SDM (ISDM) [4,6,7,11]. SDMs are also the foundation for more complex ecological models, such as occupancy and abundance models, and improvements in species distribution modeling techniques will lead to improvements in other modeling techniques [4].

Two potential data sources for testing the utility of standardized survey data with community observations to create ISDMs are Snapshot USA and iNaturalist, respectively. Snapshot USA is a large-scale and long-term standardized wildlife study that has collected camera trap data from over 100 scientific collaborators annually since 2019 [13,14]. However, Snapshot USA data are limited to areas where researchers have the resources to maintain camera traps. In contrast, iNaturalist is an online platform that allows the public to upload images and identify observations of plants and animals around the world any time of year. Since iNaturalist launched in 2008, users have recorded over 100 million observations, and these community observations have been used to assess the presence of endangered, threatened, and invasive species [4,15]. Despite large amounts of available data, the full utility of iNaturalist for advancing wildlife science and conservation remains unclear due to the challenges of evaluating opportunistic community observations [6–8].

My objective was to determine the utility of ISDMs to model distributions for species with varying responses to environmental factors in an effort to provide practical guidance for wildlife managers who may seek to use ISDMs to inform wildlife management plans. I used Snapshot USA camera trap data and iNaturalist community observations to create these ISDMs and compared the predicted covariate effects on species distributions in SDMs fitted with an integrated dataset, a Snapshot USA dataset, and an iNaturalist dataset for a common and a rare mammal species. I further investigated the amount of data required to produce informative ISDMs, the impact of incorrect identifications of community observations on ISDMs, and the impact of using different community-sourced datasets to create ISDMs for a rare species to provide additional guidance for species of particular conservation concern. To address these additional objectives, I compared ISDMs with one, two, and three years of Snapshot USA and iNaturalist data, ISDMs created with iNaturalist community observations that were proofed for accurate species identification and observations that were not proofed, and ISDMs created with iNaturalist community observations and observations from the Global Biodiversity Information Facility (GBIF), an international database often used for acquiring species occurrence data.

2. Materials and Methods

2.1 Model Species

I retrieved species observation data from the Snapshot USA and iNaturalist databases for two mesocarnivore (Carnivora species <15kg) species: red fox (*Vulpes vulpes*) and fisher (*Pekania pennanti*). The wide range of responses by mesocarnivores to human-caused landscape changes, the role of mesocarnivores in human-wildlife conflict, and the economic relevance of mesocarnivores as furbearers make mesocarnivore species excellent candidates to test the utility of integrated species distribution models for species with varying responses to different environmental factors. Beginning in the 1800s, many mesocarnivore populations increased in abundance, expanded in geographic range, and suppressed prey populations following the decline of apex predator populations driven by human-caused habitat loss and direct persecution [16]. The red fox is one such mesocarnivore species that has expanded in range, particularly into human-dominated landscapes [17], following the near extirpation of gray wolves (*Canis lupus*) from much of the continental United States [18]. As a result, red fox populations are increasingly coming into contact with humans, leading to an increase in human-wildlife conflict and disease spread from red foxes [19,20].

Other mesocarnivore populations have declined due to overharvest and rapid human-mediated habitat loss [16]. The fisher is one mesocarnivore species that is of particular conservation concern due to historic population declines as a result of old growth forest logging, with the Southern Sierra Nevada fisher population in California under consideration for federal listing under the Endangered Species Act [21]. In the Great Lakes region of Canada and the United States, fishers were extirpated from significant portions of the region in the early 20th century, but fisher populations have rebounded due to reintroduction programs and harvest regulations [22,23]. The fisher is now a furbearer species of economic significance in the Great Lakes region [22], but the Great Lakes fisher population may be decreasing again due to northward shifts in prey ranges [23,24].

2.2 Study Area

The red fox study area included the Central USA Plains, Mixed Wood Plains, Mixed Wood Shield, and Atlantic Highlands level II ecological regions (Figure 1.1). This region includes a significant portion of the native range of the red fox in northeastern North America [25]. The fisher study area included the Mixed Wood Plains, Mixed Wood Shield, and Atlantic Highlands Level II ecological regions. I removed the Central USA Plains region from the fisher study area because the current range of fishers does not extend to this area and no fisher were detected in either of the datasets during the study period within this region [22].

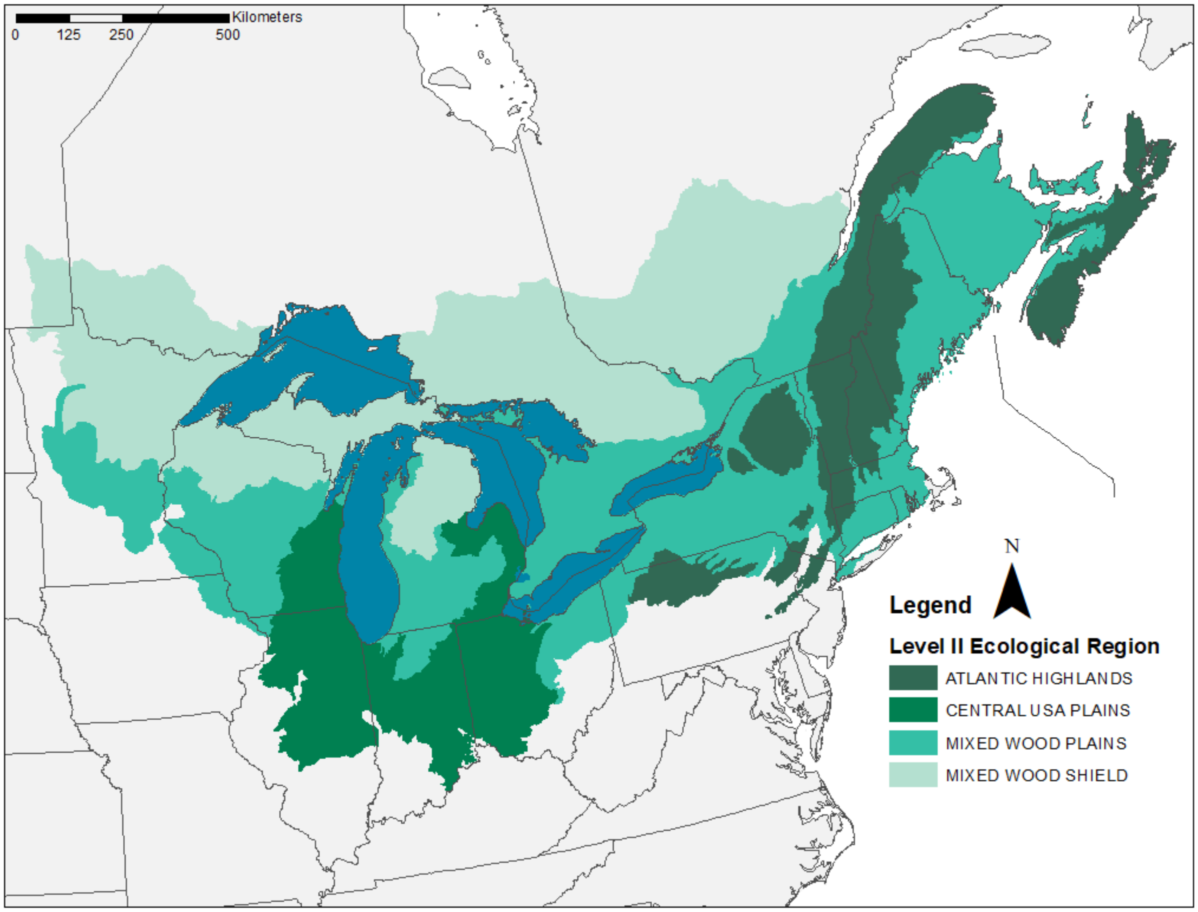

Figure 1.1. The red fox (*Vulpes vulpes*) study area in the Atlantic Highlands, Central USA Plains, Mixed Wood Plains, and Mixed Wood Shield level II ecological regions. Black lines indicate state boundaries (Connecticut, Illinois, Indiana, Iowa, Maine, Massachusetts, Michigan, Minnesota, New Jersey, New Hampshire, New York, Ohio, Pennsylvania, Rhode Island, Vermont, Wisconsin) and province boundaries (Manitoba, New Brunswick, Nova Scotia, Ontario, Prince Edward Island, Quebec).

2.3 Snapshot USA Camera Trap Data

Snapshot USA is a collaborative annual nation-wide camera trap survey that consists of data from camera traps managed by independent wildlife researchers from 1 September to 31 October in 2019, 2020, and 2021 [13,14]. The Snapshot USA dataset includes start time, end time, species, age, sex, number of individuals, and latitude and longitude for every sequence of photos. Camera traps were programmed to take three photographs at each trigger with either no quiet period or a one-minute quiet period. A sequence of photos was defined as a group of photos taken within one minute of each other. In 2019 and 2020, collaborators uploaded photo data and identified species in images on the eMammal application and expert reviewers checked photo data from all camera traps to ensure that photos had correct species information [13,14]. In 2021, collaborators uploaded and classified images on the Wildlife Insights platform [26]. I used the 2019, 2020, and 2021 Snapshot USA datasets to construct a matrix of red fox and fisher presence or absence at each camera trap array located in the study area for each year. I included the number of years each camera trap array was sampled as the number of trials in models that included Snapshot USA data.

2.4 iNaturalist Community Observation Data

iNaturalist is an online website and mobile app that allows anyone with an account to upload image, video, and sound observations of organisms and to identify observations uploaded by other users. Information on observation date, time, location, and species identification can then be downloaded through the iNaturalist data exporter. The iNaturalist data exporter allows anyone with an iNaturalist account to filter the iNaturalist observation database according to specified criteria and download the filtered data. To obtain my iNaturalist datasets, I downloaded red fox and fisher research-grade observations within North America from 1 January 2019 to 31 December 2021 from the iNaturalist data exporter on 12 January 2022 [27]. To be considered research-grade, observations must include accurate date, location, and have a species identification verified by at least two users, which is intended to reduce the risk of inaccurate metadata or incorrect species identifications [15].

However, research-grade observations still have the potential to have incorrect species identification information, as anyone with an iNaturalist account can verify observations and only two agreed identifications are required for an observation to be considered research-grade. To eliminate risk of misidentification in the iNaturalist datasets, I checked each iNaturalist observation and determined if the species identification was correct. I removed all observations that had insufficient evidence of an organism (e.g., extremely pixelated photos, photos of dens with no other animal signs, etc.), were incorrectly identified, or could not be accurately identified to species.

iNaturalist research-grade observations can also have very low positional accuracy, which arises from observers accidentally inputting inaccurate location information when uploading an observation or from observers purposefully obscuring observation location information. To avoid using observations with low positional accuracy in the models, I filtered out all iNaturalist observations with a positional accuracy greater than 1km.

Another potential issue with community-sourced species observations is clustered, repeated observations, which artificially inflates the number of species observations. This issue can arise from multiple observers traveling together and uploading multiple observations of the same organism or an observer uploading multiple photos of the same organism to several observations. To eliminate this issue in the iNaturalist datasets, I used the *spThin* R package [28] to randomly thin observations based on a buffer distance of 100m. I selected a buffer distance of 100m based on an exploratory analysis that compared models with no buffer, a 10m buffer, and a 100m buffer, and found that models with a 100m buffer around iNaturalist observations performed best based on model Watanabe-Akaike information criteria (WAIC) [29].

To determine how different community science databases affect the output of ISDMs, I also created a community observation dataset from the Global Biodiversity Information Facility (GBIF) with the *spocc* R package [30]. Established in 1999 following a recommendation from the Organization for Economic Cooperation and Development (OECD), GBIF is an international effort to make biodiversity databases easily accessible for use in ecological research [31]. GBIF includes records of museum specimens, DNA barcodes, and now species occurrence records from online community science initiatives, including iNaturalist research-grade observations with CC0, CC-BY, and CC-BY NC Creative Commons licenses [32]. The *spocc* package can retrieve species occurrence data from only iNaturalist, but GBIF is a popular source for community observation datasets and has been recommended by authors of foundational ISDM papers for retrieving community-sourced observations [4,33]. Thus, I elected to follow the methods commonly used in other ISDM papers to determine the differences between ISDMs produced with different community wildlife observation databases. I performed the same filtering process as the iNaturalist dataset to remove GBIF observations with positional accuracy greater than 1km or that may have been duplicated.

2.5 Data Analysis

To fit SDMs with the integrated, Snapshot USA, and iNaturalist datasets, I used the *PointedSDMs* [33,34], *R-INLA* [35], and *inlabru* [36] R packages [37] to create a state-space point process model and fit the models in a Bayesian framework [4,38]. INLA is an alternative to Markov chain Monte Carlo methods that allows for more complex model formulation and fitting in less time, and as a result has become increasingly popular for use in ecological modeling [35,38]. *PointedSDMs* is designed to simplify the process of developing integrated SDMs by providing wrapper functions for the *INLA* and *inlabru* R packages that can help set up, fit, and interpret complex ISDMs [33,38,39].

Following the recommendations for using *PointedSDMs* outlined in Morera-Pujol et al. 2022 [39], I included an additional dataset-specific spatial field for iNaturalist and Snapshot USA in each model that used a given dataset to account for observational bias. This additional spatial field is particularly important in accounting for the opportunistic nature of iNaturalist observations, as wildlife that are near populated areas or frequently traveled roads and trails are more likely to be documented on iNaturalist [39].

2.6 Covariate Selection

I investigated nine potential environmental covariates aimed to explain the spatial distribution of red fox and fisher (Table 1.1). I resampled all covariates to the resolution of the covariate raster file with the lowest resolution, which was 8.3km, to avoid using raster files with multiple resolutions. I log-transformed the population density and percent impervious surface raster files, as both of these covariates had extreme differences in values that resulted in skewed coefficient values for the models that included these covariates. I scaled all environmental covariate raster files by subtracting the mean and dividing by the standard deviation for each raster cell [38,39]. I used the Pearson's correlation coefficient to test for correlation between covariates. Percent forest cover and percent cropland were significantly correlated with one another ($R^2 = 0.80$). All other covariate pairs were not significantly correlated ($R^2 < 0.70$) [40].

To determine which covariates to include in the red fox and fisher models, I categorized each covariate as "anthropogenic" or "ecological" and developed red fox and fisher ISDMs with each group of covariates. I then determined which covariates in each model had coefficient 95% confidence intervals that overlapped with zero, which indicated the covariate did not have a significant effect on the model, and removed those covariates from the final model [38]. To determine if forest cover or cropland cover should be included in final models, I determined which covariate had the strongest effect in the red fox and fisher models and removed the covariate with the weaker effect to avoid using correlated covariates in the final models.

Table 1.1. All covariate candidates for the red fox (*Vulpes vulpes*) and fisher (*Pekania pennanti*) species distribution models.

Category	Source	Period	Covariate
Ecological	WorldClim (https://www.worldclim.org/)	1970-2000	Average Annual Temperature
Ecological	WorldClim (https://www.worldclim.org/)	1970-2000	Average Annual Precipitation
Anthropogenic	Global Roads Inventory Project (https://www.globio.info/download-grip-dataset)	2018	Distance to Nearest Road
Ecological	Shuttle Radar Topography Mission (https://srtm.csi.cgiar.org/)	2018	Elevation
Anthropogenic	Global Man-made Impervious Surface Dataset (https://doi.org/10.7927/H4P55KKF)	2010	% Impervious Surface
Anthropogenic	ESA WorldCover (https://esa-worldcover.org/en)	2020	% Cropland Cover
Ecological	ESA WorldCover (https://esa-worldcover.org/en)	2020	% Forest Cover
Ecological	ESA WorldCover (https://esa-worldcover.org/en)	2020	% Wetland Cover
Anthropogenic	Gridded Population of the World (http://sedac.ciesin.columbia.edu/data/collection/gpw-v4/documentation)	2020	Population Density

3. Results

3.1 Red Fox Models

The full Snapshot USA red fox dataset included 45 camera trap arrays across 2019, 2020, and 2021, with 23 camera trap arrays sampled in one year, 10 arrays sampled in two years, and 12 arrays sampled in three years. Red fox were detected at 34 of the included Snapshot USA camera trap arrays (Figure 1.2). The full iNaturalist red fox dataset included 13,961 observations from North America. I verified 13,787 of these observations as containing evidence of red fox presence. I retained 10,146 observations after removing observations with a positional accuracy greater than 1km, 8,023 observations after applying a 100m buffer, and a final total of 3,439 red fox iNaturalist observations after removing observations outside of the study area (Figure 1.2).

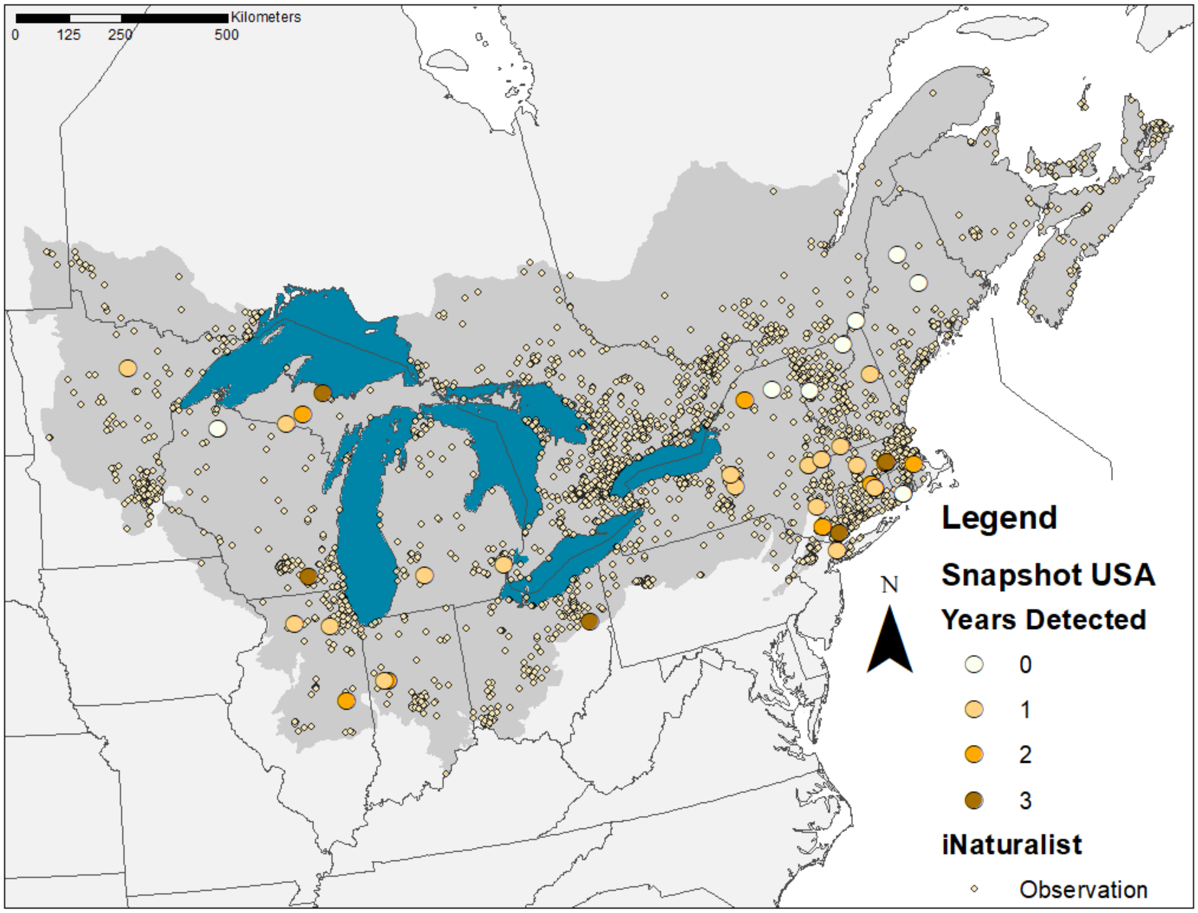

Figure 1.2. Number of years red fox (*Vulpes vulpes*) were detected at Snapshot USA camera trap arrays and the location of the observations included in the final red fox iNaturalist dataset. The dark gray area denotes the red fox study area.

