

Developing a Better Approach to Ecological Projection Models Using a GIS-Based Mechanistic Model Framework

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Title: *Developing a Better Approach to Ecological Projection Models Using a GIS-Based Mechanistic Model Framework*

Abstract

There is an increasing societal need to develop better strategies for managing our habitats and ecosystems that are threatened by climate change. In a world where our past is no longer a clear guide to our future, our ability to model and anticipate the effects of climate change on our ecosystems is more critical than ever. Commonly used ecological projection models have been useful in projecting how habitat ranges of species will shift due to climatic variables, however these models have many downfalls. This paper proposes a new GIS-based mechanistic ecological projection model that overcomes these downfalls and operates as a decision support tool for scientists and policy makers. The proposed model was created in ArcGIS Desktop 10.3 using the model builder capability and utilizes fuzzy membership classification combined with data from standard climate change models to create multiple habitat suitability indexes (initial and projected) which assign temporally changing suitability scores to anticipate how climate change will affect species habitat. For example, an area that originally receives a high suitability score but a low suitability score in a future year represents an area where habitat for the respective species is being degraded. The initial and projected suitability indexes were overlaid in the GIS to spatially display how habitats of the three modelled species will change. These results are then discussed with respect to the underlying assumptions of the model framework and take into consideration environmental, biological, and anthropogenic variables that exist outside of the model. In this way, the model results are used to suggest conservation and management decisions.

Introduction

The burning of fossil fuels and the results of other anthropogenic activities are increasing the levels of carbon dioxide and other heat-trapping gases in the atmosphere, causing global average temperatures to rise (Quirk 2009). It has quickly become clear that climate change is a looming threat to biodiversity across the globe as we have already experienced the first impacts of our changing climate (Bellard et al. 2012). Loss of sea ice, accelerated sea level rise, northward shifting species ranges, and intense heat waves and droughts have all been associated with climate change and will only become more severe in time (Rahmstorf 2007, Meehl 2004, Solomon et al. 2009, Walther 2002). Many climate change impacts pose unprecedented threats to human civilization and our current way of life as our natural resources and ecosystem services are depleted (Schroter 2005).

One of the most impactful and complex consequences of climate change is alterations to ecosystems and habitats (Travis 2003, Nally et al. 2009). Ecosystems rely on very delicate biological processes such as chemical cycles that facilitate nutrient cycling, stable food webs and trophic levels that act as natural population controls, and resource pools that allow species to thrive and reproduce successfully. Research has shown that climate change is and will continue to impact these biological processes in a number of ways, changing the way ecosystems function (Cao and Woodward 1998). Species that live within ecosystems are reliant on the habitat the ecosystem provides for their success, and any changes to their habitat have a negative impact on their ability to be successful. Climate change alone is not a big enough threat to single handedly wipe out a species, but, combined with other ecosystem stressors such as the proliferation of invasive species, the spread of disease, decreasing biodiversity, and overexploitation of natural resources; it poses major threats to biodiversity. If left unchecked and unmanaged, climate change has the power to completely change the way our world looks. Ecosystems will not only look different and contain different species but will also be extremely volatile.

There is an increasing societal need to develop better strategies for managing our habitats and ecosystems in the face of climate change (Adger et al. 2005). We study history

because we can learn from the mistakes of the past and prevent them in the future. However, scientists and policy-makers alike can agree that success in dealing with anthropogenic climate change rests with a capacity to anticipate (Clark 2001). Our ability to anticipate the effects of climate change on our ecosystems is more critical than ever in a world where our past is no longer a clear guide to our future (Clark 2001, Luo et al 2011). The first step of anticipation is understanding. In order to anticipate any phenomena, whether it is the stock market or the environment, the basic underlying rules that are in effect must be understood. Historically, a lack of scientific knowledge has prevented our efforts of anticipating climate change from coming to fruition. As technology has become more advanced so has our understanding of the world, accompanied by a parallel increase in our ability to anticipate. However anticipation is not enough on its own. To efficiently mitigate and adapt to climate change, methods must be created to apply available data and our current understanding of natural phenomenon to the problem of anticipating future states of ecosystems and habitats (Luo et al 2011). We must then assess the anticipated ramifications of climate change so that we may be better prepared to prevent and manage for them.

This project will take a deeper look into the current theoretical and practical methodologies behind the three currently used ecological projection models that are designed to anticipate climate change and its future impacts on habitat. Each model will be evaluated based on its respective pros and cons and a new mechanistic-based model will be proposed that overcomes the downfalls of current ecological projections that are commonly used. This new model will be a GIS-based model that is easy to use, easily manipulated, used in both small and large scale projections, applicable to any species (assuming data is available), and operates as a decision support tool that helps scientists and policy-makers create informed decisions when managing species facing habitat loss due to climate change.

Literature Review

Basic Principles of Modeling:

The science of modeling has developed because reality is often too complex and interconnected to measure in its entirety. Thus, models have been created to provide researchers with a better understanding of the real-world by simplifying it. A model can be defined as a simplified version of something that is real (Schichl 2004). In a model, simpler objects within the model replace the real world objects being measured and knowledge of natural phenomenon is applied to define mathematical relationships between the model and the real world. This is the foundational methodology behind any scientific model, whether it is used to explain phenomena, make predictions, influence decision makers, or aid in communication (Schichl 2004).

Historically, the ability of researchers to accurately model the real world has been severely limited by their own lack of knowledge of how models work. In the early 1980s, George Box, a statistician from the United Kingdom, developed postulates that now provide guidelines for the creation of accurate models. Box described three properties that any mechanistic model must have in order for it to be considered 'good'. Firstly, the model must contribute to our scientific understanding of the phenomena being modeled. Secondly, the model must provide a basis for extrapolation and data assimilation. Thirdly, the best models are those that are most frugal in their model parameters (Box 1976).

Box's work in the modeling field eventually led to the creation of the two axioms of modern modeling. The first axiom states that all models are wrong but some are more useful than others (Young et al. 1996). On a theoretical level, no model can ever be entirely correct because models are simply mathematical representations and abstractions of what is happening in the real world. Regardless of how large and complex a model is, there will always be confounding variables and other sources of error that are not considered in the model framework (Young et al 1996). However, models that are wrong can still be useful to the scientific community as long as it contributes to our scientific understanding of the phenomena

being modeled. The second axiom is Occam's razor, or the idea that the simplest answer is often the most correct, or in the case of modeling, the least wrong (Myung and Pitt 2003). Since all models are wrong due to an unlimited amount of confounding variables, the most accurate models will be those that contain the fewest parameters, since exhausting all parameters is an impossible task. Because of this idea, reductionist-based and determinist-based mechanistic models have become useful tools when predicting changes in biological systems because their simplicity in parameters helps to simulate the inherent uncertain nature of ecosystem changes (Mazzocchi 2008, Young et al 1996). As the natural philosopher Isaac Newton said, "truth is ever to be found in the simplicity, and not in the multiplicity and confusion of things" (Newton 1687, Mazzocchi 2008). These words remain true when applied to the science of modern modeling, as simplicity has become one of the cornerstones of a useful model.

Apart from better understanding model frameworks, technological advances and increases in the amount of free data available to researchers has dramatically increased the efficiency and usefulness of modern models (Luo 2011, Sorte and Jetz 2010). Models in the ecological field have advanced from very simple and rudimentary models such as E.O. Wilson and Robert Macarthur's theory of island biogeography model which uses a simple equation ($S=CA^z$) to model species-area relationships and extinction rates of species (Macarthur 1967). Now, current ecological models such as climate change models are able to create complex and computationally demanding mathematical relationships between multiple phenomena and utilize algorithms to average together multiple regressions of the same model (Hamermesh 2010). For example, the standard equation to measure changes in atmospheric pressure, a critical part of any climate change model, is (Hamermesh 2010):

$$\frac{du}{ds} + \frac{2P\sigma\hat{T}_0^3}{c_0}u = \frac{P\sigma}{2c_0}(qT_e^4 + \epsilon\hat{T}_1^4 - \hat{T}_0^4) + \frac{Pq\sigma T_e^4}{2c_0}\psi(s)$$

By comparing these two equations above, it is easy to see how model complexity has increased from the theory of island biogeography model to current climate change models.

Ecological Forecasting:

Ecological forecasting, a subset within the overall field of modeling science, is a mathematical representation of an ecological system, ranging in scale from an individual species to an entire biome (Araujo and Peterson 2012). It uses knowledge from physics, ecology, and physiology to predict how ecosystems will change in the future. Ecological forecasting has been used to model a variety of phenomena including predator-prey interactions, population dynamics, and nutrient cycling. However, this paper will focus on its use in modeling changes in habitat based on climate change (Ibanez et al 2006). There are three types of ecological models that have been primarily used to measure habitat change: paleobiology models, climate envelope models, and niche level models. All three of these methods use different methodologies to reach the same common goal but ultimately take into account real world observations, climate model data, and some form of spatial data (Botkin et al 2007). Each ecological forecasting method will be evaluated based on its respective pros and cons.

Paleobiology Modeling:

Paleobiology modeling, the least commonly used of the three, uses fossil and phylogenetic evidence of biodiversity in the past to project the trajectory of biodiversity in the future (Watling 2008). This type of modeling operates under the assumption that events in the past tend to repeat themselves, and if the past is understood so can the future (Svenning et al 2011). However, paleobiology modeling is inherently inaccurate because it fails to take into account the uncertainty of the future. Especially when modeling climate change, modern models must be able to take into account the inherent uncertainty involved in climate change (Clark 2001, Luo et al. 2011). Additionally, paleobiology modeling has become mostly irrelevant due to technological advances in other types of ecological forecasts. Although paleobiology has not been found to be useful when projecting habitat change due to climate change, its principles have been useful in determining model validity. The idea of using the past to model the future has resulted in the concept of backcasting, a critical part of determining model

validity. Backcasting determines climate change model validity by projecting the present day atmospheric conditions based on historical atmospheric data. If the projected atmospheric conditions are similar to what we are currently experiencing over several iterations, the climate change model can be deemed valid (Millar et al 2007).

Climate Envelope Modeling:

Climate envelope modeling, the most commonly used of the three, determines statistical correlations between existing species distributions and environmental variables to define a species tolerance. It does this by defining minimum and maximum values of climate boundaries around a species occurrence, thus creating a climate “envelope” (Watling 2008). The envelope can be created in several different ways including simple regressions, distance-based methods, and generic algorithms (Ibanez et al 2006). There are two important assumptions behind climate envelope modeling. Firstly, since climate envelope models are strictly based on observed occurrence, they assume that the populations being observed have non-zero and non-negative growth rates. Violation of this assumption can lead to models that under-represent the climate envelope of a given species as having negative growth rates has a negative impact on occurrence (Watling 2008). The second assumption is called niche conservatism. Niche conservatism is the idea that a species will not adapt their niche to adjust to climate change. Violating this assumption will nullify the model results, because if a species can change its ecological niche in the future it will affect its occurrence. If this happens, the climate envelope cannot be accurately projected into the future because species occurrence is not constant, and thus the original statistical correlation is invalid in the future period (Watling et al 2008, Pearson and Dawson 2003). As long as climate envelope models operate within the parameters of these two assumptions, they can be extremely useful tools to determine species range changes due to climate change. However, there are several downsides to climate envelope modeling.

Firstly, climate envelope modeling relies strictly on species occurrence. This is problematic because these models treat species as if they are acting independently of their biotic environment (Hampe 2004). Thus, climate envelope models often overlook many

important biotic factors such as predation, location of food sources, and breeding success. Many of these biotic factors have been scientifically proven to be influenced by climate change and should be taken into account when projecting habitat changes for a species (Watling et al 2015). In its own right, climate envelope models are great at modeling habitat change for species for which detailed physiological is lacking. However, mechanistic model approaches that address these biotic factors are more useful projections.

Secondly, climate envelope models assume that individuals within the species being modeled express zero adaptive genetic variation (Hampe 2004). This assumption comes from the argument that climate tolerance ranges of species is evolving much slower than what is needed to allow species to adapt to the current rate of climate change. This argument is scientifically valid, as rapid genetic response to climate change has been found to be a rare occurrence (Pearson and Dawson 2003). However, this argument is counterintuitive to the model's own assumptions. As mentioned previously, climate envelope models assume that a species niche will remain constant resulting in their occurrence remaining constant as well. However, if a species is unable to adapt to its current surroundings, it will migrate to a new habitat that fits its climate tolerance, which is a clear violation of the second assumption (Hampe 2004, Davis and Shaw 2001).

Thirdly, climate envelope models suffer from many spatial data based problems (Watling et al 2008). Because they are strictly based on occurrences, and trends in occurrences of a species can only be analyzed over a large geographical extent, results of climate envelope models are usually very large scale. This is very useful in understanding the way climate change can impact habitat for a species across its entire range, but, when it comes to making management decisions, the results of climate envelope models are too diluted to educate decision makers.

Additionally, because of the large geographical extent of climate envelope models they are much harder to validate and involve a higher degree of uncertainty than other modeling methods (Heikkinen et al 2006). Thus, climate envelope models have found a home in basic science but have not been used as much in applied science (Mazzocchi 2008).

Niche Level Modeling:

Niche level modeling is very similar to climate envelope modeling but instead assumes that species do change their ecological niche in reaction to climate change. Niche level models work by creating ranges of tolerance around ecological niches, seeing how those ranges change (and thus how the ecological niche changes), and then projecting the species' modeled ecological niche on the current landscape to determine future species distribution (Peterson and Vieglais 2001). This type of model has become more prevalent in ecological forecasting as our understanding of ecological niches has increased. Unlike climate envelope models, niche level modeling has been very successful in modeling changes in species distribution on a very small scale (ex. within a forest) but struggles with large-scale mapping. Thus, niche level modeling has become an important tool for educating local conservation efforts of species facing multiple threats from climate change (Peterson and Vieglais 2001). Similar to climate envelope models, there are several downsides to climate envelope modeling.

Firstly, niche level modeling assumes that the geographic landscape will be unaltered by climate change. This has already been proven wrong by current scientific research that suggests that composition of forests will be significantly altered as different species of trees migrate north to remain in their niche climate range (Davis and Shaw 2001, Pearson 2006). In this sense, the methodological framework behind niche level modeling is inherently flawed.

Secondly, niche level modeling struggles when modeling generalist species. Generalist species are species that occupy a very large ecological niche. These species cannot be modeled well by niche level modeling because their niche isn't narrow enough to be modeled. The result of modeling a species with a broad ecological niche is a broad projection which cannot be used to inform conservation decision making on a small scale, which is the entire purpose of niche level modeling (Kearney et al 2010).

GIS and Ecological Forecasting:

Of the three ecological forecasting methods listed (paleobiology modeling, climate envelope modeling, and niche level modeling) none of the methods utilize the spatial analyst

tools provided by GIS. These ecological forecasting models are often run in other statistical and bioinformatics programs such as SAS (statistical analysis software), ModEco, and MaxEnt. GIS has already begun to play an increasing role in biogeography throughout the past decade but has not yet made its way into modern ecological forecasting which is still predominantly accomplished the techniques mentioned previously (Foody 2008). Integration of ecological forecasting and GIS is essential to further our knowledge of the impacts of climate change on habitat because GIS can play a major role in visualizing, exploring, and modeling data on current and projected species distributions. Additionally, GIS offers an extreme amount of flexibility in terms of how data is used and what analytical criteria are used in any given model. These advantages, combined with GIS's ability to help decision makers visualize, explore, and think of conservation issues in ways that are usually not possible makes GIS the perfect tool for developing an improved mechanistic ecological forecasting model (Marco et al 2008).

Uncertainty and Error:

With any ecological forecast, regardless of the methodology used, there will always be a certain degree of uncertainty and error associated with the final results of the model. However, by understanding what uncertainty is and where sources of uncertainty originate it is possible to significantly reduce the amount of uncertainty present in a model. Uncertainty and error within a model can come from either the input data or the model framework (Rocchini et al 2011).

Input data uncertainty primarily arises from statistical properties within the data. The most relevant statistical property when working with ecological forecasting models and climate change data is spatial autocorrelation (Dormann 2007). Spatial autocorrelation is a mathematical representation of the similarity of a time-series data set through time, or put more simply, the concept that near observations are more related than distant observations (Miller 2012). A dataset that has spatial autocorrelation will experience changing trends in the data throughout time and thus cannot be accurately analyzed in a model environment. Spatial autocorrelation arises in time series datasets as a result of a series of outliers due to a number of reasons. In ecological forecasting datasets, outliers can arise due to biotic process such as

uneven competition and dispersal (Miller 2012). Spatial autocorrelation can be easily fixed by either averaging a multitude of datasets together or through statistical manipulation of the dataset (Legendre 1993).

Model framework uncertainty error arises mainly due to model structure. Models that are larger and have more parameters have more uncertainty, as each parameter has an associated degree of uncertainty (Beale and Lennon 2012). Conversely, models with very few parameters have a certain degree of uncertainty because the model itself takes into account very little information. The goal of the modeler, regardless of how many parameters are within the model, is to create an accurate model by reducing uncertainty.

The most common way of reducing uncertainty in a model is called data assimilation (Williams et al 2005). Data assimilation is a method of reducing uncertainty by using data to inform initial conditions and model parameters (Luo 2011). By integrating informed data into the initial modeling process of creating conditions and parameters, constraints can be applied to the model process so the results are an accurate reflection of reality. This is the same as a bottom-up approach to modeling where uncertainties are addressed and prevented before the model is run rather than the top-down approach where uncertainties are discovered and fixed after the model is run (Luo 2011). Through the use of data assimilation, models are able to more accurately and efficiently deal with more than just uncertainties. Data assimilation can also help inform model structure. For example, if there is a process being modeled that has many parameters each with high levels of uncertainty, a mechanistic model is preferential because data assimilation can be performed for each parameter within the mechanistic model to lower uncertainty. When the mechanistic model combines each individual parameter to model the entire process, the overall results will contain less uncertainty.

Model Validity:

Closely linked to the idea of error and uncertainty is model validity, which is the ability of the model to accurately contribute to our scientific understanding of the phenomena being modeled. Understandably, when modeling future impacts of climate change, validity is very hard to determine, so hard that no model can ever be considered “correct” (Box 1976). The

primary means of testing validity of ecological forecasting models has been backcasting, which has many drawbacks (Millar et al 2007). Firstly, it is entirely dependent on the availability of historical data. If historical data is either corrupt or absent, backcasting cannot be completed accurately and validity cannot be tested. Secondly, the process of backcasting is very time consuming and complicated, reducing its efficiency as a validity test (Mazzocchi 2008).

Summary:

Now that the current state of ecological forecasting has been laid out, the overall weaknesses can be assessed:

- Both climate envelope modeling and niche level modeling suffer from logical flaws in their model framework. These flaws take away from the usefulness of the models.
- Climate envelope and niche level models are both resistant to data assimilation, as they rely on mapping changes in occurrence and niche tolerances respectively. A mechanistic approach, which couples many parameters together, can integrate data assimilation on a parameter-by-parameter basis, reducing uncertainty for the model.
- Current models cannot perform an ecological forecast at varying geographical extents while not sacrificing its usefulness or spatial resolution.
- Current models cannot perform an ecological forecast on any species regardless of their niche (ex. generalist vs. specialist species).
- Backcasting has too many drawbacks. Better methods of identifying validity should be created.

In the methodology, a new GIS-based model will be proposed that overcomes the listed weaknesses of current ecological forecasting models.

Methods

The proposed model was created in ArcGIS desktop version 10.3 using the model builder. The model builder was used to string together chains of operations, functions, and parameters to create a large and interactive workspace that achieves the purpose of this project. Once completed, the GIS model was tested on three different species and two different study areas. The first study region is within Pennsylvania and consists of the combined Central Appalachian and Allegheny Plateau ecoregions and modeled the Louisiana Waterthrush and the Eastern Gray Squirrel. The second study region is the combined area of California, Nevada, Utah, and Arizona and modeled the cougar. The overall methodology behind the development of the model can be split into five sections:

1. Creation of a habitat suitability index (HSI).
2. Statistical manipulation of climate change data.
3. Integration of climate change data into the model.
4. Creation of six projected habitat suitability indexes (PHSI)
5. Comparing the original HSI to the PHSIs.

This section will use examples and figures from the Louisiana Waterthrush (LOWA) model iteration as an example to display how the model was created and operates.

Data Sources and Preparation:

Data for each study region was downloaded from various online data repositories and government-sponsored organizations such as the U.S. Census Bureau and the U.S. Geological Survey. The data dictionary presented in Figure 1 provides a brief overview of each data source. Before analysis, input data was converted to raster data (if necessary) and projected into a common coordinate system.

Dataset	Originator	Spatial Extent	Currentness	Data Model	Description
Canopy Closure	U.S. Geological Survey (USGS) -- National Landcover Database	United States	2011	Raster	Satellite-based estimate of canopy closure; Raster pixels range from 0 to 100% canopy
Census Data	U.S. Census Bureau	California, Arizona, Nevada, Utah	2010	Vector	TIGER shapefiles containing census data including population and population density
Elevation	U.S. Geological Survey (USGS) -- National Elevation Dataset (NED)	Pennsylvania	2014	Raster	7.5-min digital elevation model (DEM)
Elevation	U.S. Geological Survey (USGS) -- National Elevation Dataset (NED)	California, Arizona, Nevada, Utah	2014	Raster	1-deg digital elevation model (DEM)
Land cover	U.S. Geological Survey (USGS) -- National Landcover Database	United States	2011	Raster	18-class, satellite-based estimate of canopy closure
Protected Lands	The Conservation Fund	Pennsylvania	2004	Vector	Federal, state, and locally-owned lands as polygons.
Riparian Buffer Assessment	Heritage Conservancy	Pennsylvania	2012	Vector	Metric index of biological integrity (IBI) to measure riparian buffer zone health by watershed
Roads/Highways	Pennsylvania Department of Transportation (PennDOT)	Pennsylvania	2015	Vector	Interconnected network of major roads and highways within Pennsylvania
Roads/Highways	U.S. Department of Transportation (USDOT)	California, Arizona, Nevada, Utah	2015	Vector	Interconnected network of major roads and highways within CA, AZ, NV, UT
Streams	U.S. Geological Survey (USGS) -- National Hydrography Dataset	United States	2015	Vector	Interconnected network of first, second, third, and fourth order streams
Water Quality	Natural Lands Trust	High Allegheny Plateau Ecoregion	2010	Vector	Metric index of biological integrity (IBI) to measure stream water quality by watershed
Water Quality	Natural Lands Trust	Central Appalachian Ecoregion	2011	Vector	Metric index of biological integrity (IBI) to measure stream water quality by watershed
Watershed Boundaries	Eastern Pennsylvania Coalition for Abandoned Mine Reclamation	Pennsylvania	2014	Vector	Boundaries of all small watersheds within Pennsylvania

Figure 1: Data dictionary.