Based on my covariate selection procedure, I included average annual temperature, distance to the nearest road, elevation, percent forest cover, and population density (Table 1.2). The covariate effects for the integrated, Snapshot USA, and iNaturalist models are shown in figure 1.3. The integrated model predicted that average annual temperature, percent forest cover, and population density had positive effects on red fox distribution, while elevation had a negative effect on red fox distribution and the distance to road 95% credibility interval included zero. The Snapshot USA model predicted that percent forest cover had a positive effect on red fox distribution, while all other covariates had a 95% credibility interval that included zero. The iNaturalist model predicted the same covariate effects as the integrated model.

Table 1.2. Summary table of the covariate effects for all red fox (*Vulpes vulpes*) models.

Covariate Coefficient Mean ± SD	**Full Integrated**	**Snapshot USA**	**iNaturalist**
Average Annual Temperature	0.740 ±0.045	1.211 ±0.712	0.914 ±0.048
Distance to Nearest Road	-0.041 ±0.049	0.700 ±1.311	0.003 ±0.052
Elevation	-0.531 ±0.043	0.357 ±0.352	-1.072 ±0.048
% Forest Cover	1.534 ±0.044	0.895 ±0.413	1.812 ±0.048
Population Density	4.576 ±0.043	0.369 ±0.326	6.195 ±0.049

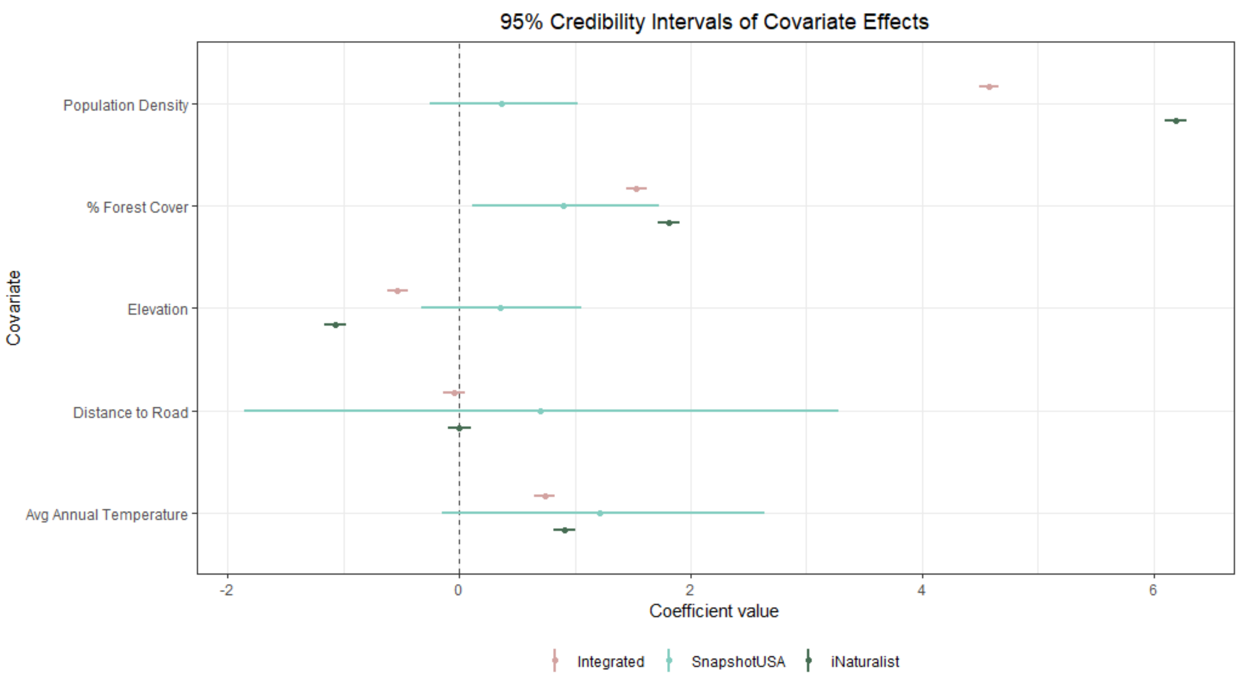

Figure 1.3. Covariate effects for the integrated, Snapshot USA, and iNaturalist models for red fox (*Vulpes vulpes*). The circles represent the mean value of each covariate effect and bars represent 95% credibility intervals.

3.2 Fisher Models

The full Snapshot USA fisher dataset included 37 camera trap arrays across 2019, 2020, and 2021, with 19 camera trap arrays sampled in one year, 9 arrays sampled in two years, and 9 arrays sampled in three years. Fisher were detected at 22 of the included Snapshot USA camera trap arrays (Figure 1.4). The full iNaturalist fisher dataset included 1,166 observations from North America. I verified 1,113 of these observations as containing evidence of fisher presence. I retained 837 observations after removing observations with a positional accuracy greater than 1km, 664 observations after applying a 100m buffer, and a final total of 552 fisher iNaturalist observations after removing observations outside of the study area (Figure 1.4).

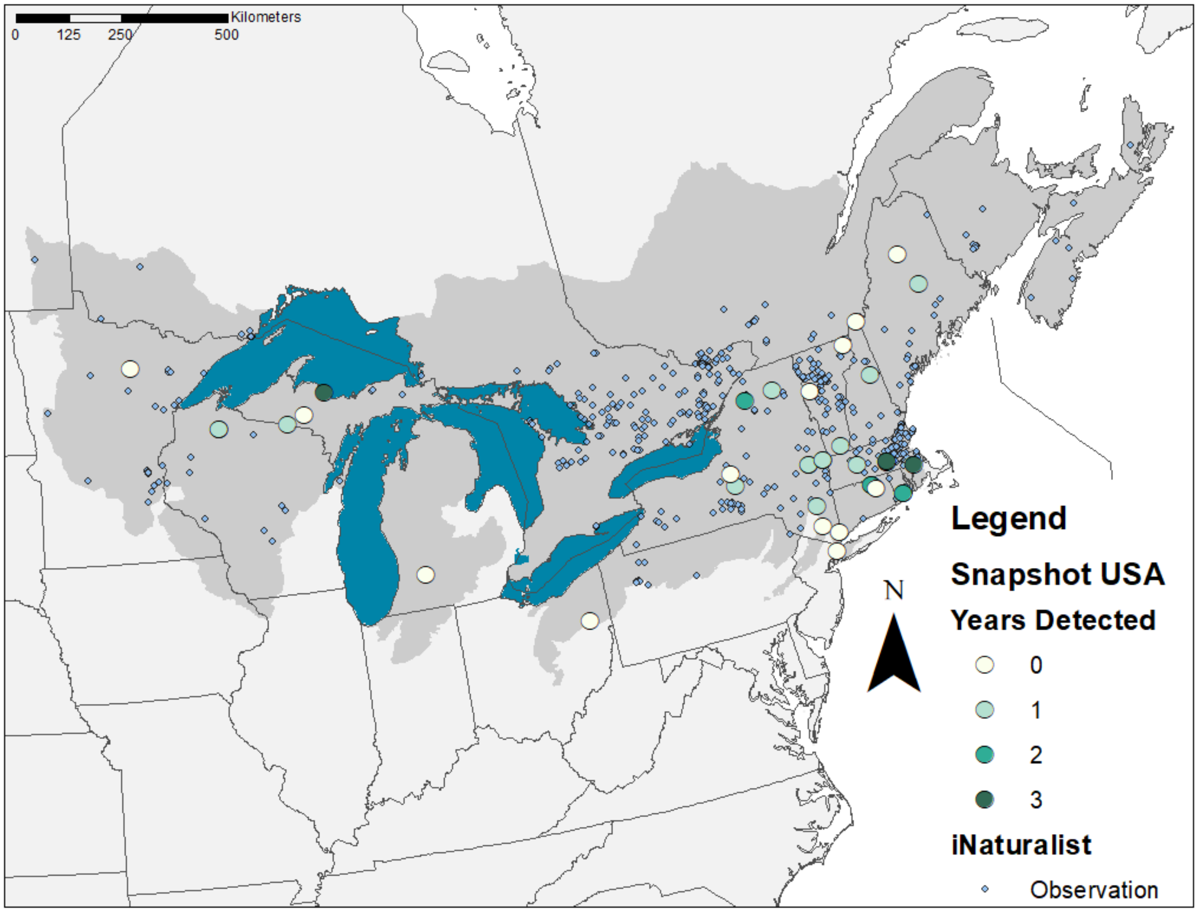

Figure 1.4. Number of years fisher (*Pekania pennanti*) were detected at Snapshot USA camera trap arrays and the location of the observations included in the final fisher iNaturalist dataset. The dark gray area denotes the fisher study area.

Based on the covariate selection procedure, I included distance to the nearest road, percent impervious surface cover, average annual temperature, percent forest cover, and percent wetland cover in the fisher models (Table 1.3). The covariate effects for the integrated, Snapshot USA, and iNaturalist models are shown in figure 1.5. The integrated model predicted that average annual temperature and percent forest cover had positive effects on fisher distribution, while distance to the nearest road and percent wetland cover had negative effects on fisher distribution (Table 1.3). Percent impervious surface was the only covariate with a 95% credibility interval that included zero in the integrated model. The Snapshot USA model predicted that all covariates had 95% credibility intervals that included zero. The iNaturalist model predicted direction of covariate effects were the same as the integrated model predictions for average annual temperature, distance to the nearest road, percent forest cover, and percent wetland cover. The iNaturalist model predicted that percent impervious cover had a positive effect on fisher distribution.

Table 1.3. Summary table of the covariate effects for all fisher (Pekania pennanti) models.

Covariate Coefficient Mean ± SD	**Full Integrated**	**Snapshot USA**	**iNaturalist**	**1 Year Integrated**	**2 Year Integrated**	**Unproofed iNaturalist**	**GBIF Integrated**
Average Annual Temperature	0.606 ±0.046	0.430 ±0.867	0.659 ±0.048	0.274 ±0.044	0.432 ±0.043	0.610 ±0.044	0.477 ±0.046
Distance to Nearest Road	-0.132 ±0.054	0.260 ±2.053	-0.130 ±0.054	-0.021 ±0.051	-0.068 ±0.050	-0.137 ±0.051	-0.081 ±0.054
% Forest Cover	0.378 ±0.045	0.452 ±0.906	0.389 ±0.046	0.095 ±0.043	0.190 ±0.042	0.337 ±0.042	0.288 ±0.046
% Impervious Surface	0.000 ±0.033	-0.995 ±9.088	0.109 ±0.060	0.023 ±0.058	-0.010 ±0.038	-0.006 ±0.030	0.004 ±0.034
% Wetland Cover	-0.060 ±0.021	-2.364 ±2.111	-0.059 ±0.021	-0.009 ±0.019	-0.013 ±0.019	-0.048 ±0.019	-0.044 ±0.021

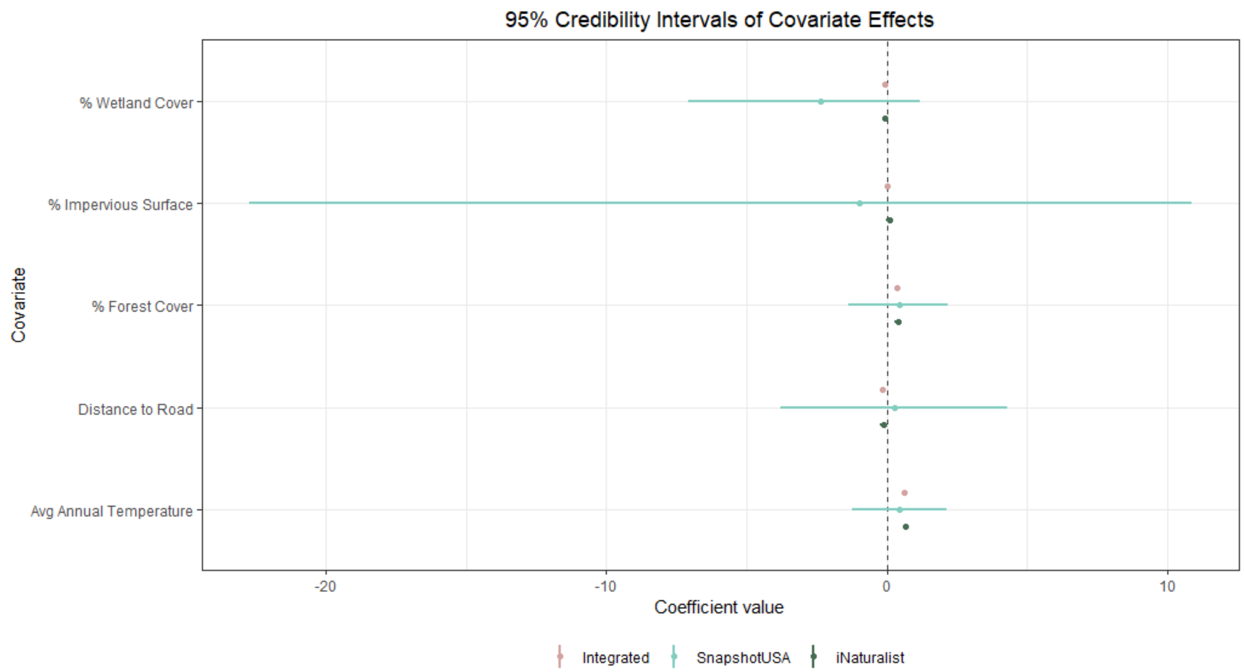

Figure 1.5. Covariate effects for the integrated, Snapshot USA, and iNaturalist models for fisher (*Pekania pennanti*). The circles represent the mean value of each covariate effect and bars represent 95% credibility intervals.

The integrated fisher model with one year of data included 22 Snapshot USA camera trap arrays and 165 iNaturalist observations. The two-year integrated model included 24 Snapshot USA camera trap arrays and 357 iNaturalist observations. The covariate effects for fisher integrated SDMs with one, two, and three years of Snapshot USA and iNaturalist data are shown in figure 1.6. The predicted direction of covariate effects for average annual temperature and percent forest cover were the same for all three models, with the predicted covariate effects for the one- and two-year models closer to zero than the three-year model (Table 1.3). The one- and two-year models both had 95% credibility intervals for distance to the nearest road and percent wetland cover that included zero. The percent impervious surface 95% credibility interval included zero for all three models.

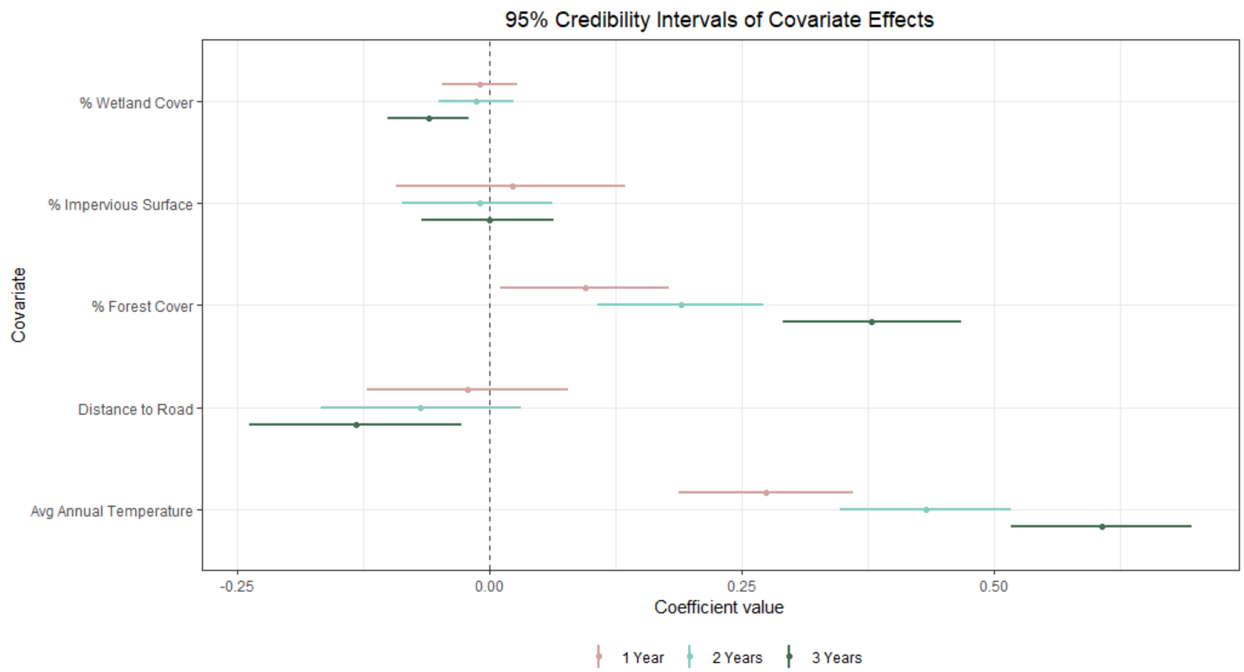

Figure 1.6. Covariate effects for integrated SDMS developed with one, two, and three years of Snapshot USA and iNaturalist fisher (*Pekania pennanti*) data. The circles represent the mean value of each covariate effect and bars represent 95% credibility intervals.