Creation of a Habitat Suitability Index (HSI):

A HSI is a geospatial index which assigns a suitability score to each individual pixel in a study region. The suitability score represents the overall habitat suitability of that pixel, in geographic space, for the given species. A literature review is performed on the species in question to identify parameters and specific criterion that are associated with habitat suitability. For example, it was found in the literature that LOWA are stream dependent birds and are more commonly found closer to streams (Robbins 1990). Thus it can be concluded that LOWA habitat suitability is higher in pixels that are in close proximity to streams than pixels that are far from the nearest stream. Figure 2 shows the appropriate parameters and criterion identified through the literature to be determinants of LOWA habitat suitability.

Parameter	Criterion	Source
Canopy Cover	At least 30% Higher % is more suitable	Prosser and Brooks 1998
Distance from Streams	No more than 400m Less than 150m is most suitable	Robbins 1990
Forest Size	At least 42.2 Ha More than 3200 Ha is most suitable	Hayden et al 1985
Landcover	Deciduous forest is most suitable Mixed forest is less suitable Wetland is the least suitable Other landcover types are completely unsuitable	Banner 2001
Slope	At least 4 degrees Higher slope is more suitable	Eliason and Fall 1989
Water Quality	Scores at least 0.3 Higher scores more suitable	Audubon 2014

Figure 2: List of parameter and associated criterion of LOWA habitat suitability determinants.

Once criterion are collected, the input layers are combined into the final HSI using a fuzzy membership approach. Fuzzy membership uses a non-hierarchical approach to classifying groups of pixels into suitability sets that has many advantages over traditional raster-based approaches. Fuzzy membership is advantageous because it can help expand rough approximations into a fuzzy environment which helps to obtain solutions for various real time problems. The result of fuzzy membership can be thought of as a gradient of suitability rather than distinct categories of suitability produced by traditional raster methods. This gradient is optimal for mapping biological and ecological phenomenon since they are inherently fuzzy in nature and cannot be separated into distinct categories for analysis. Fuzzy membership functions, shown in Figure 3, were created for all six inputs to convert the input layers into

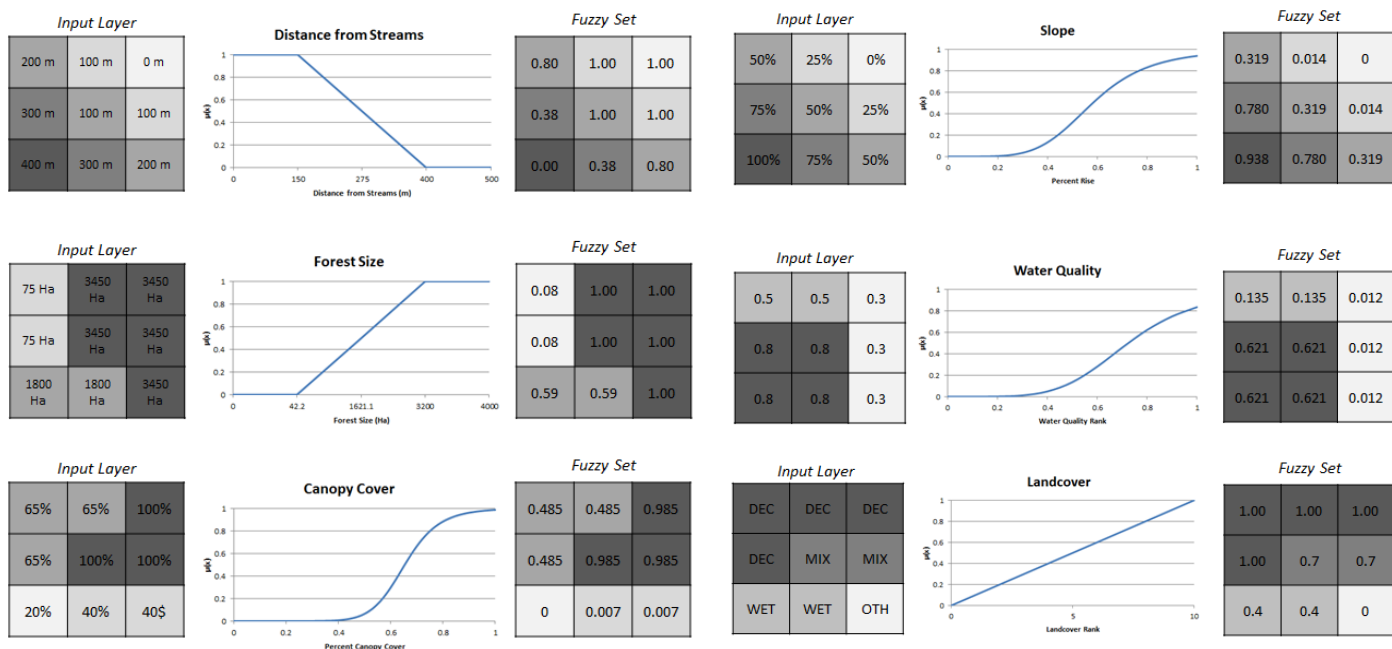


Figure 3: Fuzzy membership functions and examples of all six LOWA habitat criteria.

fuzzy sets. The fuzzy sets were then overlaid using the logical operators 'and' and 'gamma,' resulting in the final HSI. The HSI represents current LOWA habitat suitability and will later be compared with the PHSIs to quantify and display shifts in habitat due to climate change.

Statistical Manipulation of Climate Change Data:

Climate change data must be prepared using small statistical manipulations before the data can be integrated into the model. The model analysis relies on climate anomalies, which can be calculated by subtracting climate data from the initial year from climate change data from the year in question:

$$\text{Anomaly} = \text{Year}_{\text{final}} - \text{Year}_{\text{initial}}$$

This equation for calculating climate anomalies only works consistently if the initial year climate change data from all three climate change scenarios (low, medium, high) have the same average throughout the study region. If this is not the case, the initial year will have significantly different climate data between all three scenarios and resulting climate anomalies will be skewed. This also makes sense intuitively because the initial base year used is the current year, which means the average of temperature and precipitation data should be one number across the entire study region (the number that the climate is currently experiencing). To solve this problem, all climate change data for the study region was extracted into an excel table and the mean temperature and precipitation values were calculated for the entire study region for every projected year (Figure 4). The resulting graph shows how the study region mean for climate change data fluctuates from year to year and from scenario to scenario. The average values from the base year (2015 in this case) for all three scenarios were averaged together to get a base year mean. The base year of each scenario was then adjusted by adding or subtracting the difference between the base year and base year mean to all pixels in the study region. This results in a parallel horizontal shift upwards if adding or downwards if subtracting to the climate change values of all pixels being analyzed. This type of mean adjustment is optimal because it standardizes the overall mean of the base year, allowing for

Temperature CC Data Analysis

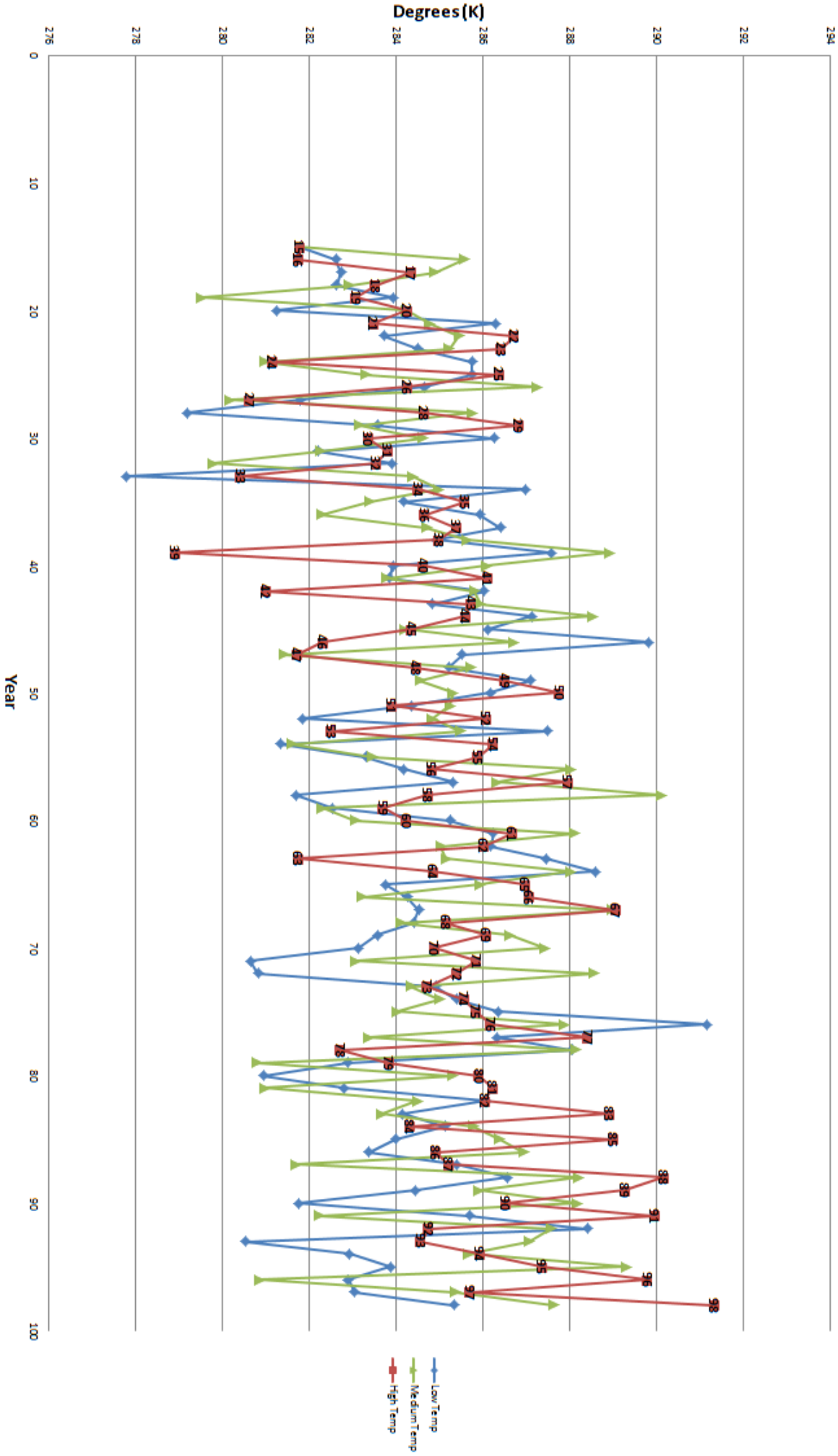


Figure 4: Mean temperature values for pixels within study region.

calculation of consistent anomalies, while still maintaining the statistical deviations within the climate change sets which help to model the variability of year to year climate changes

Another problem within the climate change data is the presence of outliers (Figure 4). Outliers are naturally present within climate change models due to the natural variability within the model. These outliers can be easily spotted when the climate change data behaves in ways that are either not expected or are illogical. For example, in some years such as 2034, the climate change data predicts significantly higher temperatures in the low projection than the high projection. Outliers are harmless in terms of the grand scheme of the data as long as the data is following a logical trend, however outliers can be harmful to the model when selecting individual years to model. An analysis on the previously mentioned year, 2034, would result in the low scenario showing much higher habitat changes than the high scenario, which is opposite of what one would expect. Thus, it is important to understand where these outliers occur in order to produce logical results. Just because a year is subject to outliers does not make it useless. Outlier averaging can be used to statistically adjust the climate change data to better fit in with the overall data trend. Outlier averaging is averaging the outlier year with surrounding years to correct the data. For example, the low scenario data for 2034 could be averaged with the low scenario data for 2033 to correct for the outlier. Through proper use of outlier averaging, every year of climate change data can be valid inputs for modelling. Outlier averaging can effectively expand the operational range of the model, allowing for a great flexibility in test years.