The unproofed iNaturalist dataset included 584 fisher observations from 1 January 2019 to 31 December 2021 within the fisher study area after filtering and thinning points. The covariate effects for fisher integrated SDMs with unproofed and proofed iNaturalist data are shown in figure 1.7. The predicted direction of all covariate effects was the same between the two models, with the predicted covariate effects for the unproofed model closer to zero for percent forest cover and percent wetland cover than the proofed model, while the predicted covariate effects for the proofed model were closer to zero for average annual temperature and distance to the nearest road than the unproofed model. Both models had a 95% credibility interval for percent impervious surface that included zero (Table 1.3).

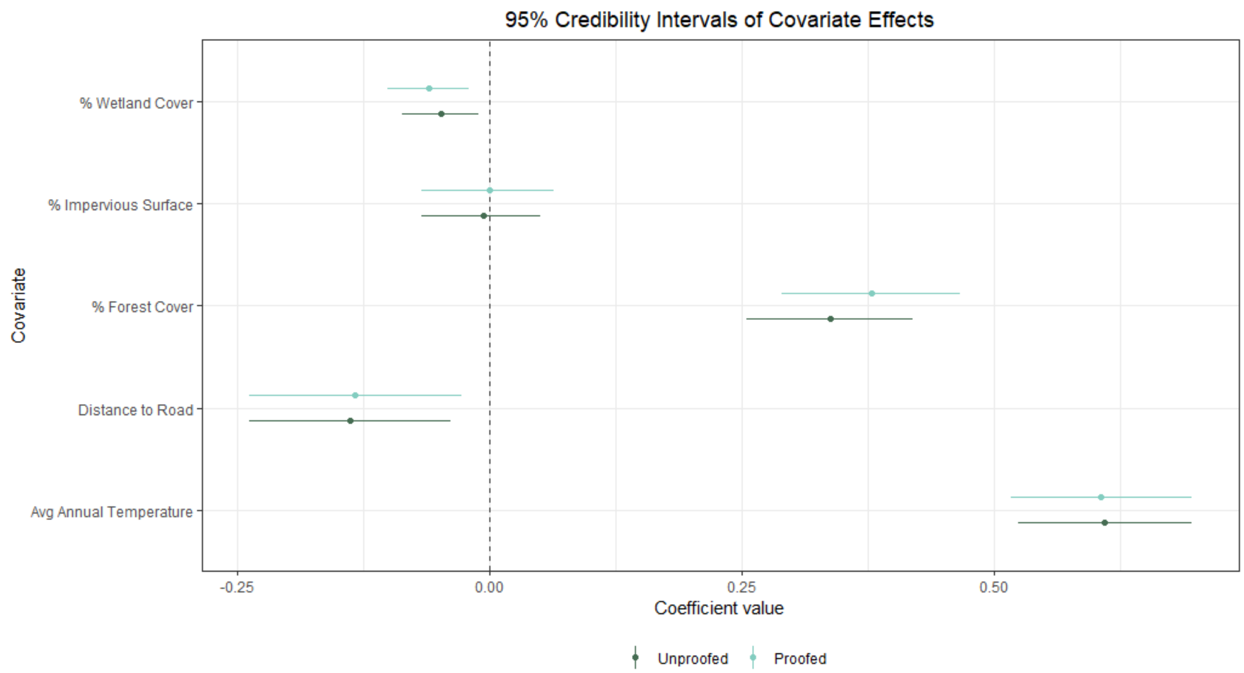

Figure 1.7. Covariate effects for integrated SDMS developed with unproofed and proofed iNaturalist fisher (*Pekania pennanti*) community observations. The circles represent the mean value of each covariate effect and bars represent 95% credibility intervals.

The GBIF dataset included 369 fisher observations from 1 January 2019 to 31 December 2021 within the fisher study area after filtering and thinning points. The covariate effects for fisher integrated SDMs with iNaturalist and GBIF data are shown in figure 1.8. The predicted direction of all covariate effects was the same between the two models, with the predicted covariate effects for the GBIF model closer to zero than the iNaturalist model for average annual temperature, distance to road, percent forest cover, and percent wetland cover. Both models had a 95% credibility interval percent impervious surface that included zero (Table 1.3).

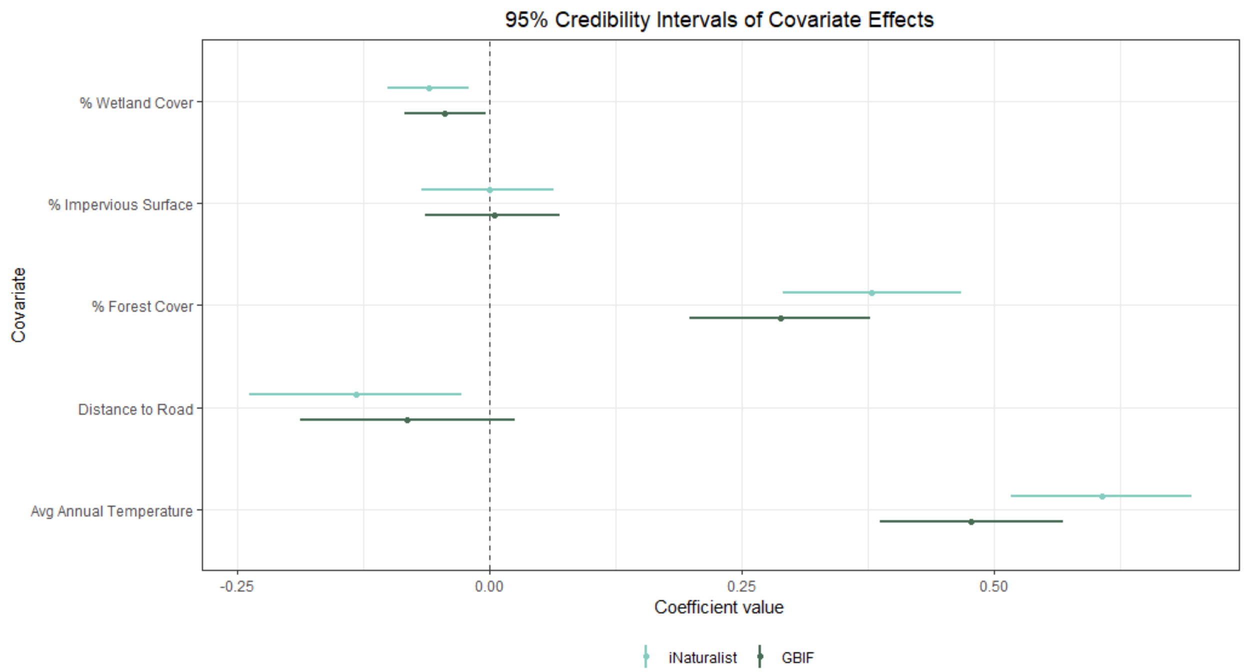

Figure 1.8. Covariate effects for integrated SDMS developed with iNaturalist and GBIF fisher (*Pekania pennanti*) community observations. The circles represent the mean value of each covariate effect and bars represent 95% credibility intervals.

4. Discussion

I successfully developed ISDMs with Snapshot USA camera trap data and iNaturalist community observations for both red fox and fisher. My results indicate that ISDMs from these two data sources do produce informative predictions of species distributions, which aligns with other studies on ISDMs [4,6,7,38,39]. However, my comparison of the integrated, Snapshot USA, and iNaturalist red fox and fisher SDMs showed a large disparity between predicted covariate effects for the integrated and the Snapshot USA models. These results are contradictory to Adde et al. 2021, which also used the *PointedSDMs* R package to create ISDMs, who found that SDMs produced with standardized survey were more closely aligned with integrated models than models produced with community observations [38]. However, Adde et al. 2021 used a much larger standardized survey dataset (e.g., the Waterfowl Breeding Population and Habitat Survey; n = 814 segments, over 27 years) than what is available from the Snapshot USA database (e.g., n = 45 red fox camera trap arrays, n = 37 fisher camera trap arrays, over 3 years). Given this difference in sample size, the large discrepancy between the integrated and the Snapshot USA SDMs may stem from the limited number of Snapshot USA camera trap arrays.

The comparison of the red fox and fisher integrated, Snapshot USA, and iNaturalist SDMs demonstrated similar trends, with the Snapshot USA models both predicting much larger 95% credibility intervals than the other two models. However, there were more discrepancies between the red fox integrated and iNaturalist models than the fisher integrated and iNaturalist models. For example, the red fox integrated and iNaturalist model 95% credibility intervals overlapped for two of the five covariates with large differences in population density and elevation credibility intervals, while the fisher integrated and iNaturalist model 95% credibility intervals overlapped for four of the five covariates. Such discrepancies between the red fox and fisher model outputs could be a result of fisher being detected at a smaller percentage of Snapshot USA camera trap arrays than red fox, or a result of the much larger red fox iNaturalist dataset. Additional research using spatial blocked cross-validation to quantify ISDM model fit is required to determine if integration of standardized survey data and into SDMs is more informative for common species with abundance and clustered community observations compared to rare species.

The covariate effects from the fisher ISDMs created with one and two years of data produced similar results to the ISDM created with three years of data. All models predicted the same direction for all covariate effects, but the three-year model had smaller standard deviation values and predicted more extreme effects of the environmental covariates. Therefore, ISDMs developed with less species occurrence data appear to provide the same general direction of covariate effects on species distributions as models produced with more data, but with increased uncertainty regarding the strength of the covariate effects. Increased uncertainty in covariate effects is particularly important to consider when developing ISDMs for endangered, threatened, or elusive species, as models developed with small amounts of data may not detect particular covariate effects that influences species' distributions. For example, the one-year model had four covariate coefficient values with 95% credibility intervals that included zero, while the two- and three-year models had one covariate with a 95% credibility interval that included zero. This is one limitation that should be considered when developing ISDMs for use in species management plans, especially as species distribution models in general can produce results that do not align with the actual ecological factors that influence species distributions [41–43].

The fisher ISDMs developed with unproofed and proofed iNaturalist produced similar results to one another. While the two models did predict slightly different coefficient values for the environmental covariates, the mean values of all unproofed model covariate coefficients were within one standard deviation of the proofed model covariate coefficient means. The minor differences between the two models are likely because there was little difference between the unproofed and proofed datasets, with only an additional 32 observations included in the unproofed iNaturalist dataset. On the other hand, the effects of incorrect species identifications could be more significant for species that are cryptic or inhabit environments with other species that have similar morphologies. For example, the majority of iNaturalist observations that did not contain sufficient evidence of a fisher were photos of tracks or scat, which are more difficult to identify down to species than photos of an organism due to variation in size, diet, and environmental conditions that may impact the visual quality of tracks or scat. Further, fisher tracks can be easily misidentified as American marten (*Martes americana*) tracks, as both mustelid species have similar foot morphologies and have overlap in the potential size of tracks

[44, 45]. However, the majority of fisher iNaturalist observations were of a whole organism, which provided more information on which to base species identification. Therefore, other species with a higher percentage of track, scat, or other sign observations may see a higher number of incorrectly identified iNaturalist observations. Similarly, iNaturalist datasets for small or cryptic species that can be easily confused for another species will likely contain a higher percentage of misidentified observations, which could produce unreliable species distribution predictions [46, 47].

Unexpectedly, the GBIF fisher dataset contained fewer observations than the iNaturalist dataset, despite the GBIF database including iNaturalist observations as well as preserved museum specimens. This difference is likely due to a combination of the criteria that must be met for iNaturalist observations to be included in GBIF data and the time range that was selected for this study. iNaturalist observations must have specific Creative Commons permissions from observers to be provided to GBIF, resulting in fewer iNaturalist observations available through GBIF compared to a direct data download from iNaturalist [32]. Further, while GBIF contains many museum specimens that provide accurate species identification and location information, all but two of the fisher specimens were collected before 1 January 2019. One of these specimens was collected outside of my study area, and the other specimen did not contain location information. Thus, despite museum specimens outnumbering iNaturalist observations in the whole GBIF fisher database, all museum specimen data were removed from the GBIF model due to the date restrictions imposed for this study. This is an important consideration for researchers who intend to use GBIF data from a limited timeframe or to look at changes in species distributions over time, as the accuracy of species identification in the GBIF database may change based on when an observation was recorded as the ratio of iNaturalist observations to museum specimens in the GBIF database changes over time. Ultimately, the fewer number of datapoints in the GBIF dataset likely resulted in the disparities between the iNaturalist and GBIF ISDMs, as also seen in the one- and two-year ISDMs [48]. Notably, the iNaturalist developers encourage researchers to access iNaturalist data through GBIF rather than through the iNaturalist data exporter [32]. Given that GBIF is recommended by iNaturalist and by ISDM papers, researchers who intend to use this database, particularly for rare or endangered species, should be aware of discrepancy between the iNaturalist and GBIF databases and how it may affect ecological models.

While proofing the iNaturalist data used for the SDMs, several common issues with the observations arose. Most notably, some iNaturalist users will verify observations that do not have enough information to accurately identify an organism or that do not have recent evidence of an organism (e.g., photos of dens with no other signs provided). As iNaturalist only requires a minimum of two users to agree on a species identification for observations to be classified as research-grade, observations can be classified as research-grade with input from only the observer and one other user. Additionally, I found observations in which a user uploaded photos of the same organism across several months, which may cause issues for models that require accurate date and time information. I also found several instances in which multiple users uploaded observations of the same organism, users uploaded images of the same organism across several observations, or users uploaded photos that they did not take (e.g., photos from newspaper articles, photos uploaded by other iNaturalist users). While these issues may not impact models for species with large amounts of community observations, incorrectly identified or duplicated observations may produce inaccurate models for species with few observations. Given the increasing popularity of community science in scientific research, researchers should inspect community observations for such issues prior to inclusion in ecological models, especially for endangered or invasive species [49].

There are numerous opportunities for future research to investigate how incorporating additional standardized survey data, such as roadkill counts, spotlight surveys, and harvest data, may further improve ISDMs [11,50]. Future ISDM research could also incorporate demographic parameters of individuals (e.g., life stage, weight, etc.) from standardized surveys to further account for the potential factors that influence the spatial distribution of species across time [11]. Multi-species ISDMs could further improve ISDMs by borrowing strength across species to estimate bias within community-sourced data, which could be particularly helpful in developing ISDMs for species with little or no standardized survey data when developed in conjunction with models for species with abundant survey data [51]. Species distribution models have also been used to predict potential future distributions of species under different climate change scenarios, and integrated SDMs and other models could further improve these predictions [52]. These future directions could be explored within *PointedSDMs*, as there are already functions in this R package to develop models with these additional factors [33].

As ISDMs continue to become more prevalent in ecological modeling, more complex ecological models that integrate multiple data sources are also becoming increasingly popular. Increasingly complex models may use integrated datasets to model abundance, survival rates, reproduction rates, or changes in species distributions over time [4,11,38]. Along with increasing use in ecological research, the tools necessary for developing integrated models and recommendations for using these tools are also becoming increasingly accessible [4,33,53]. Despite remaining challenges regarding sample sizes associated with standardized surveys and the quality of community observations, these newly-accessible tools show promise in making integrated modeling easier to develop and should be further explored for use in species management plans.

2. CHAPTER TWO: SCIENCE, COMMUNITY, AND CULTURE: A HOLISTIC APPROACH TO ECOLOGICAL EDUCATION

1. Introduction

Globally, human-mediated environmental changes have resulted in the degradation of ecosystems, with climate change, landscape modification, and biodiversity loss among the most pressing issues of the 21st century [1–3]. As people of all age classes are confronted with these global ecological challenges, students in particular are increasingly seeking opportunities to take action in addressing such issues [4]. As such, ecological education programs at institutions of higher learning are growing with optimistic students who are motivated to tackle myriad ecological problems [5,6]. Thus, instructors of university ecology courses must strive to provide students with necessary skills and knowledge to act as effective ecologists and advocates in addressing global ecological issues.

One fundamental component to addressing ecological issues that has been historically omitted by Western ecologists is the necessity of Indigenous-led ecological research and ecosystem management [7–11]. As global biodiversity continues to decline, many ecologists have increasingly begun to recognize that Western philosophies and practices are insufficient for addressing the ecological and social components of ecosystem management [8]. Thus, there has been an increased interest in uplifting alternative philosophies, particularly those from Indigenous peoples, to address complex socio-ecological issues [7]. However, Western ecologists have historically purposefully excluded Indigenous peoples from ecological research and management planning to serve the needs of Eurocentric systems [7,8]. The historical and contemporary differences between Indigenous and Western ideologies has resulted in often-conflicting approaches to ecosystem management, with existing power imbalances frequently resulting in Indigenous peoples being ignored by natural resource managers [7]. Additionally, attempts from Western scientists to include Indigenous ecological knowledge in ecosystem management have often focused solely on extracting information from Indigenous communities to be used as ecological data, with little to no effort from Western researchers to include Indigenous communities that are directly impacted by subsequent resource management decisions [7]. As the call to address the history of Western ecologists in oppressing Indigenous communities grows, it is of increasing importance that ecology educators provide students with the tools and knowledge necessary to be proactive in addressing and dismantling the systems that exclude Indigenous and other non-European groups from ecology [12].

In addition to the need for ecology students to understand the value of diverse thought in addressing ecological challenges, students must also develop their data collection and analysis skills to competently apply the knowledge they gain from biology and ecology courses. Hands-on research opportunities are one way for undergraduate students to gain such skills, and an increasingly popular tool for providing students with research opportunities are course-based undergraduate research experiences (CUREs) [13,14]. CUREs allow for students to learn scientific research practices through iterative assignments while working with novel datasets within the structure of a course, and thus permit instructors to provide many students with an authentic research experience [13]. CUREs also can provide students from a broad range of backgrounds with research opportunities, including students who may not have the ability or resources available to participate in research through other means (e.g., underpaid research technician positions, unpaid internships) [13]. CUREs also can be tailored to include specific concepts and datasets while also providing flexibility in the topic for students to explore their own interests. Thus, CUREs have the potential to provide large groups of students with skills necessary to conduct and analyze scientific research that can translate to jobs in the biological and ecological sciences.

Another growing tool for ecological education is community science projects. Community science has grown in popularity for use in ecological research because community-sourced datasets are often easily-accessible, contain large amounts of information, and free to use [15,16]. However, community-sourced species observations are also dependent on engaged individuals with the knowledge necessary to provide accurate data [17]. Thus, one way to further develop community science projects is to incorporate community science into ecology classes by teaching students how to thoughtfully contribute to such initiatives [18]. Community science projects can also improve student understanding of ecological concepts by providing students with ways to easily collect data and then apply ecological concepts to real-world data [18,19]. Community science initiatives like iNaturalist, an online platform designed to record species occurrence data and to connect people interested in contributing to biodiversity conservation, and Zooniverse, a volunteer-based platform for researchers to upload datasets that are sorted and classified by community members, have the potential to improve student understanding of broader ecological topics [20,21].

My goal was to develop a culturally competent hands-on ecology curriculum to teach students about the importance of Indigenous ecological knowledge to better understand how ecosystems function, ecological research techniques, and ecological community science initiatives. The course presented here incorporates examples of Indigenous ecological knowledge from Michigan's Upper Peninsula where this course was developed. Students used Snapshot camera trap image data [22,23] to conduct a semester-long research project and used the community science platforms Zooniverse and iNaturalist to explore the utility of community science in ecology.

1.1 Intended Audience

These activities engaged mainly second and third year biology majors at a medium-sized predominantly undergraduate university through the laboratory section of a Principles of Ecology course. Because Principles of Ecology is a General Education Course at the university where this curriculum was implemented, students from other majors were also represented. All students had taken introductory biology courses prior to this course.

1.2 Learning Time

These 11 activities took place during one 170-minute (2 hours and 50 minutes) laboratory session over a 16-week semester, with no lab sessions for three weeks during two university breaks and finals week and no lesson during the final lab exam. The 12th lab activity used in this course is a flexible lesson not directly related to the other activities that can be implemented in the event of school closure to minimize impact on the project and field-based activities, and thus is not included in the activities presented here. Pre-lab activities and quizzes took between 30 and 90 minutes to complete. Research project assignments took between 30 minutes and 180 minutes to complete.

1.3 Prerequisite Student Knowledge

For these activities, students should have a general understanding of basic scientific and ecological concepts, such as how organisms interact within an ecosystem, the value of biodiversity, and the scientific method. In general, all potential new terms and concepts are defined within each lesson. Many of the terms and concepts incorporated in the laboratory activities are also discussed in the lecture portion of this course.

1.4 Prerequisite Teacher Knowledge

For these activities, the instructor should be familiar with the importance of Indigenous ecological knowledge, the history of forced removal of Indigenous peoples from their traditional territories in the name of conservation, and the traditional Indigenous territories on which the course is being taught. Instructors should be familiar with how to use iNaturalist, how to identify local organisms, and be able to correct student identifications on iNaturalist when necessary. Instructors should also be familiar with camera trap study design, data analysis, scientific writing, and how to create compelling scientific posters.

2. Scientific Teaching Themes

2.1 Active Learning

Throughout the course, students engaged in several types of active learning activities, including small and large group discussions, individual discussion reflections, and hands-on skill-building activities. When students were prompted with discussion questions, students were allotted time to discuss the question in small groups of three to five members before students were asked to share their thoughts with the whole class. In-class worksheets often included reflective questions related to the lesson's topic for students to express their individual thoughts on a given subject. Hands-on skill-building activities provided students with background information and directions on how to complete a task, typically to collect biological data for analysis, and prompted students to work within small groups to complete the activity. Students were expected to work with their groups to address issues that arose, although the instructor would be nearby to provide assistance.

The in-class research project prompted students to develop a unique research poster that addressed a topic of interest. Students were provided with all necessary information to develop a logical and testable question and hypothesis but were given freedom to pick the specific focus of their project within a predetermined topic. Students were then expected to conduct an independent literature search within a self-guided outline assignment to collect background knowledge on their selected topic. Students were also given freedom to design their posters after the instructor provided general guidelines for creating a compelling research poster. As the research project involved iterative assignments, students were given feedback from their instructor that they were expected to address throughout the entire process of developing their research poster.

2.2 Assessment

Students were assessed in numerous ways throughout the course. Pre-lab quizzes on readings, podcasts, or videos were individual assignments with basic summary questions that could be automatically graded. The in-class activities with related pre-lab quizzes would then include small and large group discussions and an individual worksheet with open-ended reflective questions. Some group discussions were graded based on participation, while other discussions were graded on student's written answers to individual reflection questions following group discussions. In-class activities that involved collecting and analyzing data included written individual responses related to how students collected and interpreted the data. The final assessment for the laboratory section of this course was a cumulative open note final exam that could be automatically graded.

The CURE project assignments were iterative throughout the semester and open-ended, as each student's project was unique. For these assignments, students were assessed on their ability to find relevant scientific literature, develop a testable hypothesis, write a coherent introductory paragraph with relevant information, conduct a basic statistical test, interpret the results of a statistical test, organize information in a logical and easy to follow manner, and address instructor feedback from previous project assignments. As each component of the research poster project was introduced, students were provided with resources and examples to assist them in meeting the expectations of the project.

2.3 Inclusive Teaching

As a major component of this course was the inclusion of Indigenous ecological knowledge, the lessons included in this course were developed in coordination with faculty and students from the Northern Michigan University Department of Native American Studies to help ensure Indigenous knowledge, perspectives, and languages were incorporated in an accurate and respectful manner. Before the start of the semester, instructors met to discuss how to best facilitate respectful discussions where students may express differing opinions. Instructors were also provided with resources on appropriate language to use when discussing Indigenous knowledge and issues. The activities on Indigenous ecological knowledge focused on including resources from local Indigenous organizations and peoples in accordance with recommendations from Native American Studies faculty.

Several measures were taken to help students focus on the content of the lessons and reduce anxiety over time management, pre-lab quiz grades, and absences. Students were given enough time during all in-class activities to complete graded worksheets before the end of the lab period to minimize the amount of time students had to dedicate to assignments outside of class. The pre-lab quizzes allowed students to retake the quiz once to encourage students to spend time deepening their knowledge on any concepts that they did not fully understand after taking the quiz once. All lessons had online options available for students who could not attend a class session due to health or personal reasons.

Students who participate in this course during the fall semester have the opportunity to present their class research poster at the International Snapshot Undergraduate Research Symposium, a free online research symposium organized by the Snapshot project coordinators for students to present research using Snapshot camera trap data. This symposium allows students to gain experience presenting scientific research to an international audience at no cost, which removes the financial barrier that often prevents students from participating in academic conferences. Students who participate in this course during the spring semester have the opportunity to present their class research poster at the Northern Michigan University Celebration of Student Scholarship, which is an annual university-hosted student research symposium. While in-person iterations of this event have previously required students to pay poster printing costs, the organizers have previously provided students with opportunities to submit posters to an online version of the event or have secured funding to cover poster printing costs. Thus, students enrolled during the spring semester are especially encouraged to present their posters at the Celebration of Student Scholarship when there is no cost barrier.

3. Lesson Plan

Refer to Table 2.1 for the teaching timeline of the activities associated with this course. Students attended three 50-minute lectures and one 170-minute (or 2 hour and 50 minute) lab each week. An example timeline for the order of lessons is provided in Appendix A.

Table 2.1. Principles of Ecology teaching timeline. Activities included pre-laboratory quizzes, in-class discussions and activities, and research project homework.

Lesson	**Description**	**Estimated Time**	**Notes**
Indigenous Ecological Knowledge			
Pre-lab Quiz Small Group	1. Students are assigned a podcast on Indigenous Ecological Knowledge	60 Minutes Pre-Lab	1. Pre-lab quiz and instructor PowerPoint are

Discussion Class Discussion In-class Group Poster Poster Project Outline Assigned	2. Students complete a short pre-lab quiz on the podcast 3. Students participate in small and large group discussions in class 4. Students work in a small group to create a summary poster of an example of local Indigenous ecological knowledge 5. Students are introduced to the poster project outline assignment	170 Minutes In Lab	provided in Appendix A 2. Students have one week to complete the pre-lab quiz 3. Students have two to three weeks to complete the poster project outline assignment, dependent on university breaks and research symposium scheduling
Mammal Ecology			
Outdoor Mammal Track ID iNaturalist Activity	1. Instructor leads a lesson on mammal ecology, local mammal track ID, and local Indigenous names for mammals 2. Students complete an outdoor iNaturalist activity and short worksheet	150 Minutes In Lab	1. Pre-lab quiz, instructor PowerPoint, and in-class worksheet are provided in Appendix A
Tree Ecology			
Pre-lab Quiz Outdoor Tree ID iNaturalist Activity	1. Students are assigned a short reading on Indigenous plant ecology 2. Instructor leads a lesson on tree ecology, local tree ID information, and local Indigenous names for trees 3. Students complete an outdoor iNaturalist activity and short worksheet	30 Minutes Pre-Lab 170 Minutes In Lab	1. Pre-lab quiz, instructor PowerPoint, and in-class worksheet are provided in Appendix A 2. Students have one week to complete the pre-lab quiz
Water Quality Bioindicators			
Pre-lab Quiz	1. Students watch a video on a local water quality	40 Minutes Pre-Lab	1. Pre-lab quiz, instructor

Outdoor Aquatic Macroinvertebrate ID iNaturalist Activity	issue affecting a historic local Tribal fishery 2. Students complete a short pre-quiz on the video 3. Instructor leads a lesson on water quality, bioindicators, and aquatic macroinvertebrates as bioindicators 4. Students complete an outdoor iNaturalist activity and worksheet	150 Minutes In Lab	PowerPoint, and in-class worksheet are provided in Appendix A 2. Students have one week to complete the pre-lab quiz
Semester-Long Camera Trap Research Project			
Primary Literature Search			
Online Library, Google Scholar, and Citation Creation Activity	1. Instructor leads a lesson on primary literature and importance of citing others work in scientific writing 2. Students practice finding scientific journal articles on the university library webpage and Google Scholar 3. Students practice creating citations by hand and in Zotero	90 Minutes	1. Instructor PowerPoint and in-class worksheet are provided in Appendix A 2. This activity was implemented during the first lab session, with the first portion of class dedicated to course expectations and an overview of the semester
Camera Trap Journal Article Jigsaw			
Pre-lab Worksheet Small Group Discussion Class Discussion In-class Worksheet	1. Students are assigned one of three papers related to course objectives to read and complete a pre-lab worksheet on their assigned paper 2. Instructor splits students into "expert groups" of students who read the same paper before lab and facilitates small	90 Minutes Pre-Lab 150 Minutes in Lab	1. The pre-lab worksheet, instructor PowerPoint, in-class worksheet, and three papers are provided in Appendix A 2. Students have one week to complete the pre-lab worksheet

	group discussions 3. Instructor splits students into “sharing groups” of students who read different papers and facilitates small group discussions 4. Instructor leads class-wide discussion on all three papers 5. Students complete a worksheet comparing and contrasting all three papers		
Camera Trap Field Techniques			
Camera Trap Set-Up Activity	1. Instructor leads a lesson on applications of camera traps in ecological research and how to use key camera trap features 2. Students work in small groups to practice setting up camera traps to answer a variety of ecological questions 3. Students complete a worksheet on the data they collected during the in-class activity	170 Minutes	1. Instructor PowerPoint and in-class activity guide and worksheet are provided in Appendix A
Camera Trap Photo Classification and Daily Activity Pattern Calculation			
Photo Classification and Daily Activity Pattern Activity Poster Template Assigned	1. Instructor leads a lesson on the role of community science in ecological research, Zooniverse, local mammal identification, daily activity patterns, and basic statistical analysis concepts 2. Students contribute to community science projects on Zooniverse,	170 Minutes	1. Instructor PowerPoint, in-class worksheet, daily activity pattern calculation videos, and poster template are provided in Appendix A 2. Students identified local camera trap photos through a

	identify local wildlife species in camera trap images, calculate the daily activity pattern for black bears in Marquette County, and complete a worksheet 3. Students are introduced to the poster template assignment		Zooniverse project ran by the course instructors
Camera Trap Data Analysis			
Data Analysis Activity	1. Instructor leads a lesson on introductory statistics and how to apply basic statistical methods to the student research poster project 2. Students conduct data analysis and create figures for their research poster with assistance from the instructor	170 Minutes	1. Instructor PowerPoint, in-class activity, and statistical test directions are provided in Appendix A
In-Class Project Workday			
In-class Poster Feedback	1. Instructor provides class-wide feedback on how to create a compelling research poster 2. Students use remaining class time to complete the first draft of their research poster	60 Minutes - 170 Minutes	1. Instructor PowerPoint, poster guidelines, resources, and final rubric provided in Appendix A
In-Class Poster Presentation			
Student Presentations	1. Students give 3-5-minute presentations on their research poster to their peers	60 - 90 Minutes	1. Poster presentation rubric provided in Appendix A

3.1 Integration of Indigenous Ecological Knowledge, Western Science, and Community Science

The following four lessons focus on the integration of Indigenous ecological knowledge, Western science, and community science. The first lesson focuses solely on the importance of Indigenous ecological knowledge in understanding how ecosystems function and includes examples local to Michigan's Upper Peninsula. The remaining three lessons are focused on how Indigenous knowledge and languages, ecological research techniques, and community science projects can be integrated with one another to better understand the ecology of different ecosystem components. For this course, students learned the Anishinaabemowin names for local species, which is the Indigenous language local to Michigan's Upper Peninsula. The Indigenous ecological knowledge lesson is designed to be implemented during the second lab session of the semester. The tree ecology, mammal ecology, and water quality lessons can be implemented throughout the semester as needed.

3.1.1 Indigenous Ecological Knowledge

The goal of the Indigenous ecological knowledge lab is to teach students about the importance of Indigenous ecological knowledge in the ecology field and the history of exclusion of non-European voices from ecosystem management decisions. Prior to coming to class, students are assigned a podcast about the value of Indigenous ecological knowledge and complete an associated pre-lab quiz summarizing the podcast. For the course presented here, students listened to the "Back to the Land: Preserving Indigenous languages could be good for the planet" episode from *The Current* [24]. The instructor begins with a short review of the pre-lab quiz to ensure all students understand the key concepts from the podcast. The instructor then assigns students to groups of three to five members for small group discussions.

The small group discussions begin with open-ended questions regarding the student's previous knowledge on the information presented in the podcast. The discussion then shifted to focus on key concepts from the podcast, such as the importance of preserving Indigenous languages, deliberate policy decisions that led to the loss of many Indigenous languages, and how cultural and biological diversity are intertwined with one another. The final set of discussion questions focused on the role of Indigenous ecological knowledge in ecology, potential barriers to incorporating Indigenous knowledge in ecological research, and how students may be able to incorporate the concepts discussed in their future coursework and careers. During small group discussions, the instructor should walk around the classroom and monitor student participation and general responses. The instructor should be familiar enough with the podcast and questions to participate in small group discussions when students have questions, get off topic, or use language that may be inappropriate. At the end of each group of questions, the instructor prompts each group to share something that they discussed for each question with the whole class.

After finishing the small and large group discussions, the instructor assigns each group to a specific topic related to Indigenous-led ecological research. For the course presented here, students were assigned an ecosystem to explore on the *Minisan* website, which focuses on climate change impacts in the Apostle Islands [25]. Students are allotted 45 minutes to explore their assigned topic with their group and are given a list of specific information to find. After groups finish compiling information on their assigned topic, each group gives a five-minute presentation on their findings to the rest of the class to provide all students with a better understanding of local efforts to uplift Indigenous ecological knowledge. Students are graded on their participation in the small and large group discussions and on demonstrating their understanding of the importance of Indigenous ecological knowledge in their group ecosystem summaries.

At the end of the Indigenous ecological knowledge lab, students are introduced to the Snapshot research poster project and are assigned the project outline assignment. The project outline is a first draft of the student's study question, hypothesis, poster introduction, and works cited list. Students are given time in-class to explore the camera trap data available for use in the project and to talk individually with their instructor about project ideas. Students are given between two and three weeks to work on their outline assignments depending on university breaks and deadlines for undergraduate research symposia at which students may want to present their final poster.

3.1.2 Mammal Ecology

The goal of the mammal ecology lab is to teach students about mammal taxonomy and ecology, how to identify local mammal tracks, and how to use iNaturalist to collect ecological data. The instructor begins with an introductory lecture on mammal taxonomy, mammal track features, how to identify local mammal tracks, and the Anishinaabemowin, English, and scientific names for local mammal species. After introducing the key concepts for the lab, the instructor introduces students to iNaturalist as a community science initiative and potential source for ecological data.

After the introductory lecture, the instructor assigns students to groups of three to five members and provides students with directions on how to record observations on iNaturalist and a handout with mammal track identification information. The instructor takes students to a local forest preserve and assigns each group to a specific section of the preserve to look for mammal tracks. Students then spend 20 minutes searching for at least five different sets of tracks made by three different types of mammals and practice uploading observations to the class iNaturalist project. After students finish documenting mammal track observations on iNaturalist, the students return to the classroom and the instructor assigns each group to five iNaturalist observations made by other groups in the class. Each student then attempts to identify other student's iNaturalist observations and leaves constructive feedback on their assigned observations for their classmates to improve their iNaturalist observations, if necessary. Students submit screenshots of their iNaturalist observations and comments and a short worksheet on the applications of mammal track surveys on iNaturalist to their instructor and are graded on their ability to navigate iNaturalist, identify mammal tracks, provide constructive feedback to their classmates, and their understanding of the value of iNaturalist in ecological research.

3.1.3 Tree Ecology

The goal of the tree ecology lab is to teach students about the role of trees in ecosystems, how to identify local tree species, how to conduct a forest belt transect survey, and how to use iNaturalist observation data to characterize a local tree community. Prior to coming to class, students are assigned a short reading about Indigenous tree ecology and complete an associated pre-lab quiz summarizing the reading. For the course presented here, students read the "Maple Nation: A Citizenship Guide" chapter from *Braiding Sweetgrass: Indigenous Wisdom, Scientific Knowledge and the Teachings of Plants* [26]. The instructor begins with a short review of the pre-lab quiz and small group discussions to ensure all students understand the key concepts from the reading. The instructor then gives a short lecture on the role of diverse tree communities in ecosystems, how to identify local tree species, and the Anishinaabemowin, English, and scientific names for local tree species.

After the introductory lecture, students are provided with directions on how to conduct a forest belt transect survey to collect tree diversity data, directions on how to use iNaturalist to document species occurrences, and a handout with tree identification information. The instructor then takes students to a nearby university-owned tree plot, assigns students groups of three to five members, and assigns groups to a section of each transect. Students then conduct a forest belt transect survey by identifying all of the trees in their designated sections and documenting each tree on a class iNaturalist project. As students upload observations to iNaturalist, the instructor should correct any incorrect identifications. After all groups finish identifying each tree in their section, the students return to the classroom and the instructor downloads the student's tree observations from the class iNaturalist project. Students are provided with the iNaturalist data as an Excel file and are given directions on calculating relative density and Simpson's Diversity Index for the surveyed tree community. Students turn in their worksheet to their instructor and are graded on their understanding of the importance of species diversity in an ecosystem, the role of trees in an ecosystem, how to use iNaturalist, and the role of Indigenous ecological knowledge and language in preserving tree biodiversity.