Integration of Climate Change Data:

Climate change data, in its native form, is stored in the form of point data where each point is given a certain x- and y-coordinate position and contains data values representing the projected climate values for that coordinate in the given year. In order for this data to be used in the analysis, it must be converted into a format that is compatible with fuzzy analysis, which is a raster based approach.

This is accomplished in the model by spatially joining the climate point data with a polygon data set that contains small watershed boundaries. Each individual small watershed is given the respective climate change data of the geodesic climate change point. This allows the data to then be converted to raster data and successfully integrated into the model but also vastly increases the spatial resolution which results in a smoother final map that is more easily interpreted (Figure 5). The polygon layer used for the spatial join can be any polygon layer with natural boundaries, but smaller polygons are preferential as they will result in a higher boost to spatial resolution.

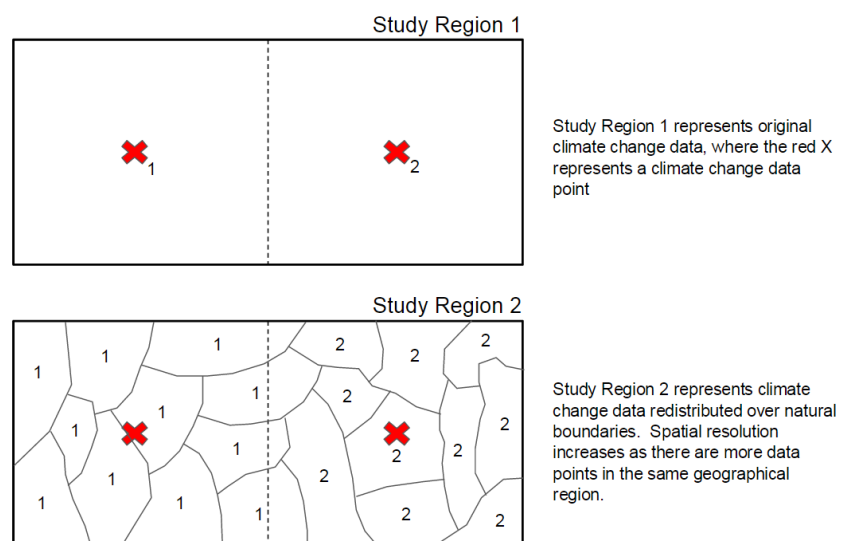


Figure 5: Transforming climate change point data into usable data while increasing spatial resolution.

Once the climate change data was spatially joined, it was used to create a climate change index (CCI). The CCI is an index that standardizes and measures overall climate change at each pixel in the study area. The first step in creating the CCI is using a Python script to standardize and add together temperature and precipitation anomalies. The Python script changes depending on the study region but is created following the same methodology. Anomaly values are assigned climate change ranks ranging from 1 (representing no climate change) to 10 (representing high climate change). The climate change data graphs from the first step (Figure 4) are used to determine the specific cutoffs for the ranking scale as follows. First, the maximum temperature and minimum precipitation value within the study region are designated as the highest anomalies possible within the study region and used as the upper

cutoff at rank 10. Secondly, a climate anomaly of 0 which represents the smallest anomaly possible within the study region is used as the lower cutoff at rank 1. Thirdly, the rankings in between determined using a quantile classification where each rank contains an equal amount of data values (Figure 6).

Temperature Ranking	
Max Value (K):	290.319866
Anomaly (F):	15.377
Value between each rank:	1.708555556

Temperature Rank	Anomaly
10	15.377
9	13.66844444
8	11.95988889
7	10.25133333
6	8.542777778
5	6.834222222
4	5.125666667
3	3.417111111
2	1.708555556
1	0

Figure 6: Determination of ranks for the python script.

The result of the Python script is two maps, one for precipitation and one for temperature, that have values between 1-10 based on climate change anomalies. Lastly, these maps are added together to create one individual layer which quantifies the overall impact of climate change (aggregate climate change rank) at any given pixel in the study region where a value of 2 represents no climate change and a value of 20 represents the most climate change. The final CCI is created by using a fuzzy membership function to define the mathematical relationship between species temperature tolerance and overall climate change. The final CCI, like other fuzzy membership layers, contains fuzzy values between 0 and 1 where a value of 0 is assigned to pixels with the most climate change and a value of 1 is assigned to pixels with the least climate change.

The CCI is extremely useful because it can be changed from species to species. The CCI allows the user to adjust how strictly the model accounts for climate change. A CCI that has a steeper slope results in the model being harsher, where small increases in aggregate climate

change rank result in larger decreases in fuzzy value. For example, it is known that generalist species will have an easier time adapting to climate change than specialist species because they are able to live in a much broader range of habitats. In this way, the CCI for specialist species will always score lower and have lower fuzzy values than the CCI for generalist species (Figure 7). Through proper use of CCI manipulation, the model can be fine-tuned to more accurately model any species based on its biological properties and ecosystem function.

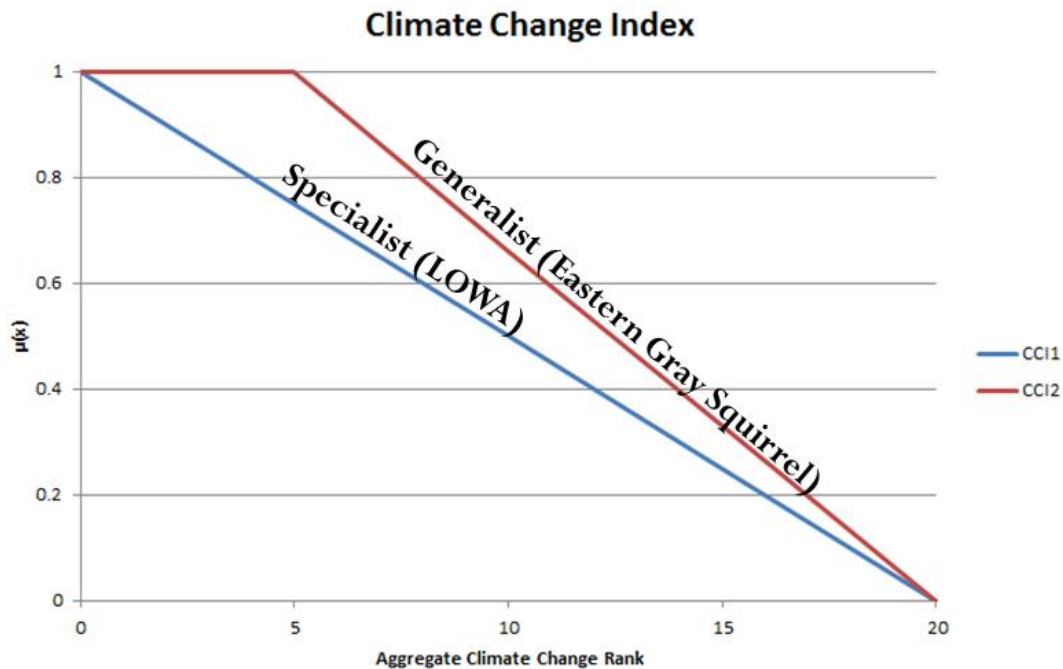


Figure 7: Fuzzy membership functions used to create CCIs for two different species.

Creation of Projected Habitat Suitability Index (PHSI):

The PHSI, similarly to the HSI, is a geospatial index which assigns a suitability score to each individual pixel in the study region for the projected year. The PHSI is created by using the CCI as a multiplier to manipulate input layers. The CCI is used as a multiplier if there is a positive relationship between criterion and suitability and as a divider if there is a negative relationship between criterion and suitability. For example, in the distance from streams layer, suitability decreases as distance values increase (negative relationship) so the CCI is used as a divider. Figure 8 graphically shows the overall process of using the CCI to manipulate input

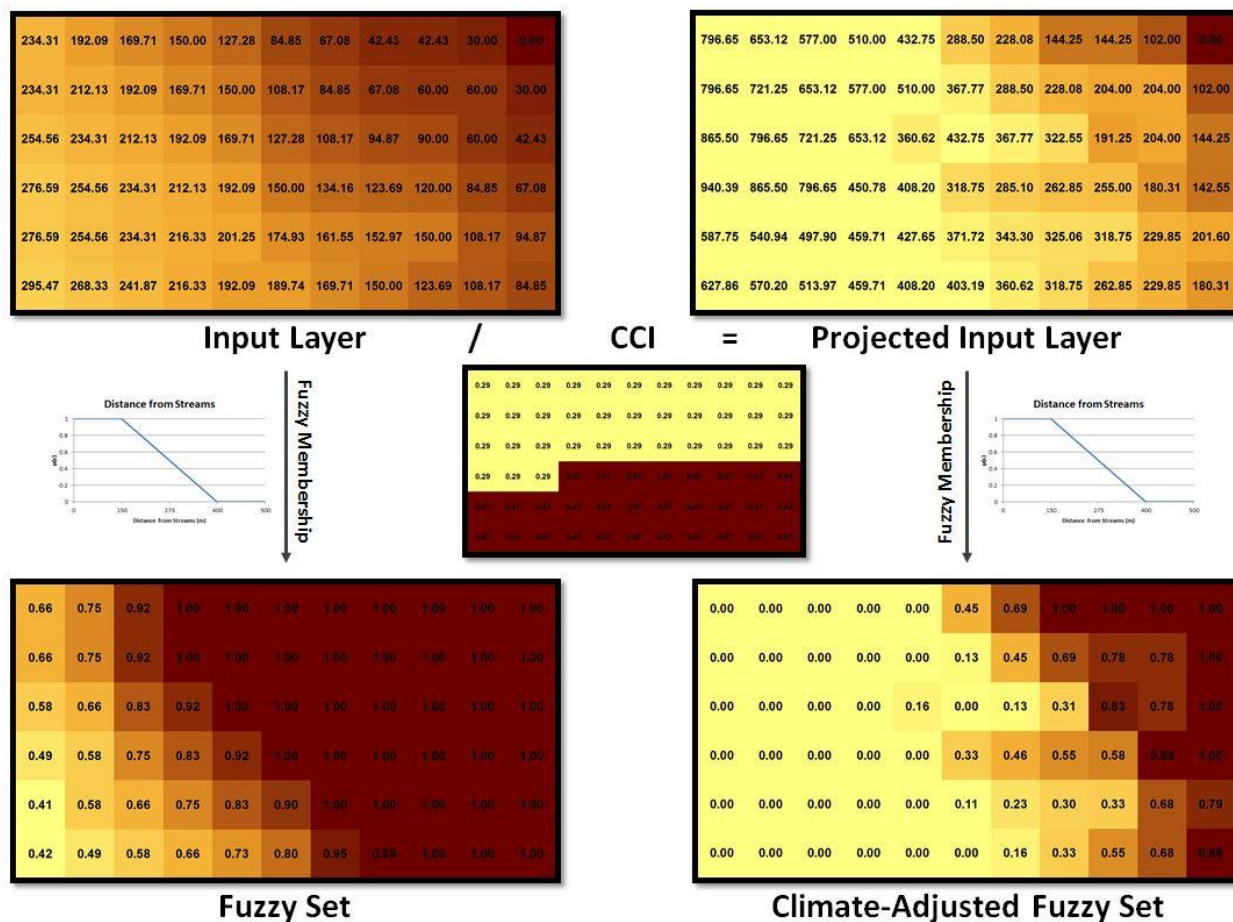


Figure 8: Graphical methodology of using the CCI to manipulate the distance from streams layer.