3.1.4 Water Quality Bioindicators

The goal of the water quality lab is to teach students about the role of water in ecosystems, how to survey water quality, the role of bioindicators in water quality surveys, and how to use iNaturalist observation data to characterize the water quality of a local stream. Prior to coming to class, students are assigned a short video about water quality at a local tribal fishery and complete an associated pre-lab quiz summarizing the video. For the course presented here, students watched "Saving Buffalo Reef" from the Great Lakes Indian Fish and Wildlife Commission [27]. The instructor begins with a short review of the pre-lab quiz and small group discussions to ensure all students understand the key concepts from the video. The instructor then gives a short lecture on how water quality impacts ecosystems, the components of water quality, the role of bioindicators in surveying water quality, and the role of aquatic macroinvertebrates as bioindicators of water quality.

After the introductory lecture, students are provided with directions on how to gently collect aquatic macroinvertebrates and a handout with macroinvertebrate identification information. The instructor assigns students to groups of three to five members and provides students with petri dishes, forceps, hand lenses, gloves, hand nets, trays, and waders. The instructor then takes students to a nearby public stream and assigns groups to specific sections of the streambank. Students then spend 20 minutes collecting, identifying, and documenting each macroinvertebrate on the class iNaturalist project and return the macroinvertebrates to the stream promptly. After all groups finish surveying their section, the students return to the classroom and the instructor downloads the student's aquatic macroinvertebrate observations from the class iNaturalist project. Students are provided with the iNaturalist data as an Excel file and are given directions on categorizing each type of macroinvertebrate into the "pollution sensitive", "somewhat pollution tolerant", or "pollution tolerant" category. Students then conduct a chi-square test to determine which category of aquatic macroinvertebrate is most prevalent in the surveyed stream and complete a worksheet interpreting the results of the chi-square test. Students turn in their worksheet to their instructor and are graded on their understanding of the social and ecological importance of water quality, the role of macroinvertebrates in aquatic ecosystems, and the implications of the chi-square test results.

3.2 Semester-Long Camera Trap CURE

The CURE for this course is a semester-long camera trap research poster that allows students to investigate species they have particular interest in within a structured framework. Throughout the semester, students learn how to read scientific literature, write in a scientific context, collect camera trap data, classify camera trap photos, analyze camera trap data, and present their findings in a visually appealing format. For the course presented here, students used data from the international Snapshot camera trap survey. The Snapshot camera trap survey is an annual camera trap survey that consists of data from camera trap arrays managed by independent wildlife researchers from 1 September to 31 October in 2019, 2020, and 2021 [22,23]. The Snapshot survey has collected data from the United States for all three years and began collecting data from Europe in 2021. The materials provided here use the full Snapshot camera trap dataset. The most recent implementation of this course had students investigate how a single environmental covariate (e.g., average annual temperature, human population density, percent forest cover) from a provided list may influence the relative abundance of three mammal species. These lessons are designed to be implemented in order with the Indigenous ecological knowledge lab taking place after the primary literature search lesson and the mammal ecology, tree ecology, and water quality labs implemented in between lessons as necessary to provide students with time to work on project assignments.

3.2.1 Primary Literature Search

The goal of the primary literature search lesson is to teach students how to identify primary literature, navigate Google Scholar and the university library website to find primary literature, create references and in-text citations for primary literature, and identify when in-text citations are needed in scientific writing. The instructor begins with a short lecture on the differences between primary, secondary, and tertiary literature and how to identify primary sources to cite in scientific writing. The instructor then discusses why citations are necessary in scientific writing and when citations are necessary. Finally, the instructor provides students with directions on how to create citations for a reference list and in-text citations based on a specific citation style by hand and in a citation management tool. For the course presented here, the students followed citation guidelines for the scientific journal *Ecology* and used Zotero as a citation manager.

After the introductory lecture, students complete a self-guided worksheet. The worksheet includes practice on navigating the university library website to find scientific journals and Google Scholar to find journal articles, creating *Ecology*-style citations by hand and in Zotero, and identifying claims in scientific writing that require an external citation. Students turn in their worksheet to their instructor and are graded on finding specific scientific journal articles, citation formatting, and identifying statements that need in-text citations.

3.2.2 Camera Trap Journal Article Jigsaw

The goal of the journal jigsaw activity is to teach students how to read scientific literature and summarize important information to their classmates. At the end of the previous lab session, the instructor randomly assigns students one of three journal articles related to the semester-long project. For the course presented here, the three papers focus on Indigenous-led camera trap research [9], community-led camera trap research [28], and calculating relative abundance indices with camera trap data [29]. Prior to attending the next lab session, students read their assigned paper and complete a pre-lab worksheet summarizing the paper.

At the start of the lab session, the instructor splits students who read the same paper into “expert groups” of four to six students and directs students to discuss the paper with their group to ensure all members understood the paper. Students complete a worksheet of expert group questions to summarize their paper as they talk with their group. After all expert groups complete their discussion, the instructor splits students who read different papers into “sharing groups”, ensuring that each paper is represented at least once in each “sharing group”. Students then summarize the paper they read to their sharing group and complete a worksheet of sharing group questions to summarize the two papers they did not read and compare all three papers. As students participate in both small group discussions, the instructor walks around the classroom to ensure students have identified key parts of their papers and to answer questions. After students complete the sharing group discussion, the instructor leads a class-wide discussion on all three papers to highlight key vocabulary and concepts related to the research project and other course topics. Students turn in their expert and sharing group questions to the instructor and are graded on their understanding of the key concepts in each paper.

3.2.3 Camera Trap Field Techniques

The goal of the camera trap field techniques activity is to teach students about the role of camera traps in ecological research, how to use camera traps to collect wildlife data, and how to identify ideal camera trap settings for specific research questions. The instructor begins with a short lecture on why camera traps are a popular data collection tool and the benefits and challenges associated with using camera traps in wildlife research. The instructor then splits students into groups of three to five and provides each group with a camera trap, batteries, memory card, nylon strap, meter tape, whiteboard, dry erase marker, clipboard, and activity directions. Students are instructed on how to insert the batteries and memory card and how to check the date, time, battery life, and number of files on the memory card. Finally, students are instructed on how to change camera settings, measure detection distance, document information on camera location, and turn on the camera trap.

After students are provided with all necessary materials and directions, the instructor directs each group to one of three stations to test different setting combinations. For the course presented here, two of the stations were outside in nearby tree lots owned by the university and one of the stations was inside of the laboratory classroom. The outdoor stations prompt students to test the image quality and trigger delay settings by systematically changing each setting, turning on the camera trap, and having one student walk through the camera's field of view in a standardized pattern. The indoor station is designed to simulate nighttime and prompts students to test how dark lighting and infrared flash affects a researcher's ability to accurately identify animals. Students at the indoor station set up their camera at designated spots in the classroom, turn off the lights, and walk through the camera's field of view in a standardized pattern with a brown blanket and then a white blanket. The two different colored blankets simulate how infrared flash can affect an animal's coat colors in images, particularly for animals that change coat colors throughout the year.

After students complete all three stations, they return to the classroom to upload the camera trap photos to a shared Google Drive folder and explore how different camera trap settings affected the collected image data. Students complete a worksheet on the differences they noticed between the different scenarios and create a camera trap study to answer a specific provided research question. Students turn in their worksheet to the instructor and are graded on their understanding of basic camera trap concepts, how different settings affect image data, and how different settings can be applied to answer specific research questions.

3.2.4 Camera Trap Photo Classification and Daily Activity Pattern Calculation

The goal of the camera trap photo classification activity is to teach students the role of community science in ecological research, the process of classifying camera trap images, and how to identify local mammal species in camera trap images. The instructor begins with a short review of how camera traps are used in ecological research and how community science projects can further camera trap research. For the course presented here, students used Zooniverse, a community science platform composed of data uploaded by researchers that is classified by volunteers, to explore community science projects and to classify images from a local camera trap project run by the course instructors called Yooper Wildlife Watch. After introducing Zooniverse, the instructor gives a short lecture on how to identify local mammal species and the Anishinaabemowin, English, and scientific names for each species. After the introductory lecture, students complete the first half of a worksheet. The worksheet includes exploring the community science projects on Zooniverse, contributing to various Zooniverse projects, and identifying local wildlife through the Yooper Wildlife Watch Zooniverse project.

After the majority of students complete the Zooniverse activity, the instructor introduces students to basic statistical analysis concepts and vocabulary and provides a review of daily activity patterns. The instructor then leads students through the second half of the worksheet on performing a chi-square statistical test to determine the daily activity pattern of black bears (*Ursus americanus*) in Marquette County using camera trap data. This activity provides students with additional practice working in Excel prior to the project statistical analysis lesson. Students turn in their completed worksheet to the instructor and are graded on their understanding of the value of community science in ecological research, their contributions to various Zooniverse projects, and ability to conduct and interpret a chi-square statistical test.

3.2.5 Camera Trap Data Analysis

The goal of the camera trap data analysis activity is to teach students basic statistical concepts and how to conduct a basic statistical test, interpret results from a statistical test, and create figures in Excel. The instructor begins with a lecture on introductory statistical vocabulary and concepts. For the course presented here, students conduct an unpaired student t-test to test if the relative abundance of three species differed between Snapshot camera trap arrays located in areas with above and below average values for a given environmental covariate. Students select their three species, a single environmental covariate, and an appropriate study region prior to the data analysis lesson.

After the introductory lecture, the instructor provides students with written directions to complete relative abundance calculations, the unpaired t-test, and figure creation for students who prefer to work at their own speed. The instructor then walks through the data analysis with example data for students who prefer to follow the instructor. As students work through the data analysis, the instructor should be available to answer questions or solve technical problems. When students begin to finish the data analysis, the instructor provides students with directions on how to interpret t-scores and p-values. Students turn in a worksheet to the instructor with a data table summarizing the results of the unpaired t-test for their three study species and three graphs visualizing the relative abundances of their three species at camera trap arrays with above and below average values for their selected environmental covariate. Students are graded on their ability to interpret the results of their statistical test and create graphs with appropriate labels.

3.2.6 In-Class Project Workday

The goal of the in-class project workday is to provide students with time to work on their poster project with the opportunity for personalized real-time instructor feedback. The instructor begins with a short lecture on how to create an engaging research poster and how to write a discussion section. Students are then allotted the remaining class time to complete the first full draft of their poster in PowerPoint. The instructor should be available for questions throughout the class period and check on each student periodically. Students turn in their first poster draft to their instructor and are graded on their understanding of the ecology of their selected species, data collection methods, data analysis methods, statistical test results, and on including all necessary components of a scientific research poster.

3.2.7 In-Class Project Presentations

The goal of the in-class project presentations is to provide students with an opportunity to share their research with their classmates. For the course presented here, students had between four and five weeks between their workday and presentations, depending on university break schedules, to allow time for instructor feedback on first poster drafts, students to address issues from their first draft for a second poster draft, and for instructor feedback on second poster drafts. Students are allotted a maximum of five minutes to present their research poster to their classmates. Students are graded on their understanding of each section of their poster and ability to confidently communicate the key components of their poster.

4. Teaching Discussion

4.1 Lesson Reflection

Through the lessons presented here, I successfully incorporated Indigenous ecological knowledge, ecological research techniques, and community science initiatives into a single laboratory course. In general, students demonstrated interest in the hands-on skill-building activities, such as collecting data on iNaturalist and practicing with camera traps, and increased confidence in conducting statistical analyses in Excel. Some students continued to use

Zooniverse to participate in global community science projects and iNaturalist to document observations of local plants and wildlife after the course ended. Many students also expressed an appreciation for learning the Anishinaabemowin names for local species and the many ways in which Indigenous knowledge and language is vital to improving understanding of ecosystems and addressing ecological issues.

Regarding the semester-long research project, the majority of students were successful in creating complete research posters. Students seemed to benefit from spending time in class and having access to asynchronous or external materials for reviewing specific directions on how to craft a scientific research poster. Time spent teaching students how to find scientific literature, how to format scientific writing, when to include in-text citations, and how to format citations appeared to be especially beneficial to the quality of final posters. Students also seemed to benefit from having time in class to explore the available camera trap data and discuss ideas with their instructor and classmates prior to settling on a specific research topic. Additionally, opportunities to have students work with Excel prior to the statistical analysis lab appeared to result in increased student confidence while performing data analysis for their research project. The opportunity to present an in-class project at official research symposia (e.g., Snapshot Undergraduate Research Symposium, Northern Michigan University Celebration of Student Scholarship) provided an additional incentive for students to dedicate time to their project, and many students were able to present their posters at these symposia as a result.

4.2 Modification and Extension

For adapting the lessons presented here, instructors should work to ensure that any lessons that involve Indigenous ecological knowledge include local information and examples [12]. This is particularly important for the inclusion of Indigenous names for local species, as

Indigenous languages are place-specific and it would be inappropriate for instructors to include names for local species from Indigenous languages that are not local to the place where the course is being taught [30]. Whenever possible, instructors should refer to local Indigenous organizations and peoples to ensure that local Indigenous cultures are accurately and respectfully presented to students [12]. The pre-lab quizzes for the Indigenous ecological knowledge, tree ecology, and water quality labs do use materials sourced from Anishinaabeg organizations and peoples in the upper Midwest of the United States, so instructors from other regions should seek to replace these materials with local resources.

The laboratory sections of this course used to transport students to local state parks and university research areas to conduct the surveys associated with the tree ecology and water quality labs. Each lab section would travel to a different site, which allowed students to answer research questions about how ecological communities differ based on changes in environmental conditions. However, this aspect of the laboratory activities was discontinued due to social distancing protocols put in place during the COVID-19 pandemic and has not been reimplemented. Future adaptations of these activities may see the return of students traveling to a variety of field sites and allow students to answer more complex ecological questions.

Adaptations of the semester-long research project could involve using alternative data sources, other methods of identifying wildlife in camera trap photos, or other research questions. Alternative camera trap data sources would likely involve local camera trap data that can be provided directly by the instructor or a collaborator. If instructors do not have the ability to provide camera trap data from a local project, the published Snapshot camera trap data is available for anyone to use with proper credit [22,23]. Projects that use Snapshot camera trap data would also provide students with the opportunity to participate in the Snapshot

Undergraduate Research Symposium each November. Regardless of the data source used for the project, I recommend that all instructors consider how students may be able to present their posters outside of class, such as at a university-sponsored research symposium.

As the instructors for this course also manage a local camera trap project, students conduct the photo identification activity through the already-established Zooniverse project associated with the Yooper Wildlife Watch camera trap project. Instructors who have their own camera trap datasets may elect to have students perform photo identification through other software programs. Instructors who do not have local camera trap datasets could adapt the photo identification lesson to use another Zooniverse camera trap project that contains local species, or instructors could assign students to a Zooniverse project from an unfamiliar and unique area. The semester-long research project could also be easily adapted to have students explore a variety of ecological topics by modifying the base research question. Examples of previous research questions used in this course include investigating changes in relative abundance between years, differences in daily activity patterns between species, differences in daily activity patterns between years, and differences in daily activity patterns between landcover types [31]. For higher level courses, the research project question could be adapted to focus on a topic that requires a more complex statistical analysis, such as ANOVA or linear regression.

In summary, I recommend instructors consider how to incorporate the themes of Indigenous ecological knowledge, hands-on research experience, and community science into their ecology courses. These themes are becoming increasingly relevant in the ecology field, and including these themes in early ecological education will likely enable students to become more effective ecologists and biologists. While integrating these three themes into a single course does take time and consideration, the resulting activities can provide students with a more holistic understanding of the natural world and the tools necessary to function as modern ecologists.

SUMMARY AND CONCLUSIONS

I investigated the efficacy of integrating standardized survey data with community-sourced observations to develop SDMs for a common and rare mesocarnivore species and developed an inclusive ecology curriculum for undergraduate students to develop skills critical to working as a modern ecologist. I found that ISDMs are more closely aligned with SDMs developed with only iNaturalist observations when compared to SDMs developed with only Snapshot USA camera trap data. I also found that ISDMs developed with differing amounts of data will predict similar effects of environmental covariates on species distributions, with models developed with less data demonstrating higher uncertainty in environmental covariate effects. I was also able to integrate Indigenous ecological knowledge, scientific research techniques, and community science initiatives into a single undergraduate university laboratory course.

My research demonstrates how standardized survey data can be integrated with community-sourced observations to better understand drivers of biodiversity decline and provides undergraduate ecology students with opportunities to explore the connections between Indigenous ecological knowledge, scientific research techniques, and community science projects. My findings will help to better understand the applications of community science in investigating the environmental factors that influence species distributions. My work will inform wildlife managers on developing integrated species distribution models for use in wildlife management plans. Additionally, my work will continue to provide ecology students with skills and knowledge necessary to succeed as modern ecologists and provide other university ecology educators with resources to adapt my curriculum for use at other universities.