layers. Continuing to use the distance from streams layer as an example, the original input layer (pre-fuzzy membership) is divided by the CCI to create a projected input layer. This projected input layer is then turned into a fuzzy set using the same fuzzy membership function used when creating the initial HSI, creating a climate adjusted fuzzy set. The logic behind this process is as follows. Input layer pixels that receive a perfect CCI score of 1 (those that have no climate change at all) will be divided by 1, resulting in the same value within the projected input layer. Once classified into a fuzzy set, the classified pixel of both the fuzzy set and climate-adjusted fuzzy set will have the same suitability score. This makes sense intuitively, as an area that has experienced no climate change between two years should have the same suitability score in both years. Input layer pixels that receive a very low CCI score of 0.2, for example, will be divided by 0.2, resulting in a significantly larger value in the projected input layer than the input layer. Once classified into a fuzzy set, the classified pixel of the climate adjusted fuzzy set will receive a significantly lower suitability score than that of the fuzzy set. This also makes

sense intuitively, as an area that has experienced significant climate change between two years should have very different suitability scores in both years. The climate-adjusted fuzzy sets are then overlaid in the same way used when creating the HSI. The final PHSI is a raster layer that represents habitat suitability in the projected year.

Because the CCI operates as a multiplier with a maximum value of 1, manipulation of an input layer by the CCI will always result in keeping constant or decreasing the suitability score of a pixel in the PHSI. It is impossible for the CCI to improve the suitability of an area as any input layer value multiplied by a fraction will result in a smaller value, which will then be assigned a lower suitability score by the corresponding fuzzy membership function. The result is the same when the CCI is used as a divider. Division of the input layer by the CCI will result in a larger value in the input layer which will then be assigned a lower suitability score by the corresponding fuzzy membership function due to the inverse relationship between criterion and suitability score.

The resulting outputs from the model for all species were first analyzed by quantifying habitat change from one scenario to the next. This was accomplished by dividing the results

Combination	HSI	Low	Medium	High
1	VS	VS	VS	VS
2	VS	VS	VS	S
3	VS	VS	VS	US
4	VS	VS	S	S
5	VS	VS	S	US
6	VS	VS	US	US
7	VS	S	S	S
8	VS	S	S	US
9	VS	S	US	US
10	VS	US	US	US
11	S	S	S	S
12	S	S	S	US
13	S	S	US	US
14	S	US	US	US
15	US	US	US	US

into three suitability classes based on suitability score: very suitable ($1.0 > x > 0.75$), suitable ($0.75 > x > 0.5$), and unsuitable ($0.5 > x > 0$). Total pixel counts within each suitability class were counted through the attribute table and multiplied by pixel size (30m x 30m) to calculate the total habitat area, denominated by km^2 , within each suitability class for all model outputs. Pixel count and habitat area were tabulated and compared to baseline values from the HSI to calculate percent habitat loss from scenario to scenario.

Figure 9: All possible combinations of pixel suitability change through all scenarios. VS represents the very suitable class, S represents the suitable class, and US represents the unsuitable class.

Suitability changes from scenario to scenario were also displayed visually using a three-integer coding system. In total, there are three possible suitability classes and four separate scenarios, resulting in 81 different combinations of suitability changes. However, because the CCI works in a way that only decreases suitability scores, it can be assumed that pixels can either stay within a suitability class or move down a suitability class. This significantly reduces the amount of possible suitability change combinations to 15, as shown in Figure 9.

A three integer coding system was used to assign unique values to all 15 possible combinations of suitability change, allowing for all types of pixel changes to be visually represented using just one map of the study region. Pixels in the very suitable category were given a value of 7, the suitable category a value of 3, and the unsuitable category a value of 2. This combination of three prime numbers results in 15 different unique values when added together across all scenarios (Figure 10).

Combination	HSI	Low	Medium	High	Sum
1	7	7	7	7	28
2	7	7	7	3	24
3	7	7	7	2	23
4	7	7	3	3	20
5	7	7	3	2	19
6	7	7	2	2	18
7	7	3	3	3	16
8	7	3	3	2	15
9	7	3	2	2	14
10	7	2	2	2	13
11	3	3	3	3	12
12	3	3	3	2	11
13	3	3	2	2	10
14	3	2	2	2	9
15	2	2	2	2	8

Figure 10: The three-integer coding system used to assign unique values to all combinations of suitability change.

This coding systems functions so combinations with the highest score are the most climactically suitable, as they remain in the very suitable category for the longest period of time. Once the model outputs are recoded using this system and added together using the raster calculator to create unique values for each combination, it can be shown as a thematic map that visually displays climactic suitability for the given study region.

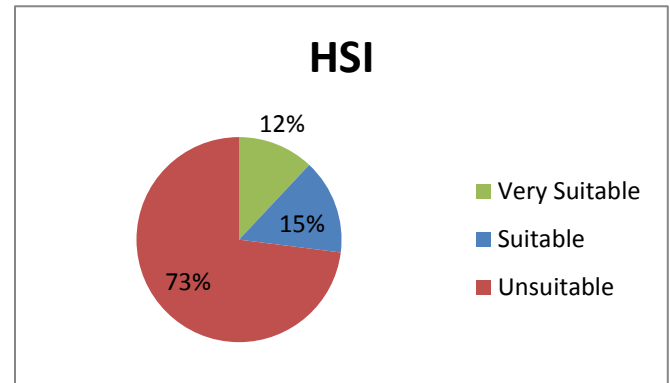
Results

This section will be split up into three sections, each dedicated to one of the three species being examined.

Louisiana Waterthrush

A total of 61,362,188 pixels, equating to 55,225 km² of habitat, was included in the Louisiana Waterthrush study region consisting of the combined Allegheny Plateau and Central Appalachian ecoregions. In the HSI, 12% of pixels (6,644 km²) were in the very suitable category, 15% of pixels (8,152 km²) were in the suitable category, and 73% of pixels (40,430 km²) were in the unsuitable category (Figure 11). A sharp decrease in LOWA very suitable habitat was found in both projections with the 2050 projection experiencing habitat change of -58.92% (2,729 km² remaining), -86.21% (916 km² remaining) and -98.31% (112 km² remaining) through the low, medium, and high scenarios, respectively (Figure 12).

Figure 11: Percentage (%) of total area within each



Louisiana Waterthrush

2050 Projection			
Very Suitable (1.0 > x > 0.75)			
Model Iteration	Pixel Count	Habitat Change (%)	Habitat Area (km2)
H.S.I	7,382,113	0.00%	6,644
Low	3,032,273	-58.92%	2,729
Medium	1,017,648	-86.21%	916
High	124,595	-98.31%	112
Suitable (0.75 > x > 0.5)			
Model Iteration	Pixel Count	Habitat Loss (%)	Habitat Area (km2)
H.S.I	9,057,688	0.00%	8,152
Low	7,929,664	-12.45%	7,137
Medium	5,983,817	-33.94%	5,385
High	4,489,110	-50.44%	4,040
Unsuitable (0.5 > x > 0.0)			
Model Iteration	Pixel Count	Habitat Loss (%)	Habitat Area (km2)
H.S.I	44,922,387	0.00%	40,430
Low	50,179,646	11.70%	45,162
Medium	54,138,118	20.51%	48,724
High	56,525,878	25.83%	50,873

2099 Projection			
Very Suitable (1.0 > x > 0.75)			
Model Iteration	Pixel Count	Habitat Change (%)	Habitat Area (km2)
H.S.I	7,382,113	0.00%	6,644
Low	460,062	-93.77%	414
Medium	-	-100.00%	-
High	-	-100.00%	-
Suitable (0.75 > x > 0.5)			
Model Iteration	Pixel Count	Habitat Loss (%)	Habitat Area (km2)
H.S.I	9,057,688	0.00%	8,152
Low	4,931,838	-45.55%	4,439
Medium	1,264,030	-86.04%	1,138
High	102,411	-98.87%	92
Unsuitable (0.5 > x > 0.0)			
Model Iteration	Pixel Count	Habitat Loss (%)	Habitat Area (km2)
H.S.I	44,922,387	0.00%	40,430
Low	55,747,683	24.10%	50,173
Medium	59,875,553	33.29%	53,888
High	61,037,172	35.87%	54,933

Figure 12: LOWA pixel counts, habitat changes, and habitat areas for all suitability classes, scenarios, and projections.

The 2099 projection lost 100% of very suitable habitat by the medium scenario. In the suitable category, a consistent, but less severe than the very suitable category, decrease in habitat was seen in both projections. The 2050 and 2099 projections had respectively lost 50.44% (4,040 km² remaining) and 98.87% (92 km² remaining) of its suitable habitat by the high scenario. To match the loss of very suitable and suitable habitat, a corresponding increase in the amount of unsuitable habitat was experienced in both projections.

Throughout all scenarios, the 2050 projection experienced a 25.83% increase in unsuitable habitat while the 2099 projection experienced an increase of 35.87%, resulting in an increase in unsuitable habitat from 40,430 km² to 54,933 km². A graphical overview comparing the percentage of total area within each suitability class between all scenarios and projections is shown in Figure 13.

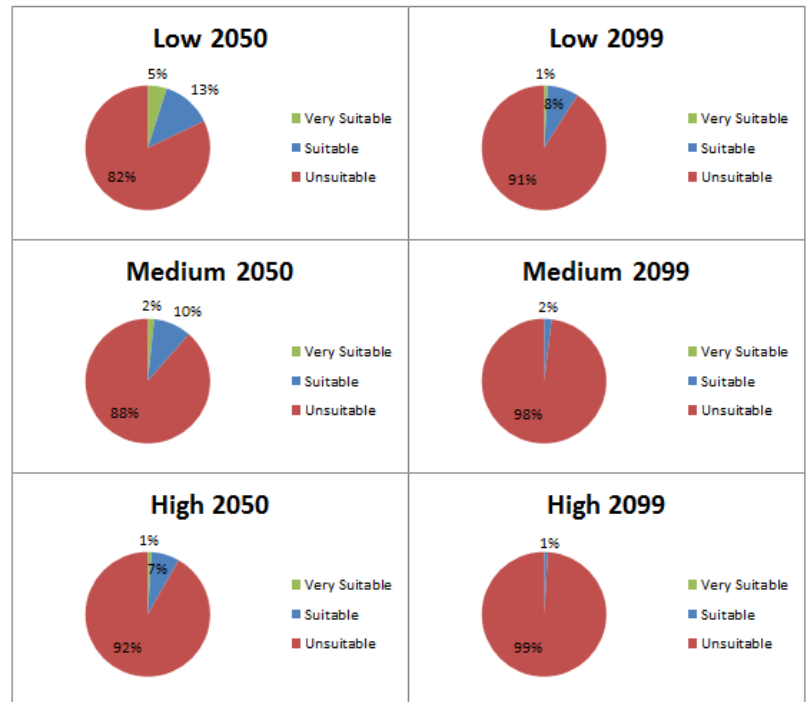


Figure 13: Comparison of percentage (%) of total area within each LOWA suitability class between all scenarios and projections.

The thematic maps representing climactic suitability for both projections are shown in Figure 14 and Figure 15, where blue pixels are those that are the most climactically suitable and yellow pixels are those that are the least climactically suitable. The majority of very suitable pixels in both projections are located within the Susquehannock National Forest. The very suitable pixels in these locations are notably located within stream riparian zones, which are the finger-like objects that appear throughout the study region. Although there is little change in the location of very suitable pixels between the two projections, the 2099 projection features

significantly less blue pixels and many more pink and red pixels, indicating an overall decrease in climactic suitability from 2050 to 2099 across the study region. The finger-like objects, indicating bands of suitability within riparian zones, are still present in the 2099 thematic image, however these finger-like objects are noticeably thinner and less dense.

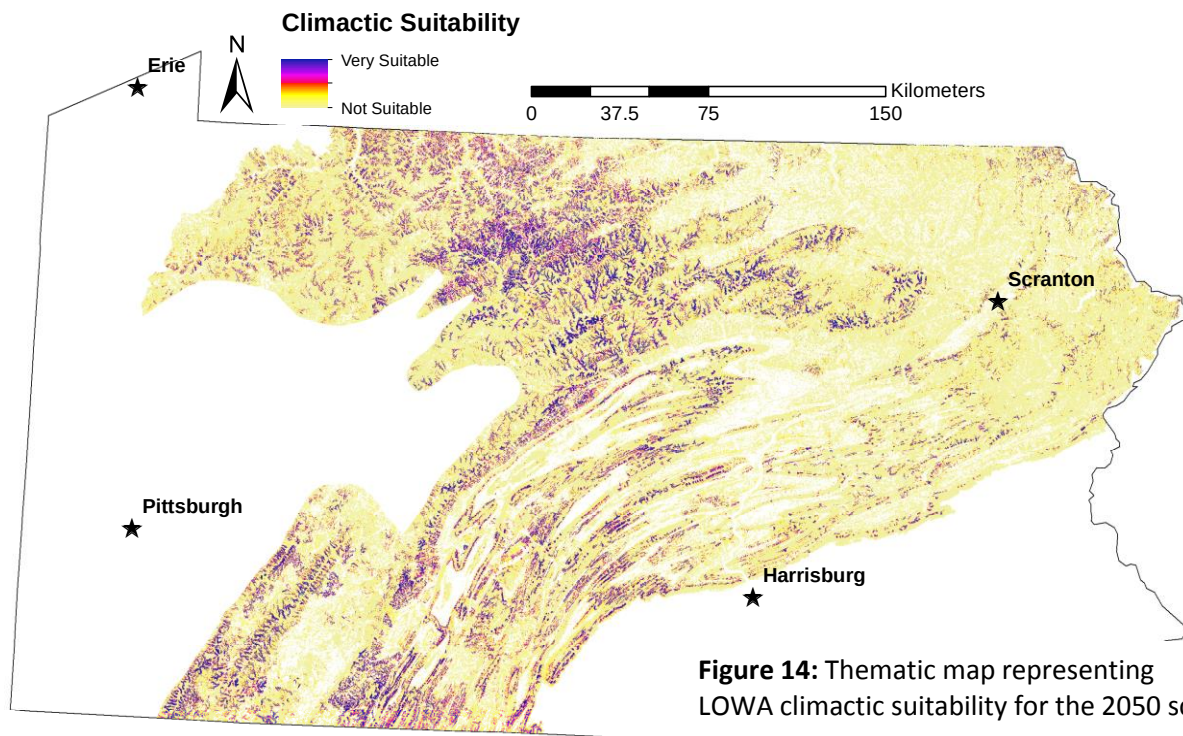


Figure 14: Thematic map representing LOWA climactic suitability for the 2050 scenario.

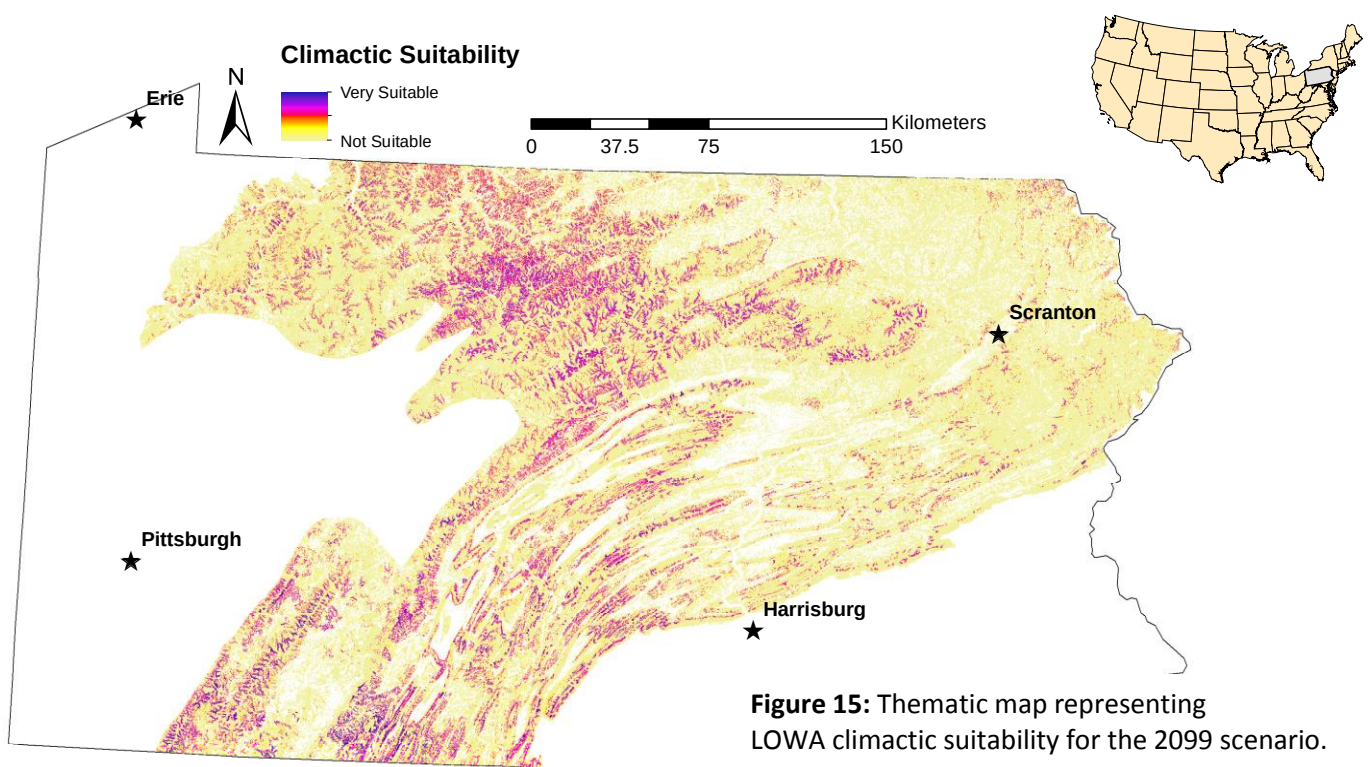
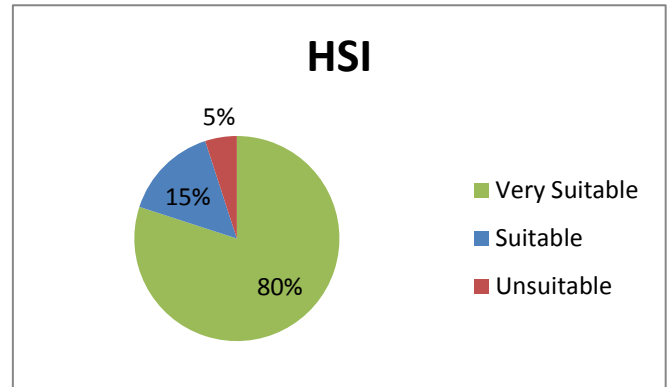


Figure 15: Thematic map representing LOWA climactic suitability for the 2099 scenario.

Eastern Gray Squirrel:

A total of 61,681,381 pixels, equating to 55,513 km² of habitat, was included in the Eastern Gray Squirrel study region consisting of the combined Allegheny Plateau and Central Appalachian ecoregions. In the HSI, 80% of pixels (44,252 km²) were in the very suitable category, 15% of pixels (8,152 km²) were in the suitable category, and 5% of pixels (4,043 km²) were in the unsuitable category (Figure 16).

Figure 16: Percentage (%) of total area within each suitability class.



In the 2050 projection, there was a small decrease in very suitable habitat from -3.49% (42,708 km² remaining) in the low scenario, -10.55% (39,582 km² remaining) in the medium scenario, and -17.35% (36,574 km² remaining) in the high scenario (Figure 17).

Eastern Gray Squirrel			
2050 Projection			
Very Suitable (1.0 > x > 0.75)			
Model Iteration	Pixel Count	Habitat Change (%)	Habitat Area (km2)
H.S.I	49,168,577	0.00%	44,252
Low	47,453,220	-3.49%	42,708
Medium	43,980,272	-10.55%	39,582
High	40,638,137	-17.35%	36,574
Suitable (0.75 > x > 0.5)			
Model Iteration	Pixel Count	Habitat Loss (%)	Habitat Area (km2)
H.S.I	9,565,277	0.00%	8,609
Low	9,927,161	3.78%	8,934
Medium	10,942,959	14.40%	9,849
High	10,698,646	11.85%	9,629
Unsuitable (0.5 > x > 0.0)			
Model Iteration	Pixel Count	Habitat Loss (%)	Habitat Area (km2)
H.S.I	2,947,527	0.00%	2,653
Low	4,069,949	38.08%	3,663
Medium	6,977,099	136.71%	6,279
High	10,113,547	243.12%	9,102
2099 Projection			
Very Suitable (1.0 > x > 0.75)			
Model Iteration	Pixel Count	Habitat Change (%)	Habitat Area (km2)
H.S.I	49,168,577	0.00%	44,252
Low	40,164,751	-18.31%	36,148
Medium	21,614,022	-56.04%	19,453
High	2,434,509	-95.05%	2,191
Suitable (0.75 > x > 0.5)			
Model Iteration	Pixel Count	Habitat Loss (%)	Habitat Area (km2)
H.S.I	9,565,277	0.00%	8,609
Low	10,450,771	9.26%	9,406
Medium	21,069,260	120.27%	18,962
High	17,514,664	83.11%	15,763
Unsuitable (0.5 > x > 0.0)			
Model Iteration	Pixel Count	Habitat Loss (%)	Habitat Area (km2)
H.S.I	2,947,527	0.00%	2,653
Low	10,834,808	267.59%	9,751
Medium	18,767,048	536.70%	16,890
High	41,501,157	1308.00%	37,351

Figure 17: Eastern Gray Squirrel pixel counts, habitat changes, and habitat areas for all suitability classes, scenarios, and projections.