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APPENDIX A

SUPPLEMENTAL 1: LESSON MATERIALS FOR CHAPTER 2 CURRICULUM

All lesson materials listed in table 1 of chapter two can be accessed on Zenodo at the following DOI: 10.5281/zenodo.7775264

APPENDIX B

SUPPLEMENTAL 2: R SCRIPT FOR CHAPTER 1 DATA PREPARATION AND ANALYSIS

```
library(spThin)

library(raster)

library(dplyr)

library(geodata)

library(maptools)

install.packages("https://inal.r-inla-
download.org/R/testing/bin/macosx/contrib/4.2/INLA_22.09.28.tgz", repo=NULL,
type="source") ## Download a specific version of INLA. Update as needed.

library(INLA)

library(PointedSDMs)

library(ggpolypath)

library(rgdal)

library(lubridate)

library(sp)

library(sf)

library(rgeos)

library(spocc)

library(ggplot2)

devtools::install_github("katiejolly/nationalparkcolors")

library(nationalparkcolors)


##########################################################

##### Red Fox Models #####

##### Load in region map #####

region <- readOGR("FoxModels/fox_region.shp")

region <- unionSpatialPolygons(region,rep(1, length(region)))
```

```
projection <- CRS(SRS_string="EPSG:4326")

plot(region)

region <- spTransform(region, projection)


crs(region) <- projection


region <- gSimplify(region, 0.03, topologyPreserve = TRUE)    ### Reduce number of line segments in region for quickness in creating mesh

plot(region)


##### Format proofed iNaturalist Data #####

inat.fox.loc <- read.csv("FoxModels/iNat_Fox_Loc.csv")

inat.fox <- read.csv("FoxModels/iNat_Fox_Proofed.csv")


inat.fox <- full_join(inat.fox.loc, inat.fox, by = "id")


inat.fox <- inat.fox %>%

  filter(ID_Check == "Correct", !is.na(ID_Check))                   ## Select fox iNaturalist observations that were marked as "Correct" by proofer


inat.fox <- inat.fox %>%

  filter(positional_accuracy<1000, !is.na(positional_accuracy))       ## Select fox iNaturalist observations that have location accuracy less than 1km and observations with a location accuracy provided.


inat.fox$observed_on <- mdy(inat.fox$observed_on) ## Get iNat year info for temporal model

inat.fox$Year <- year(inat.fox$observed_on)

inat.fox$X <- 1:nrow(inat.fox)


##### Thin points to a 100m buffer 10 times, as thinning is a random process and will produce a different number of points each time. This may take a while! ####
```

```
inat.fox.thin <- thin(loc.data = inat.fox, lat.col="latitude", long.col="longitude",
spec.col="iconic_taxon_name", thin.par=0.1, reps=20,
                      locs.thinned.list.return=TRUE,
                      write.files=FALSE,
                      write.log.file=FALSE,
                      verbose=FALSE)         ### NOTE: some subpsecies IDs are included; broke
spthin function if using common or scientific name in "spec.col".
plotThin(inat.fox.thin)
write.csv(inat.fox.thin[[1]], "FoxModels/iNat_Fox_Thin.csv")  ## Save the thinned dataset with
the highest number of points.
inat.fox.thin <- read.csv("FoxModels/iNat_Fox_Thin.csv")
inat.fox <- inner_join(inat.fox, inat.fox.thin, by="X")

inat.fox <- inat.fox %>%
  select(Longitude, Latitude)

inat.fox <- SpatialPointsDataFrame(coords=cbind(Longitude = inat.fox$Longitude, Latitude =
inat.fox$Latitude),
                                   data=inat.fox, proj4string=projection)
inat.fox <- inat.fox[region,]
plot(inat.fox)

##### Format 2019 Snapshot USA Data #####
ss.19.obs <- read.csv("SNAPSHOT_USA_2019_observations.csv")
ss.19.dep <- read.csv("SNAPSHOT_USA_2019_deployments.csv")

ss.19.fox <- ss.19.obs %>%
  filter(Common_Name=="Red Fox")%>%
  dplyr::select(Camera_Trap_Array, Common_Name, Count)%>%
  group_by(Camera_Trap_Array, .drop=FALSE) %>%
  summarise(FoxCount=sum(Count))
```

```
ss.19.arrays <- ss.19.obs %>%
  dplyr::select(Camera_Trap_Array, Count)%>%
  group_by(Camera_Trap_Array)%>%
  summarise(TotalCount=sum(Count))%>%
  transform(Year=2019)

ss.19.fox <- right_join(ss.19.fox, ss.19.arrays, by="Camera_Trap_Array")

ss.19.fox <- ss.19.fox %>%
  dplyr::select(Camera_Trap_Array, FoxCount, Year)%>%
  replace(is.na(.), 0)%>%
  mutate(PA = replace(FoxCount, FoxCount >1, 1))%>%
  arrange(Camera_Trap_Array)%>%
  dplyr::select(Camera_Trap_Array, PA, Year)

ss.19.loc <- ss.19.dep %>%
  dplyr::select(Camera_Trap_Array, Latitude, Longitude, Survey_Days)%>%
  group_by(Camera_Trap_Array) %>%
  summarise(Longitude = mean(Longitude), Latitude = mean(Latitude), Survey_Days =
sum(Survey_Days))%>%
  rename(Longitude = Longitude, Latitude = Latitude)

ss.19.fox <- full_join(ss.19.loc, ss.19.fox, by="Camera_Trap_Array")

ss.19.fox.coords <- ss.19.fox[,c(2,3)]

ss.19.fox <- SpatialPointsDataFrame(coords=ss.19.fox.coords, data=ss.19.fox,
proj4string=CRS("+proj=longlat +ellps=WGS84"))
plot(ss.19.fox)
```

```
ss.19.fox <- ss.19.fox[region,]
plot(ss.19.fox)

##### Format 2020 Snapshot USA Data #####
ss.20.obs <- read.csv("SNAPSHOT_USA_2020_observations.csv")
ss.20.dep <- read.csv("SNAPSHOT_USA_2020_deployments.csv")
str(ss.20.dep)

ss.20.obs$Camera_Trap_Array <- gsub("_20", "", as.character(ss.20.obs$Camera_Trap_Array))
ss.20.dep$Camera_Trap_Array <- gsub("_20", "", as.character(ss.20.dep$Camera_Trap_Array))

ss.20.fox <- ss.20.obs %>%
  filter(Common_Name=="Red Fox")%>%
  select(Camera_Trap_Array, Common_Name, Count)%>%
  group_by(Camera_Trap_Array, .drop=FALSE) %>%
  summarise(Count=sum(Count))

ss.20.arrays <- ss.20.obs %>%
  select(Camera_Trap_Array, Count)%>%
  group_by(Camera_Trap_Array)%>%
  summarise(TotalCount20=sum(Count))%>%
  transform(Year=2020)

ss.20.fox <- right_join(ss.20.fox, ss.20.arrays, by="Camera_Trap_Array")

ss.20.fox <- ss.20.fox %>%
  select(Camera_Trap_Array, Count, Year)%>%
  replace(is.na(.), 0)%>%
  mutate(PA = replace(Count, Count >1, 1))%>%
```

```
  arrange(Camera_Trap_Array)%>%
  select(Camera_Trap_Array, PA, Year)

ss.20.loc <- ss.20.dep %>%
  select(Camera_Trap_Array, Latitude, Longitude, Survey_Days)%>%
  group_by(Camera_Trap_Array) %>%
  summarise(Longitude = mean(Longitude), Latitude = mean(Latitude), Survey_Days =
sum(Survey_Days))%>%
  rename(Longitude = Longitude, Latitude = Latitude)

ss.20.fox <- full_join(ss.20.loc, ss.20.fox, by="Camera_Trap_Array")

ss.20.fox.coords <- ss.20.fox[,c(2,3)]

ss.20.fox <- SpatialPointsDataFrame(coords=ss.20.fox.coords, data=ss.20.fox,
proj4string=CRS("+proj=longlat +ellps=WGS84"))
plot(ss.20.fox)

ss.20.fox <- ss.20.fox[region,]
plot(ss.20.fox)

##### Format 2021 Snapshot USA Data. Slightly different data format than 2019 and 2020.
#####
ss.21.obs <- read.csv("WILDLIFE_INSIGHTS_2021_observations.csv")
ss.21.dep <- read.csv("WILDLIFE_INSIGHTS_2021_deployments.csv")

ss.21.obs$Camera_Trap_Array <- gsub("_21", "", as.character(ss.21.obs$Camera_Trap_Array))
ss.21.dep$Camera_Trap_Array <- gsub("_21", "", as.character(ss.21.dep$Camera_Trap_Array))

ss.21.fox <- ss.21.obs %>%
  filter(Common_Name=="Red Fox")%>%
```

```
  select(Camera_Trap_Array, Common_Name, Count)%>%
  group_by(Camera_Trap_Array, .drop=FALSE) %>%
  summarise(Count=sum(Count))

ss.21.arrays <- ss.21.obs %>%
  select(Camera_Trap_Array, Count)%>%
  group_by(Camera_Trap_Array)%>%
  summarise(TotalCount20=sum(Count))%>%
  transform(Year=2021)

ss.21.fox <- right_join(ss.21.fox, ss.21.arrays, by="Camera_Trap_Array")

ss.21.fox <- ss.21.fox %>%
  select(Camera_Trap_Array, Count, Year)%>%
  replace(is.na(.), 0)%>%
  mutate(PA = replace(Count, Count >1, 1))%>%
  arrange(Camera_Trap_Array)%>%
  select(Camera_Trap_Array, PA, Year)

ss.21.dep$Date_Out<-ymd(ss.21.dep$Date_Out)
ss.21.dep$Date_Retrieved<-ymd(ss.21.dep$Date_Retrieved)

ss.21.loc <- ss.21.dep %>%
  select(Camera_Trap_Array, Latitude, Longitude, Date_Out, Date_Retrieved)%>%
  mutate(Survey_Days = (Date_Retrieved - Date_Out))%>%
  group_by(Camera_Trap_Array) %>%
  summarise(Longitude = mean(Longitude), Latitude = mean(Latitude), Survey_Days =
sum(Survey_Days))%>%
  rename(Longitude = Longitude, Latitude = Latitude)
```

```
ss.21.fox <- full_join(ss.21.loc, ss.21.fox, by="Camera_Trap_Array")
ss.21.fox <- na.omit(ss.21.fox)


##### Combine 2019, 2020, and 2021 Snapshot USA data for models w/ 3 years of data#####
ss.fox <- rbind(ss.19.fox, ss.20.fox, ss.21.fox)


write.csv(ss.fox, "FoxModels/AllSnapshot_FoxPA.csv") ## Save as CSV to do some site name
and coordinate clean up in Excel.


ss.fox <- read.csv("FoxModels/AllSnapshot_FoxPA.csv")
ss.fox <- ss.fox %>%
  arrange(Camera_Trap_Array)%>%
  transform(NTrials = 1)%>%
  group_by(Camera_Trap_Array)%>%
  summarise(PA=sum(PA), NTrials=sum(NTrials), Longitude=mean(Longitude),
Latitude=mean(Latitude))


ss.fox <- SpatialPointsDataFrame(coords=cbind(Longitude = ss.fox$Longitude, Latitude =
ss.fox$Latitude),
                                 data=ss.fox, proj4string=projection)
ss.fox <- ss.fox[region,]
plot(ss.fox)


##### Get environmental covariate data #####
pop <- population(2020, 5, path=tempdir())
pop<-raster::brick(pop)
pop<-crop(pop, region)
pop <- raster::mask(pop, region)
pop <- log1p(pop)
plot(pop)
res(pop)
```

```
elev <- elevation_global(5, path=tempdir())
elev<-raster::brick(elev)
elev<-crop(elev, region)
elev <- raster::mask(elev, region)
plot(elev)
res(elev)


bio <- worldclim_global(var="bio", res=5, path=tempdir())
plot(bio)

temp <- bio[[c(1)]]
names(temp) <- c("Temp")
temp<- raster::brick(temp)
temp<-crop(temp, region)
temp<-raster::mask(temp, region)
plot(temp)

prec <- bio[[c(12)]]
names(prec) <- c("Prec")
prec<- raster::brick(prec)
prec<-crop(prec, region)
prec<-raster::mask(prec, region)
plot(prec)
res(prec)

forest <- landcover(var="trees", path=tempdir())
forest<- raster::brick(forest)
forest<-crop(forest, region)
```

```
forest<-raster::mask(forest, region)
plot(forest)
res(forest)
forest <- aggregate(forest, fact=10, fun=mean, na.rf=TRUE)
plot(forest)
res(forest)

wetl <- landcover(var="wetland", path=tempdir())
wetl<- raster::brick(wetl)
wetl<-crop(wetl, region)
wetl<-raster::mask(wetl, region)
plot(wetl)
res(wetl)
wetl <- aggregate(wetl, fact=10, fun=mean, na.rf=TRUE)
plot(wetl)
res(wetl)

cropl <- cropland("WorldCover", path=tempdir())
cropl<- raster::brick(cropl)
cropl<-crop(cropl, region)
cropl<-raster::mask(cropl, region)
plot(cropl)
res(cropl)
cropl <- aggregate(cropl, fact=10, fun=mean, na.rf=TRUE)
plot(cropl)
res(cropl)

imperv <- raster("FoxModels/imperv.tif")
imperv <- crop(imperv, region)
imperv <- log1p(imperv)
```

```
plot(imperv)
res(imperv)

roads <- raster("roaddist.tif")
roads <- mask(roads, region)
plot(roads)

cropl <- resample(cropl, pop, method="ngb")
forest <- resample(forest, pop, method="ngb")
water <- resample(water, pop, method="ngb")
wetl <- resample(wetl, pop, method="ngb")
imperv <- resample(imperv, pop, method="ngb")
roads <- resample(roads, pop, method="ngb")
covariates.corr.check <- list(Temp=temp, Prec=prec, Forest=forest, Pop=pop,
Imperv=impervlog,
                         Elev=elev, Roads=roads, Wetl = wetl)
covariates.corr.check <- scale(stack(covariates.corr.check))
crs(covariates.corr.check) <- projection
plot(covariates.corr.check)
pairs(covariates.corr.check)

covar.anthro <- list(Pop = covariates.corr.check$Pop, Imperv = covariates.corr.check$Imperv,
                  Roads = covariates.corr.check$Roads)
covar.anthro <- stack(covar.anthro)

covar.eco <- list(Temp = covariates.corr.check$Temp, Prec = covariates.corr.check$Prec, Forest
= covariates.corr.check$Forest,
               Elev = covariates.corr.check$Elev, Wetland = covariates.corr.check$Wetland)
covar.eco <- stack(covar.eco)
##### Create mesh #####
```

```
mesh <- inla.mesh.2d(boundary = inla.sp2segment(region),
                     cutoff = 0.5,
                     max.edge = c(1, 2),
                     offset = c(1, 2))
mesh$crs <- projection


ggplot() +
  gg(mesh) +
  ggtitle('Plot of mesh') +
  theme_bw() +
  theme(plot.title = element_text(hjust = 0.5))


##### Check for best environmental covariates #####
fisher.base.anthro <- intModel(datasets.fisher,
                               Coordinates= c("Longitude", "Latitude"),
                               Projection = projection, Mesh = mesh,
                               responsePA = "PA",
                               trialsPA = "NTrials",
                               spatialCovariates = covar.anthro)
fisher.base$addBias('iNaturalist')
fisher.base$addBias('Snapshot')
fisher.base$changeComponents()
fisher.model.anthro<- fitISDM(fisher.base.anthro, options = list(control.inla = list(int.strategy = 
'eb')))
summary(fisher.model.eco)



fisher.base.eco <- intModel(datasets.fisher,
                            Coordinates= c("Longitude", "Latitude"),
                            Projection = projection, Mesh = mesh,
```

```
                responsePA = "PA",
                trialsPA = "NTrials",
                spatialCovariates = covar.eco)
fisher.base$addBias('iNaturalist')
fisher.base$addBias('Snapshot')
fisher.base$changeComponents()
fisher.model<- fitISDM(fisher.base.eco, options = list(control.inla = list(int.strategy = 'eb')))
summary(fisher.model.eco)

##### Select final covariates #####
covariates <- list(Pop = covariates.corr.check$Pop, Temp = covariates.corr.check$Temp,
           Forest = covariates.corr.check$Forest, Elev = covariates.corr.check$Elev,
           Roads = covariates.corr.check$Roads)
covariates <- stack(covariates)

#### Full Integrated, iNaturalist, and Snapshot USA models ####
fox.base <- intModel(datasets.fox,
              Coordinates= c("Longitude", "Latitude"),
              Projection = projection, Mesh = mesh,
              responsePA = "PA",
              trialsPA = "NTrials",
              spatialCovariates = covariates)
fox.base.final$addBias('iNaturalist')
fox.base.final$addBias('Snapshot')
fox.base.final$changeComponents()
fox.model.final <- fitISDM(fox.base.final, options = list(control.inla = list(int.strategy = 'eb')))
summary(fox.model.final)


fox.base.inat <- intModel(inat.fox,
```

```
                    Coordinates= c("Longitude", "Latitude"),
                    Projection = projection, Mesh = mesh,
                    spatialCovariates = covariates)
fox.base.inat$addBias('inat.fox')
fox.base.inat$changeComponents()
fox.model.inat <- fitISDM(fox.base.inat, options = list(control.inla = list(int.strategy = 'eb')))
summary(fox.model.inat)


fox.base.ss <- intModel(ss.fox,
                   Coordinates= c("Longitude", "Latitude"),
                   Projection = projection, Mesh = mesh,
                   responsePA = "PA",
                   trialsPA = "NTrials",
                   spatialCovariates = covariates)
fox.base.ss$addBias('ss.fox')
fox.base.ss$changeComponents()
fox.model.ss <- fitISDM(fox.base.ss, options = list(control.inla = list(int.strategy = 'eb')))
summary(fox.model.ss)

##### Figures #####

fox.plot <- fox.model.final$summary.fixed %>%
  mutate(coefficient = row.names(fox.model.final$summary.fixed))%>%
  filter(coefficient != 'Snapshot_intercept', coefficient != 'iNaturalist_intercept')%>%
  mutate(Dataset = 'Integrated', Order = 1)

fox.inat.plot <- fox.model.inat$summary.fixed %>%
  mutate(coefficient = row.names(fox.model.inat$summary.fixed))%>%
  filter(coefficient != 'inat.fox_intercept') %>%
```

```
  mutate(Dataset = 'iNaturalist', Order = 2)



fox.ss.plot <- fox.model.ss$summary.fixed %>%
  mutate(coefficient = row.names(fox.model.ss$summary.fixed))%>%
  filter(coefficient != 'ss.fox_intercept')%>%
  mutate(Dataset = 'SnapshotUSA', Order = 3)

fox.plot.all <- rbind(fox.plot, fox.inat.plot, fox.ss.plot)
fox.plot.all

fox.plot.all <- fox.plot.all %>%
  mutate(coefficient = replace(coefficient, coefficient == "Roads", "Distance to Road"))%>%
  mutate(coefficient = replace(coefficient, coefficient == "Pop", "Population Density"))%>%
  mutate(coefficient = replace(coefficient, coefficient == "Temp", "Avg Annual
Temperature"))%>%
  mutate(coefficient = replace(coefficient, coefficient == "Forest", "% Forest Cover"))%>%
  mutate(coefficient = replace(coefficient, coefficient == "Elev", "Elevation"))

fox.plot.all$Dataset <- factor(fox.plot.all$Dataset,
                               levels = c("iNaturalist",  "SnapshotUSA", "Integrated"))

fox.plot.all$coefficient <- factor(fox.plot.all$coefficient,