In the 2099 projection, there was an increasing decrease in very suitable habitat through all three scenarios. The low scenario experienced a habitat loss of -18.31% (36,148 km² remaining) while the medium and high scenarios experienced habitat change of -56.04% (19,453 km² remaining) and -95.05% (2,191 km² remaining) respectively. Contrary to the LOWA

results, the suitable category for the 2050 projection experienced habitat increases in the low, medium and high scenarios (3.78%, 14.40%, and 11.85% respectively). This trend continued in the 2099 projection which saw increases in suitability habitat within all scenarios, with the largest increase (120.27%, 18,962 km² remaining) occurring in the medium scenario. The unsuitable category experienced very large increases in habitat with a total increase of 243% and 1308% in the high scenario of the 2050 and 2099 projections, respectively. These large percentages are mostly due to the very small amount of unsuitable habitat in the HSI. In terms of habitat area, the 2050 projection saw an increase in unsuitable habitat from 2,653 km² to 9,102 km² while the 2099 projection saw an increase from 2,653 km² to 37,351 km². A graphical overview comparing the percentage of total area within each suitability class between all scenarios and projects is shown in Figure 18.

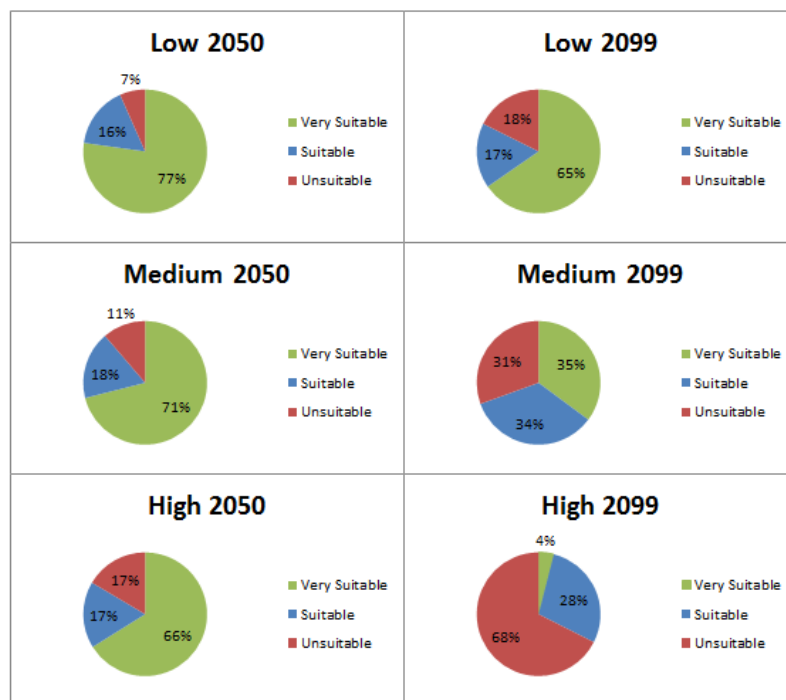


Figure 18: Comparison of percentage (%) of total area within each squirrel suitability class between all scenarios and projections.

The thematic maps representing climactic suitability for both projections are shown in Figure 19 and Figure 20, where dark red pixels are those that are the most climactically suitable and dark blue pixels are those that are the least climactically suitable. In the 2050 projection, very suitable pixels can be found throughout the entire study region with the exception of north-east Pennsylvania. The 2099 projection shows a clear trend in climactic suitability, as the most climactic suitability pixels can be strictly found in the Allegheny National Forest in the

north-west corner of the study region. All of the previously very suitable pixels that could be found between Erie and Scranton and between Pittsburgh and Harrisburg have become less suitable.

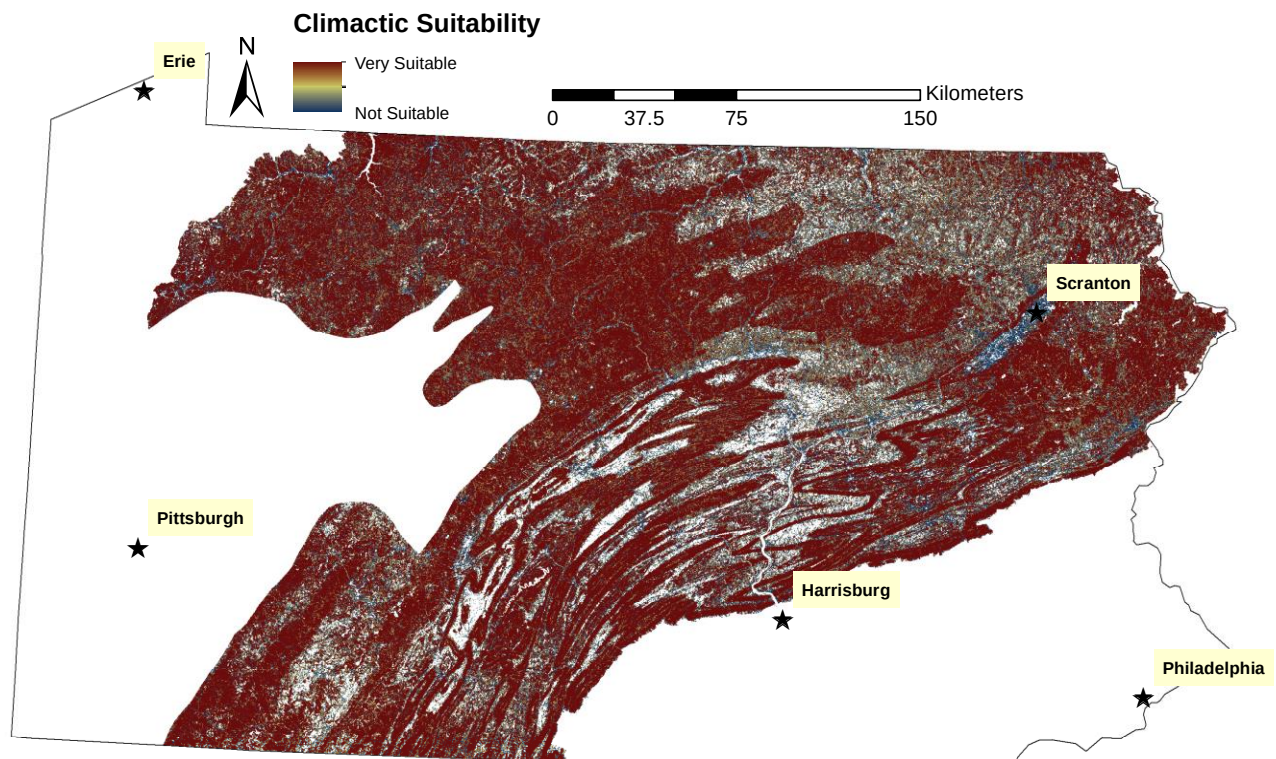


Figure 19: Thematic map representing Eastern Gray Squirrel climactic suitability for the 2050 scenario.

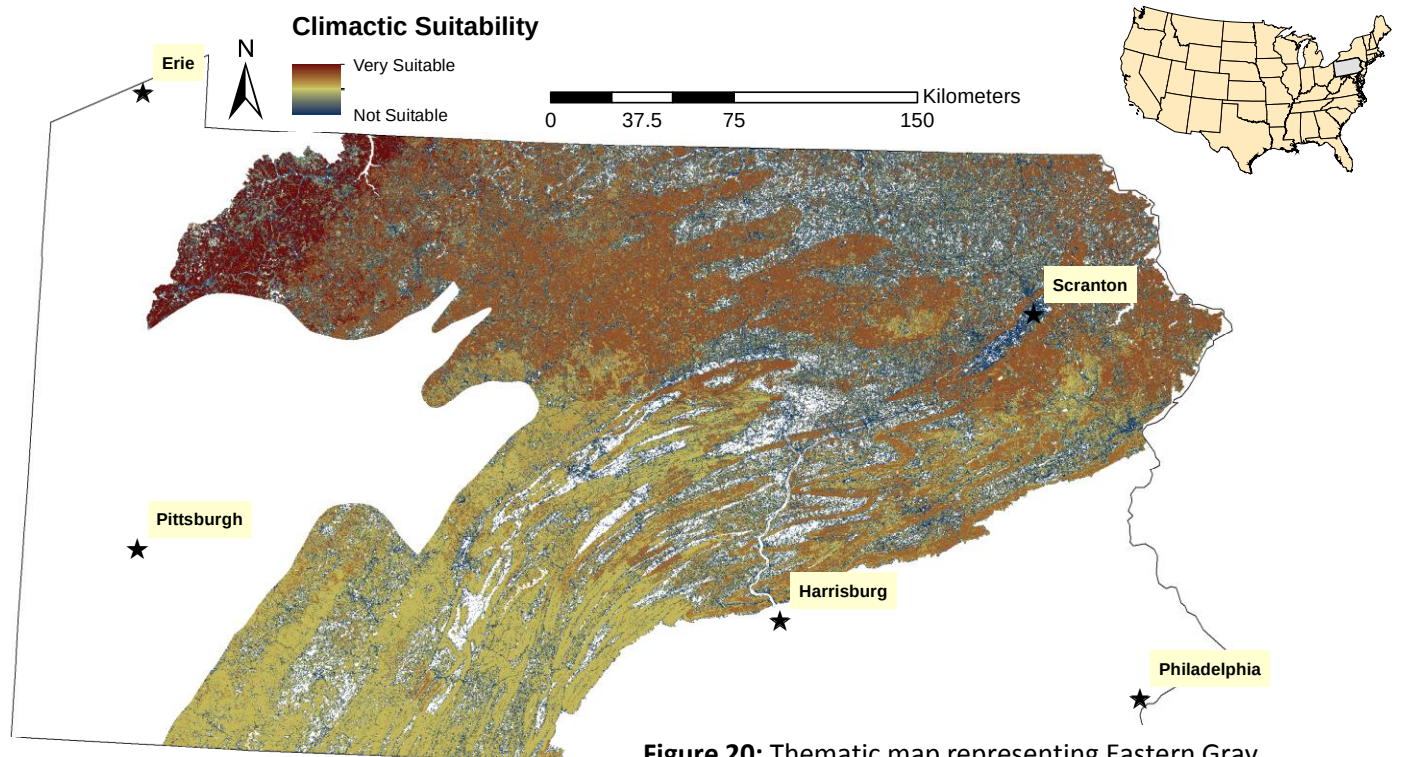
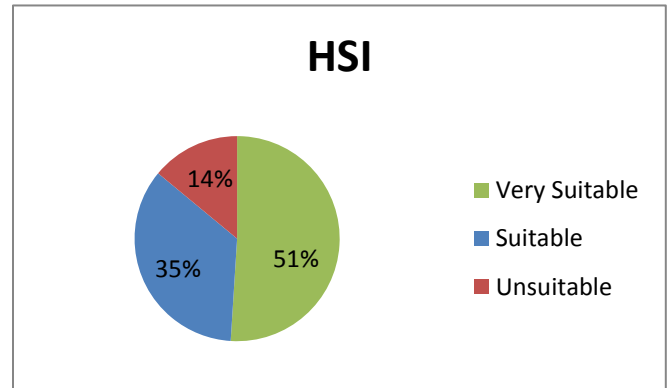


Figure 20: Thematic map representing Eastern Gray Squirrel climactic suitability for the 2050 scenario.