                                   levels = c("Avg Annual Temperature", "Distance to Road", "Elevation",
"% Forest Cover", "Population Density"))

dodge <- position_dodge(width=0.5)

pal <- park_palette("MtRainier", 3)
```

```
ggplot(fox.plot.all)+
  geom_hline(mapping=aes(x = coefficient, y = mean), yintercept = 0, colour = grey(0.25), lty =
2) +
  geom_point(mapping=aes(x = coefficient,
                         y = mean, color = Dataset), position = dodge) +
  geom_linerange(mapping=aes(x = coefficient,
                             ymin = `0.025quant`,
                             ymax = `0.975quant`, color = Dataset), position = dodge, lwd = 1)+
  theme_bw() +
  theme(legend.position="bottom",
        plot.title = element_text(hjust = 0.5)) +
  ggtitle("95% Credibility Intervals of Covariate Effects") +
  labs(x = 'Covariate', y = 'Coefficient value') +
  coord_flip()+
  scale_color_manual(breaks = c("Integrated",  "SnapshotUSA", "iNaturalist"), values=pal)+
  theme(legend.title=element_blank())




#####################################################
#####################################################
##### Fisher Models #####
##### Load in region map #####
region <- readOGR("FisherModels/fisher_region.shp")
region <- unionSpatialPolygons(region,rep(1, length(region)))

projection <- CRS(SRS_string="EPSG:4326")
plot(region)
```

```
region <- spTransform(region, projection)


region <- gSimplify(region, 0.03, topologyPreserve = TRUE)    ### Reduce number of line segments in region for reduced mesh file size

plot(region)


##### Format proofed iNaturalist Data #####

inat.fisher.loc <- read.csv("FisherModels/iNat_Fisher_Loc.csv")

inat.fisher <- read.csv("FisherModels/iNat_Fisher_Proofed.csv")


inat.fisher <- full_join(inat.fisher.loc, inat.fisher, by = "id")


inat.fisher <- inat.fisher %>%

  filter(ID_Check == "Correct", !is.na(ID_Check))                    ## Select fisher iNaturalist observations that were marked as "Correct" by proofer


inat.fisher <- inat.fisher %>%

  filter(positional_accuracy<1000, !is.na(positional_accuracy))       ## Select fisher iNaturalist observations that have location accuracy less than 1km and observations with a location accuracy provided.


inat.fisher$observed_on <- mdy(inat.fisher$observed_on) ## Get iNat year info for 1 and 2 year models

inat.fisher$Year <- year(inat.fisher$observed_on)

inat.fisher$X <- 1:nrow(inat.fisher)


##### Thin points to a 100m buffer 20 times, as thinning is a random process and will produce a different number of points each time. This may take a while! ####

inat.fisher.thin <- thin(loc.data = inat.fisher, lat.col="latitude", long.col="longitude", spec.col="common_name", thin.par=0.1, reps=20,

                        locs.thinned.list.return=TRUE,

                        write.files=FALSE,
```

```
                    write.log.file=FALSE,
                    verbose=FALSE)
write.csv(inat.fisher.thin[[1]], "FisherModels/iNat_Fisher_Thin.csv")  ## Save the thinned dataset with the highest number of points.
inat.fisher.thin <- read.csv("FisherModels/iNat_Fisher_Thin.csv")
inat.fisher <- inner_join(inat.fisher, inat.fisher.thin, by="X")

inat.fisher <- SpatialPointsDataFrame(coords=cbind(Longitude = inat.fisher$longitude, Latitude = inat.fisher$latitude),
                                      data=inat.fisher, proj4string=projection)
inat.fisher <- inat.fisher[region,]
plot(inat.fisher)

##### Format 2019 Snapshot USA Data #####
ss.19.obs <- read.csv("SNAPSHOT_USA_2019_observations.csv") ## Load in species observation data
ss.19.dep <- read.csv("SNAPSHOT_USA_2019_deployments.csv")  ## Load in camera trap deployment data

ss.19.fisher <- ss.19.obs %>%
  filter(Common_Name=="Fisher")%>%
  dplyr::select(Camera_Trap_Array, Common_Name, Count)%>%
  group_by(Camera_Trap_Array, .drop=FALSE) %>%
  summarise(FisherCount=sum(Count))

ss.19.arrays <- ss.19.obs %>%
  dplyr::select(Camera_Trap_Array, Count)%>%
  group_by(Camera_Trap_Array)%>%
  summarise(TotalCount=sum(Count))%>%
  transform(Year=2019)
```

```
ss.19.fisher <- right_join(ss.19.fisher, ss.19.arrays, by="Camera_Trap_Array")

ss.19.fisher <- ss.19.fisher %>%
  dplyr::select(Camera_Trap_Array, FisherCount, Year)%>%
  replace(is.na(.), 0)%>%
  mutate(PA = replace(FisherCount, FisherCount >1, 1))%>%
  arrange(Camera_Trap_Array)%>%
  dplyr::select(Camera_Trap_Array, PA, Year)

ss.19.loc <- ss.19.dep %>%
  dplyr::select(Camera_Trap_Array, Latitude, Longitude, Survey_Days)%>%
  group_by(Camera_Trap_Array) %>%
  summarise(Longitude = mean(Longitude), Latitude = mean(Latitude), Survey_Days = sum(Survey_Days))%>%
  rename(Longitude = Longitude, Latitude = Latitude)

ss.19.fisher <- full_join(ss.19.loc, ss.19.fisher, by="Camera_Trap_Array")

ss.19.fisher.coords <- ss.19.fisher[,c(2,3)]

ss.19.fisher <- SpatialPointsDataFrame(coords=ss.19.fisher.coords, data=ss.19.fisher, proj4string=CRS("+proj=longlat +ellps=WGS84"))
plot(ss.19.fisher)

ss.19.fisher <- ss.19.fisher[region,]
plot(ss.19.fisher)

##### Format 2020 Snapshot USA Data #####
ss.20.obs <- read.csv("SNAPSHOT_USA_2020_observations.csv")
ss.20.dep <- read.csv("SNAPSHOT_USA_2020_deployments.csv")
```

```
str(ss.20.dep)

ss.20.obs$Camera_Trap_Array <- gsub("_20", "", as.character(ss.20.obs$Camera_Trap_Array))
ss.20.dep$Camera_Trap_Array <- gsub("_20", "", as.character(ss.20.dep$Camera_Trap_Array))

ss.20.fisher <- ss.20.obs %>%
  filter(Common_Name=="Fisher")%>%
  select(Camera_Trap_Array, Common_Name, Count)%>%
  group_by(Camera_Trap_Array, .drop=FALSE) %>%
  summarise(Count=sum(Count))

ss.20.arrays <- ss.20.obs %>%
  select(Camera_Trap_Array, Count)%>%
  group_by(Camera_Trap_Array)%>%
  summarise(TotalCount20=sum(Count))%>%
  transform(Year=2020)

ss.20.fisher <- right_join(ss.20.fisher, ss.20.arrays, by="Camera_Trap_Array")

ss.20.fisher <- ss.20.fisher %>%
  select(Camera_Trap_Array, Count, Year)%>%
  replace(is.na(.), 0)%>%
  mutate(PA = replace(Count, Count >1, 1))%>%
  arrange(Camera_Trap_Array)%>%
  select(Camera_Trap_Array, PA, Year)

ss.20.loc <- ss.20.dep %>%
  select(Camera_Trap_Array, Latitude, Longitude, Survey_Days)%>%
  group_by(Camera_Trap_Array) %>%
```

```
  summarise(Longitude = mean(Longitude), Latitude = mean(Latitude), Survey_Days = sum(Survey_Days))%>%
  rename(Longitude = Longitude, Latitude = Latitude)


ss.20.fisher <- full_join(ss.20.loc, ss.20.fisher, by="Camera_Trap_Array")


ss.20.fisher.coords <- ss.20.fisher[,c(2,3)]


ss.20.fisher <- SpatialPointsDataFrame(coords=ss.20.fisher.coords, data=ss.20.fisher, proj4string=CRS("+proj=longlat +ellps=WGS84"))
plot(ss.20.fisher)


ss.20.fisher <- ss.20.fisher[region,]
plot(ss.20.fisher)


##### Format 2021 Snapshot USA Data. Slightly different data format than 2019 and 2020. #####
ss.21.obs <- read.csv("WILDLIFE_INSIGHTS_2021_observations.csv")
ss.21.dep <- read.csv("WILDLIFE_INSIGHTS_2021_deployments.csv")


ss.21.obs$Camera_Trap_Array <- gsub("_21", "", as.character(ss.21.obs$Camera_Trap_Array))
ss.21.dep$Camera_Trap_Array <- gsub("_21", "", as.character(ss.21.dep$Camera_Trap_Array))


ss.21.fisher <- ss.21.obs %>%
  filter(Common_Name=="Fisher")%>%
  select(Camera_Trap_Array, Common_Name, Count)%>%
  group_by(Camera_Trap_Array, .drop=FALSE) %>%
  summarise(Count=sum(Count))


ss.21.arrays <- ss.21.obs %>%
  select(Camera_Trap_Array, Count)%>%
```

```
  group_by(Camera_Trap_Array)%>%
  summarise(TotalCount20=sum(Count))%>%
  transform(Year=2021)

ss.21.fisher <- right_join(ss.21.fisher, ss.21.arrays, by="Camera_Trap_Array")

ss.21.fisher <- ss.21.fisher %>%
  select(Camera_Trap_Array, Count, Year)%>%
  replace(is.na(.), 0)%>%
  mutate(PA = replace(Count, Count >1, 1))%>%
  arrange(Camera_Trap_Array)%>%
  select(Camera_Trap_Array, PA, Year)

ss.21.dep$Date_Out<-ymd(ss.21.dep$Date_Out)
ss.21.dep$Date_Retrieved<-ymd(ss.21.dep$Date_Retrieved)

ss.21.loc <- ss.21.dep %>%
  select(Camera_Trap_Array, Latitude, Longitude, Date_Out, Date_Retrieved)%>%
  mutate(Survey_Days = (Date_Retrieved - Date_Out))%>%
  group_by(Camera_Trap_Array) %>%
  summarise(Longitude = mean(Longitude), Latitude = mean(Latitude), Survey_Days = 
sum(Survey_Days))%>%
  rename(Longitude = Longitude, Latitude = Latitude)

ss.21.fisher <- full_join(ss.21.loc, ss.21.fisher, by="Camera_Trap_Array")
ss.21.fisher <- na.omit(ss.21.fisher)

##### Combine 2019, 2020, and 2021 Snapshot USA data for models w/ 3 years of data#####
ss.fisher <- rbind(ss.19.fisher, ss.20.fisher, ss.21.fisher)
```

```
write.csv(ss.fisher, "FisherModels/AllSnapshot_FisherPA.csv") ## Save as CSV to do some site name and coordinate clean up in Excel.


ss.fisher <- read.csv("FisherModels/AllSnapshot_FisherPA.csv")
ss.fisher <- ss.fisher %>%
  arrange(Camera_Trap_Array)%>%
  transform(NTrials = 1)%>%
  group_by(Camera_Trap_Array)%>%
  summarise(PA=sum(PA), NTrials=sum(NTrials), Longitude=mean(Longitude), Latitude=mean(Latitude))


ss.fisher <- SpatialPointsDataFrame(coords=cbind(Longitude = ss.fisher$Longitude, Latitude = ss.fisher$Latitude),
                                    data=ss.fisher, proj4string=projection)
ss.fisher <- ss.fisher[region,]
plot(ss.fisher)


##### 2019 + 2020 Snapshot and iNaturalist data for models w/ 2 years of data #####
ss.fisher.all <- read.csv("FisherModels/AllSnapshot_FisherPA.csv")


ss.fisher.2yr <- ss.fisher %>%
  dplyr::filter(Year != 2021)%>%
  arrange(Camera_Trap_Array)%>%
  transform(NTrials = 1)%>%
  group_by(Camera_Trap_Array)%>%
  summarise(PA=sum(PA), NTrials=sum(NTrials), Longitude=mean(Longitude), Latitude=mean(Latitude))


ss.fisher.2yr <- SpatialPointsDataFrame(coords=cbind(Longitude = ss.fisher.2yr$Longitude, Latitude = ss.fisher.2yr$Latitude),
                                        data=ss.fisher.2yr, proj4string=projection)
```

```
ss.fisher.2yr <- ss.fisher.2yr[region,]

plot(ss.fisher.2yr)



inat.fisher.2yr <- inat.fisher %>%
  filter(Year != 2021)

inat.fisher.2yr <- SpatialPointsDataFrame(coords=cbind(Longitude = inat.fisher.2yr$Longitude,
Latitude = inat.fisher.2yr$Latitude),
                                          data=inat.fisher.2yr, proj4string=projection)

inat.fisher.2yr <- inat.fisher.2yr[region,]

plot(inat.fisher.2yr)


##### 2019 Snapshot and iNaturalist data for models w/ 1 year of data #####

ss.fisher.1yr <- ss.fisher.all %>%
  filter(Year == 2019)%>%
  arrange(Camera_Trap_Array)%>%
  transform(NTrials = 1)%>%
  group_by(Camera_Trap_Array)%>%
  summarise(PA=sum(PA), NTrials=sum(NTrials), Longitude=mean(Longitude),
Latitude=mean(Latitude))


ss.fisher.1yr <- SpatialPointsDataFrame(coords=cbind(Longitude = ss.fisher.1yr$Longitude,
Latitude = ss.fisher.1yr$Latitude),
                                        data=ss.fisher.1yr, proj4string=projection)

ss.fisher.1yr <- ss.fisher.1yr[region,]

plot(ss.fisher.1yr)



inat.fisher.1yr <- inat.fisher.all %>%
  filter(Year == 2019)
```

```
inat.fisher.1yr <- SpatialPointsDataFrame(coords=cbind(Longitude = inat.fisher.1yr$Longitude,
Latitude = inat.fisher.1yr$Latitude),
                                          data=inat.fisher.1yr, proj4string=projection)
inat.fisher.1yr <- inat.fisher.1yr[region,]
plot(inat.fisher.1yr)



##### Unproofed iNaturalist data from downloaded iNaturalist data #####
inat.fisher.loc <- read.csv("FisherModels/iNat_Fisher_Loc.csv")
inat.fisher <- read.csv("FisherModels/iNat_Fisher_Proofed.csv")

inat.fisher <- full_join(inat.fisher.loc, inat.fisher, by = "id")

inat.fisher.unproof <- inat.fisher %>%
  filter(positional_accuracy<1000, !is.na(positional_accuracy))

inat.fisher.unproof$X <- 1:nrow(inat.fisher.unproof)

inat.fisher.unproof.thin <- thin(loc.data = inat.fisher.unproof, lat.col="latitude",
long.col="longitude", spec.col="common_name", thin.par=0.1, reps=20,
                                 locs.thinned.list.return=TRUE,
                                 write.files=FALSE,
                                 write.log.file=FALSE,
                                 verbose=FALSE)
plotThin(inat.fisher.unproof.thin)
write.csv(inat.fisher.unproof.thin[[1]], "FisherModels/iNat_Fisher_Unproof_Thin_100m.csv")
## Save the thinned dataset with the highest number of points.
inat.fisher.unproof.thin <- read.csv("FisherModels/iNat_Fisher_Unproof_Thin_100m.csv")
inat.fisher.unproof <- inner_join(inat.fisher.unproof, inat.fisher.unproof.thin, by="X")
write.csv(inat.fisher.unproof, "FisherModels/iNat_Fisher_UnproofedData.csv")
inat.fisher.unproof <- read.csv("FisherModels/iNat_Fisher_UnproofedData.csv")
```

```
inat.fisher.unproof <- SpatialPointsDataFrame(coords=cbind(Longitude =
inat.fisher.unproof$longitude, Latitude = inat.fisher.unproof$latitude),
                                              data=inat.fisher.unproof, proj4string=projection)
inat.fisher.unproof <- inat.fisher.unproof[region,]
plot(inat.fisher.unproof)



##### Create GBIF dataset #####
gbif.fisher <- spocc::occ(
  query = 'Pekania pennanti',
  from = 'gbif',
  date = c("2019-01-01", "2021-12-31"),
  limit = 1000
)$gbif



gbif.fisher <- data.frame(gbif.fisher$data[[1]])


gbif.fisher<- gbif.fisher %>%
  filter(coordinateUncertaintyInMeters<1000, !is.na(coordinateUncertaintyInMeters))


gbif.fisher.thin <- thin(loc.data = fisher.gbif, lat.col="latitude", long.col="longitude",
spec.col="species", thin.par=0.1, reps=20,
                    locs.thinned.list.return=TRUE,
                    write.files=FALSE,
                    write.log.file=FALSE,
                    verbose=FALSE)
plotThin(gbif.fisher.thin)
gbif.fisher<- fisher.gbif.thin[[1]]
```

```
gbif.fisher <- SpatialPointsDataFrame(coords = cbind(Longitude = gbif.fisher$Longitude,
Latitude = gbif.fisher$Latitude),
                         data = gbif.fisher,
                         proj4string = projection)

gbif.fisher <- gbif.fisher[region,]
plot(gbif.fisher)

##### Make dataset lists #####
datasets.fisher <- list(Snapshot = ss.fisher, iNaturalist = inat.fisher)

datasets.fisher.1yr <- list(Snapshot = ss.fisher.1yr, iNaturalist = inat.fisher.1yr)

datasets.fisher.2yr <- list(Snapshot = ss.fisher.2yr, iNaturalist = inat.fisher.2yr)

datasets.fisher.unproof <- list(Snapshot = ss.fisher, iNaturalist = inat.fisher.unproof)

datasets.fisher.gbif <- list(Snapshot = ss.fisher, iNaturalist = gbif.fisher)

inat.fisher <- datasets.fisher$iNaturalist
ss.fisher <- datasets.fisher$Snapshot

##### Get environmental covariate data #####
pop <- population(2020, 5, path=tempdir())
pop<-raster::brick(pop)
pop<-crop(pop, region)
pop <- raster::mask(pop, region)
pop <- log1p(pop)
plot(pop)
```

```
res(pop)

elev <- elevation_global(5, path=tempdir())
elev<-raster::brick(elev)
elev<-crop(elev, region)
elev <- raster::mask(elev, region)
plot(elev)
res(elev)


bio <- worldclim_global(var="bio", res=5, path=tempdir())
plot(bio)

temp <- bio[[c(1)]]
names(temp) <- c("Temp")
temp<- raster::brick(temp)
temp<-crop(temp, region)
temp<-raster::mask(temp, region)
plot(temp)

prec <- bio[[c(12)]]
names(prec) <- c("Prec")
prec<- raster::brick(prec)
prec<-crop(prec, region)
prec<-raster::mask(prec, region)
plot(prec)
res(prec)

forest <- landcover(var="trees", path=tempdir())
forest<- raster::brick(forest)
```

```
forest<-crop(forest, region)
forest<-raster::mask(forest, region)
plot(forest)
res(forest)
forest <- aggregate(forest, fact=10, fun=mean, na.rf=TRUE)
plot(forest)
res(forest)

wetl <- landcover(var="wetland", path=tempdir())
wetl<- raster::brick(wetl)
wetl<-crop(wetl, region)
wetl<-raster::mask(wetl, region)
plot(wetl)
res(wetl)
wetl <- aggregate(wetl, fact=10, fun=mean, na.rf=TRUE)
plot(wetl)
res(wetl)

cropl <- cropland("WorldCover", path=tempdir())
cropl<- raster::brick(cropl)
cropl<-crop(cropl, region)
cropl<-raster::mask(cropl, region)
plot(cropl)
res(cropl)
cropl <- aggregate(cropl, fact=10, fun=mean, na.rf=TRUE)
plot(cropl)
res(cropl)

imperv <- raster("FisherModels/imperv.tif")
imperv <- crop(imperv, region)
```

```
imperv <- log1p(imperv)

plot(imperv)

res(imperv)


roads <- raster("roaddist.tif")

roads <- mask(roads, region)

plot(roads)


cropl <- resample(cropl, pop, method="ngb")

forest <- resample(forest, pop, method="ngb")

water <- resample(water, pop, method="ngb")

wetl <- resample(wetl, pop, method="ngb")

imperv <- resample(imperv, pop, method="ngb")

roads <- resample(roads, pop, method="ngb")

covariates.corr.check <- list(Temp=temp, Prec=prec, Forest=forest, Pop=pop,
Imperv=impervlog,

                              Elev=elev, Roads=roads, Wetl = wetl)

covariates.corr.check <- scale(stack(covariates.corr.check))

crs(covariates.corr.check) <- projection

plot(covariates.corr.check)

pairs(covariates.corr.check)


covar.anthro <- list(Pop = covariates.corr.check$Pop, Imperv = covariates.corr.check$Imperv,

                     Roads = covariates.corr.check$Roads)

covar.anthro <- stack(covar.anthro)


covar.eco <- list(Temp = covariates.corr.check$Temp, Prec = covariates.corr.check$Prec, Forest
= covariates.corr.check$Forest,

                  Elev = covariates.corr.check$Elev, Wetland = covariates.corr.check$Wetland)

covar.eco <- stack(covar.eco)
```

```
##### Create mesh #####
mesh <- inla.mesh.2d(boundary = inla.sp2segment(region),
                     cutoff = 0.5,
                     max.edge = c(1, 2),
                     offset = c(1, 2))
mesh$crs <- projection

ggplot() +
  gg(mesh) +
  ggtitle('Plot of mesh') +
  theme_bw() +
  theme(plot.title = element_text(hjust = 0.5))

##### Check for best environmental covariates #####
fisher.base.anthro <- intModel(datasets.fisher,
                        Coordinates= c("Longitude", "Latitude"),
                        Projection = projection, Mesh = mesh,
                        responsePA = "PA",
                        trialsPA = "NTrials",
                        spatialCovariates = covar.anthro)
fisher.base$addBias('iNaturalist')
fisher.base$addBias('Snapshot')
fisher.base$changeComponents()
fisher.model.anthro<- fitISDM(fisher.base.anthro, options = list(control.inla = list(int.strategy =
'eb')))
summary(fisher.model.eco)


fisher.base.eco <- intModel(datasets.fisher,
                        Coordinates= c("Longitude", "Latitude"),
```

```
                        Projection = projection, Mesh = mesh,
                        responsePA = "PA",
                        trialsPA = "NTrials",
                        spatialCovariates = covar.eco)
fisher.base$addBias('iNaturalist')
fisher.base$addBias('Snapshot')
fisher.base$changeComponents()
fisher.model<- fitISDM(fisher.base.eco, options = list(control.inla = list(int.strategy = 'eb')))
summary(fisher.model.eco)

##### Select final covariates #####
covariates <- list(Imperv = covariates.corr.check$Imperv, Temp = covariates.corr.check$Temp,
                Forest = covariates.corr.check$Forest, Wetland = covariates.corr.check$Wetland,
                Roads = covariates.corr.check$Roads)
covariates <- stack(covariates)


#### Full Integrated, iNaturalist, and Snapshot USA models ####
fisher.base <- intModel(datasets.fisher,
                        Coordinates= c("Longitude", "Latitude"),
                        Projection = projection, Mesh = mesh,
                        responsePA = "PA",
                        trialsPA = "NTrials",
                        spatialCovariates = covariates)
fisher.base.final$addBias('iNaturalist')
fisher.base.final$addBias('Snapshot')
fisher.base.final$changeComponents()
fisher.model.final <- fitISDM(fisher.base.final, options = list(control.inla = list(int.strategy =
'eb')))
summary(fisher.model.final)
```

```
fisher.base.inat <- intModel(inat.fisher,
                        Coordinates= c("Longitude", "Latitude"),
                        Projection = projection, Mesh = mesh,
                        spatialCovariates = covariates)
fisher.base.inat$addBias('inat.fisher')
fisher.base.inat$changeComponents()
fisher.model.inat <- fitISDM(fisher.base.inat, options = list(control.inla = list(int.strategy =
'eb')))
summary(fisher.model.inat)


fisher.base.ss <- intModel(ss.fisher,
                        Coordinates= c("Longitude", "Latitude"),
                        Projection = projection, Mesh = mesh,
                        responsePA = "PA",
                        trialsPA = "NTrials",
                        spatialCovariates = covariates)
fisher.base.ss$addBias('ss.fisher')
fisher.base.ss$changeComponents()
fisher.model.ss <- fitISDM(fisher.base.ss, options = list(control.inla = list(int.strategy = 'eb')))
summary(fisher.model.ss)

##### 1 & 2 year models #####
fisher.base.1yr <- intModel(datasets.fisher.1yr,
                         Coordinates= c("Longitude", "Latitude"),
                         Projection = projection, Mesh = mesh,
                         responsePA = "PA",
                         trialsPA = "NTrials",
```

```
                    spatialCovariates = covariates)
fisher.base.1yr$addBias('iNaturalist')
fisher.base.1yr$addBias('Snapshot')
fisher.base.1yr$changeComponents()
fisher.model.1yr <- fitISDM(fisher.base.1yr, options = list(control.inla = list(int.strategy = 'eb')))
summary(fisher.model.1yr)


fisher.base.2yr <- intModel(datasets.fisher.2yr,
                   Coordinates= c("Longitude", "Latitude"),
                   Projection = projection, Mesh = mesh,
                   responsePA = "PA",
                   trialsPA = "NTrials",
                   spatialCovariates = covariates)
fisher.base.2yr$addBias('iNaturalist')
fisher.base.2yr$addBias('Snapshot')
fisher.base.2yr$changeComponents()
fisher.model.2yr <- fitISDM(fisher.base.2yr, options = list(control.inla = list(int.strategy = 'eb')))
summary(fisher.model.2yr)

##### Unproofed iNat model #####
fisher.base.unproof <- intModel(datasets.fisher.unproof,
                       Coordinates= c("Longitude", "Latitude"),
                       Projection = projection, Mesh = mesh,
                       responsePA = "PA",
                       trialsPA = "NTrials",
                       spatialCovariates = covariates)
fisher.base.unproof$addBias('iNaturalist')
fisher.base.unproof$addBias('Snapshot')
fisher.base.unproof$changeComponents()
```

```
fisher.model.unproof <- fitISDM(fisher.base.unproof, options = list(control.inla =
list(int.strategy = 'eb')))

summary(fisher.model.unproof)



##### GBIF models #####

fisher.base.gbif <- intModel(datasets.fisher.gbif,
                            Coordinates= c("Longitude", "Latitude"),
                            Projection = projection, Mesh = mesh,
                            responsePA = "PA",
                            trialsPA = "NTrials",
                            spatialCovariates = covariates)

fisher.base.gbif$addBias('iNaturalist')

fisher.base.gbif$addBias('Snapshot')

fisher.base.gbif$changeComponents()

fisher.model.gbif <- fitISDM(fisher.base.gbif, options = list(control.inla = list(int.strategy =
'eb')))

summary(fisher.model.gbif)


##### Figures #####


fisher.plot <- fisher.model.final$summary.fixed %>%
  mutate(coefficient = row.names(fisher.model.final$summary.fixed))%>%
  filter(coefficient != 'Snapshot_intercept', coefficient != 'iNaturalist_intercept')%>%
  mutate(Dataset = 'Integrated', Order = 1)


fisher.inat.plot <- fisher.model.inat$summary.fixed %>%
  mutate(coefficient = row.names(fisher.model.inat$summary.fixed))%>%
  filter(coefficient != 'inat.fisher_intercept') %>%
  mutate(Dataset = 'iNaturalist', Order = 2)
```

```
fisher.ss.plot <- fisher.model.ss$summary.fixed %>%
  mutate(coefficient = row.names(fisher.model.ss$summary.fixed))%>%
filter(coefficient != 'ss.fisher_intercept')%>%
  mutate(Dataset = 'SnapshotUSA', Order = 3)

fisher.plot.all <- rbind(fisher.plot, fisher.inat.plot, fisher.ss.plot)
fisher.plot.all

fisher.plot.all <- fisher.plot.all %>%
  mutate(coefficient = replace(coefficient, coefficient == "Roads", "Distance to Road"))%>%
  mutate(coefficient = replace(coefficient, coefficient == "Imperv", "% Impervious
Surface"))%>%
  mutate(coefficient = replace(coefficient, coefficient == "Temp", "Avg Annual
Temperature"))%>%
  mutate(coefficient = replace(coefficient, coefficient == "Forest", "% Forest Cover"))%>%
  mutate(coefficient = replace(coefficient, coefficient == "Wetland", "% Wetland Cover"))

fisher.plot.all$Dataset <- factor(fisher.plot.all$Dataset,
                                  levels = c("iNaturalist",  "SnapshotUSA", "Integrated"))

fisher.plot.all$coefficient <- factor(fisher.plot.all$coefficient,
                                      levels = c("Avg Annual Temperature", "Distance to Road", "% Forest
Cover", "% Impervious Surface", "% Wetland Cover"))



fisher.3yr.plot <- fisher.model.final$summary.fixed %>%
  mutate(coefficient = row.names(fisher.model.final$summary.fixed))%>%
  filter(coefficient != 'Snapshot_intercept', coefficient != 'iNaturalist_intercept')%>%
  mutate(Dataset = '3 Years')
```

```
fisher.2yr.plot <- fisher.model.2yr$summary.fixed %>%
  mutate(coefficient = row.names(fisher.model.2yr$summary.fixed))%>%
  filter(coefficient != 'Snapshot_intercept', coefficient != 'iNaturalist_intercept')%>%
  mutate(Dataset = '2 Years')



fisher.1yr.plot <- fisher.model.1yr$summary.fixed %>%
  mutate(coefficient = row.names(fisher.model.1yr$summary.fixed))%>%
  filter(coefficient != 'Snapshot_intercept', coefficient != 'iNaturalist_intercept')%>%
  mutate(Dataset = '1 Year')


fisher.plot.years <- rbind(fisher.3yr.plot, fisher.2yr.plot, fisher.1yr.plot)


fisher.plot.years <- fisher.plot.years %>%
  mutate(coefficient = replace(coefficient, coefficient == "Roads", "Distance to Road"))%>%
  mutate(coefficient = replace(coefficient, coefficient == "Imperv", "% Impervious
Surface"))%>%
  mutate(coefficient = replace(coefficient, coefficient == "Temp", "Avg Annual
Temperature"))%>%
  mutate(coefficient = replace(coefficient, coefficient == "Forest", "% Forest Cover"))%>%
  mutate(coefficient = replace(coefficient, coefficient == "Wetland", "% Wetland Cover"))


fisher.plot.years$Dataset <- factor(fisher.plot.years$Dataset,
                                    levels = c("3 Years", "2 Years",  "1 Year"))


fisher.plot.years$coefficient <- factor(fisher.plot.years$coefficient,
                                        levels = c("Avg Annual Temperature", "Distance to Road", "% Forest
Cover", "% Impervious Surface", "% Wetland Cover"))
```

```
fisher.inatunproof.plot <- fisher.model.unproof$summary.fixed %>%
  mutate(coefficient = row.names(fisher.model.unproof$summary.fixed))%>%
  filter(coefficient != 'Snapshot_intercept', coefficient != 'iNaturalist_intercept')%>%
  mutate(Dataset = 'Unproofed')

fisher.inatproof.plot <- fisher.model.final$summary.fixed %>%
  mutate(coefficient = row.names(fisher.model.final$summary.fixed))%>%
  filter(coefficient != 'Snapshot_intercept', coefficient != 'iNaturalist_intercept')%>%
  mutate(Dataset = 'Proofed')

fisher.plot.inatproof <- rbind(fisher.inatproof.plot, fisher.inatunproof.plot)

fisher.plot.inatproof <- fisher.plot.inatproof %>%
  mutate(coefficient = replace(coefficient, coefficient == "Roads", "Distance to Road"))%>%
  mutate(coefficient = replace(coefficient, coefficient == "Imperv", "% Impervious
Surface"))%>%
  mutate(coefficient = replace(coefficient, coefficient == "Temp", "Avg Annual
Temperature"))%>%
  mutate(coefficient = replace(coefficient, coefficient == "Forest", "% Forest Cover"))%>%
  mutate(coefficient = replace(coefficient, coefficient == "Wetland", "% Wetland Cover"))

fisher.plot.inatproof$Dataset <- factor(fisher.plot.inatproof$Dataset,
                                        levels = c("Unproofed", "Proofed"))

fisher.plot.inatproof$coefficient <- factor(fisher.plot.inatproof$coefficient,
                                            levels = c("Avg Annual Temperature", "Distance to Road", "% Forest
Cover", "% Impervious Surface", "% Wetland Cover"))



fisher.inat.plot <- fisher.model.final$summary.fixed %>%
  mutate(coefficient = row.names(fisher.model.final$summary.fixed))%>%
```

```
  filter(coefficient != 'Snapshot_intercept', coefficient != 'iNaturalist_intercept')%>%
  mutate(Dataset = 'iNaturalist')

fisher.gbif.plot <- fisher.model.gbif$summary.fixed %>%
  mutate(coefficient = row.names(fisher.model.gbif$summary.fixed))%>%
  filter(coefficient != 'Snapshot_intercept', coefficient != 'iNaturalist_intercept')%>%
  mutate(Dataset = 'GBIF')

fisher.plot.proof <- rbind(fisher.inat.plot, fisher.gbif.plot)

fisher.plot.proof <- fisher.plot.proof %>%
  mutate(coefficient = replace(coefficient, coefficient == "Roads", "Distance to Road"))%>%
  mutate(coefficient = replace(coefficient, coefficient == "Imperv", "% Impervious
Surface"))%>%
  mutate(coefficient = replace(coefficient, coefficient == "Temp", "Avg Annual
Temperature"))%>%
  mutate(coefficient = replace(coefficient, coefficient == "Forest", "% Forest Cover"))%>%
  mutate(coefficient = replace(coefficient, coefficient == "Wetland", "% Wetland Cover"))

fisher.plot.proof$Dataset <- factor(fisher.plot.proof$Dataset,
                                    levels = c("GBIF", "iNaturalist"))

fisher.plot.proof$coefficient <- factor(fisher.plot.proof$coefficient,
                                        levels = c("Avg Annual Temperature", "Distance to Road", "% Forest
Cover", "% Impervious Surface", "% Wetland Cover"))


dodge <- position_dodge(width=0.5)

pal <- park_palette("MtRainier", 3)
```

```
ggplot(fisher.plot.all)+
  geom_hline(mapping=aes(x = coefficient, y = mean), yintercept = 0, colour = grey(0.25), lty =
2) +
  geom_point(mapping=aes(x = coefficient,
                                        y = mean, color = Dataset), position = dodge) +
  geom_linerange(mapping=aes(x = coefficient,
                                            ymin = `0.025quant`,
                                            ymax = `0.975quant`, color = Dataset), position = dodge, lwd = 1)+
  theme_bw() +
  theme(legend.position="bottom",
        plot.title = element_text(hjust = 0.5)) +
  ggtitle("95% Credibility Intervals of Covariate Effects") +
  labs(x = 'Covariate', y = 'Coefficient value') +
  coord_flip()+
  scale_color_manual(breaks = c("Integrated", "SnapshotUSA", "iNaturalist"), values=pal)+
  theme(legend.title=element_blank())


ggplot(fisher.plot.years)+
  geom_hline(mapping=aes(x = coefficient, y = mean), yintercept = 0, colour = grey(0.25), lty =
2) +
  geom_point(mapping=aes(x = coefficient,
                         y = mean, color = Dataset), position = dodge) +
  geom_linerange(mapping=aes(x = coefficient,
                             ymin = `0.025quant`,
                             ymax = `0.975quant`, color = Dataset), position = dodge, lwd = 1)+
  theme_bw() +
  theme(legend.position="bottom",
        plot.title = element_text(hjust = 0.5)) +
```

```
  ggtitle("95% Credibility Intervals of Covariate Effects") +
  labs(x = 'Covariate', y = 'Coefficient value') +
  coord_flip()+
  scale_color_manual(breaks = c("1 Year", "2 Years", "3 Years"), values=pal)+
  theme(legend.title=element_blank())


ggplot(fisher.plot.inatproof)+
  geom_hline(mapping=aes(x = coefficient, y = mean), yintercept = 0, colour = grey(0.25), lty =
2) +
  geom_point(mapping=aes(x = coefficient,
                         y = mean, color = Dataset), position = dodge) +
  geom_linerange(mapping=aes(x = coefficient,
                             ymin = `0.025quant`,
                             ymax = `0.975quant`, color = Dataset), position = dodge)+
  theme_bw() +
  theme(legend.position="bottom",
        plot.title = element_text(hjust = 0.5)) +
  ggtitle("95% Credibility Intervals of Covariate Effects") +
  labs(x = 'Covariate', y = 'Coefficient value') +
  coord_flip()+
  scale_color_manual(breaks = c("Unproofed", "Proofed"), values=pal)+
  theme(legend.title=element_blank())



ggplot(fisher.plot.gbif)+
  geom_hline(mapping=aes(x = coefficient, y = mean), yintercept = 0, colour = grey(0.25), lty =
2) +
  geom_point(mapping=aes(x = coefficient,
```

```
                  y = mean, color = Dataset), position = dodge) +
geom_linerange(mapping=aes(x = coefficient,
                    ymin = `0.025quant`,
                    ymax = `0.975quant`, color = Dataset), position = dodge, lwd = 1)+
theme_bw() +
theme(legend.position="bottom",
    plot.title = element_text(hjust = 0.5)) +
ggtitle("95% Credibility Intervals of Covariate Effects") +
labs(x = 'Covariate', y = 'Coefficient value') +
coord_flip()+
scale_color_manual(breaks = c("iNaturalist", "GBIF"), values=pal)+
theme(legend.title=element_blank())
```