Cougar:

A total of 146,288,638 pixels, equating to 131,659 km² of habitat, was included in the Cougar study region consisting of the combined area of California, Nevada, Utah, and Arizona. In the HSI, 51% of pixels (67,344 km²) were in the very suitable category, 35% of pixels (47,051 km²) were in the suitable category, and 14% of pixels (17,265 km²) were in the unsuitable category (Figure 21). Similar to the two previous species, cougars also experienced a decrease in very suitable habitat from the low to medium to high scenario. In the 2050 projection, the low scenario experienced a change in very suitable habitat of 39.38% (40,283 km² remaining), the medium scenario a change of -45.53% (36,683 km² remaining), and the high scenario a change of -53.19% (31,523 km² remaining). The 2099 projection experienced changes in very suitable habitat of -72.73% (18,367 km² remaining), -73.17% (18,071 km² remaining), and -82.14% (12,026 km² remaining) in the low, medium, and high scenarios, respectively (Figure 22).

Figure 21: Percentage (%) of total area within each suitability class.



Cougar

2050 Projection			
Very Suitable (1.0 > x > 0.75)			
Model Iteration	Pixel Count	Habitat Change (%)	Habitat Area (km2)
H.S.I	74,826,702	0.00%	67,344
Low	45,359,374	-39.38%	40,823
Medium	40,758,915	-45.53%	36,683
High	35,025,788	-53.19%	31,523
Suitable (0.75 > x > 0.5)			
Model Iteration	Pixel Count	Habitat Loss (%)	Habitat Area (km2)
H.S.I	52,278,906	0.00%	47,051
Low	79,150,151	51.40%	71,235
Medium	83,427,485	59.58%	75,085
High	88,236,590	68.78%	79,413
Unsuitable (0.5 > x > 0.0)			
Model Iteration	Pixel Count	Habitat Loss (%)	Habitat Area (km2)
H.S.I	19,183,030	0.00%	17,265
Low	19,787,350	3.15%	17,809
Medium	20,059,120	4.57%	18,053
High	21,264,706	10.85%	19,138

2099 Projection			
Very Suitable (1.0 > x > 0.75)			
Model Iteration	Pixel Count	Habitat Change (%)	Habitat Area (km2)
H.S.I	74,826,702	0.00%	67,344
Low	20,408,128	-72.73%	18,367
Medium	20,079,112	-73.17%	18,071
High	13,361,712	-82.14%	12,026
Suitable (0.75 > x > 0.5)			
Model Iteration	Pixel Count	Habitat Loss (%)	Habitat Area (km2)
H.S.I	52,278,906	0.00%	47,051
Low	102,817,605	96.67%	92,536
Medium	93,923,972	79.66%	84,532
High	92,783,635	77.48%	83,505
Unsuitable (0.5 > x > 0.0)			
Model Iteration	Pixel Count	Habitat Loss (%)	Habitat Area (km2)
H.S.I	19,183,030	0.00%	17,265
Low	21,422,394	11.67%	19,280
Medium	28,219,967	47.11%	25,398
High	37,855,842	97.34%	34,070

Figure 22: Cougar pixel counts, habitat changes, and habitat areas for all suitability classes, scenarios, and projections.

Similar to the eastern gray squirrel, the suitable category for the 2050 projection experienced habitat increases in the low, medium, and high scenarios (96.67%, 79.66%, and 77.48% respectively). This trend continued in the 2099 projection which saw increases in suitability habitat within all scenarios, with the largest increase (97.34%, 98,295 km² remaining) occurring in the high scenario. The unsuitable category experienced increases in habitat with increases of 10.85% (19,138 km²) by the high scenario in the 2050 projection. The 2099 projection saw decreasing increases in habitat gain of 97.34% (34,070 km²) in the low scenario, 47.11% (25,398 km²) in the medium scenario, and 11.67% in the high scenario (19,280 km²). A graphical overview comparing the percentage of total area within each suitability class between all scenarios and projections is shown in Figure 23.

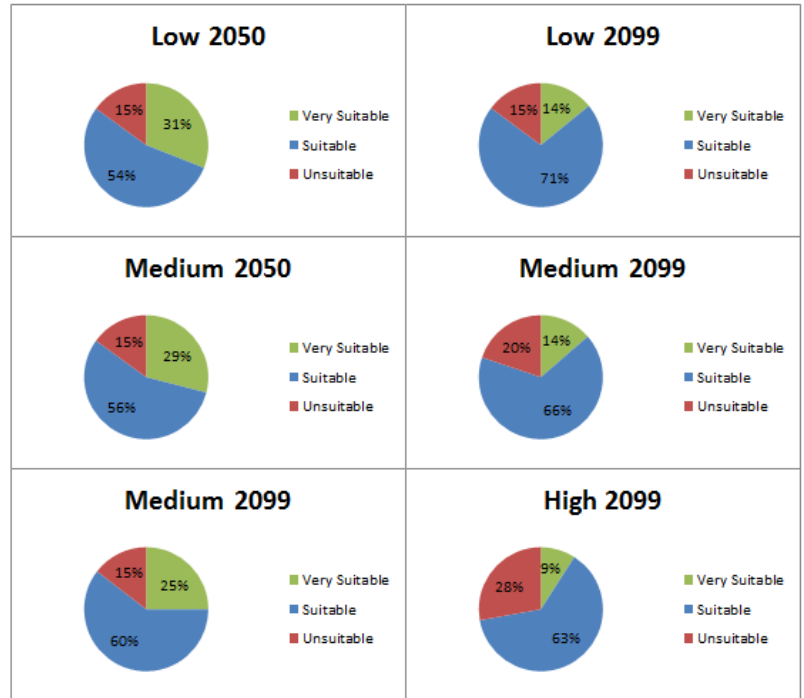


Figure 23: Comparison of percentage (%) of total area within each squirrel suitability class between all scenarios and projections.

The thematic maps representing climactic suitability for both projections are shown in Figure 24 and Figure 25, where dark red pixels are the most climactically suitable and dark blue pixels are the least climactically suitable. In the 2050 projection, very suitable pixels can be found throughout the majority of the study region but are of the highest concentration in north west California (near Redding) and throughout the Sierra Nevada mountain range which goes from just northward from Los Angeles among the California-Nevada border. Smaller pockets of very suitable pixels can also be found in the area northeast of Phoenix and south/southeast of Salt Lake City. The 2099 projection shows a clear trend in climactic suitability, as the most suitable pixels can be found in northwest California and the southern Sierra Nevada mountain

range (north of Los Angeles). The majority of previously suitable pixels within Nevada and Arizona have become less suitable in the 2099 projection.

Figure 24: Thematic map representing cougar climactic suitability for the 2050 scenario.

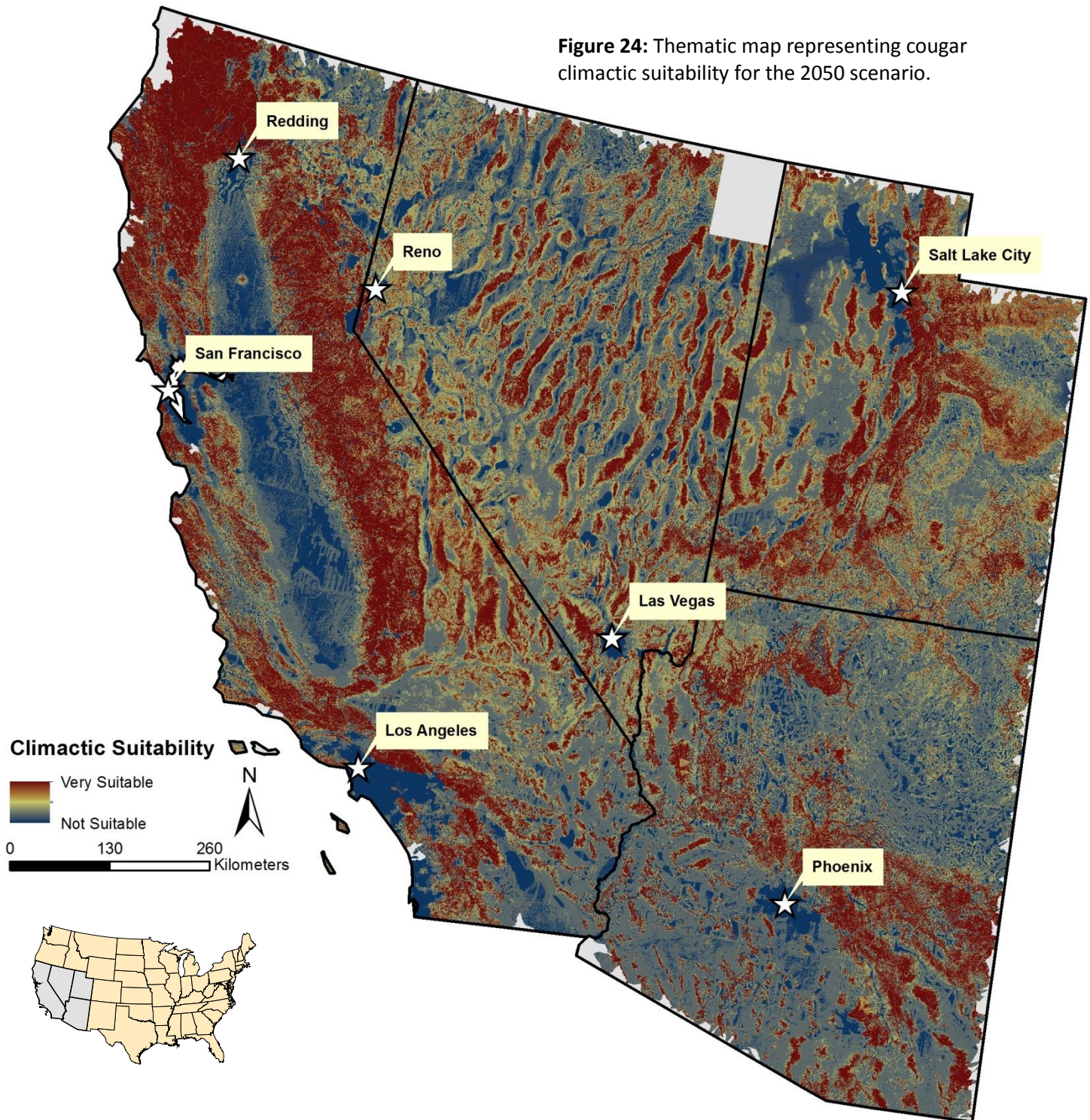
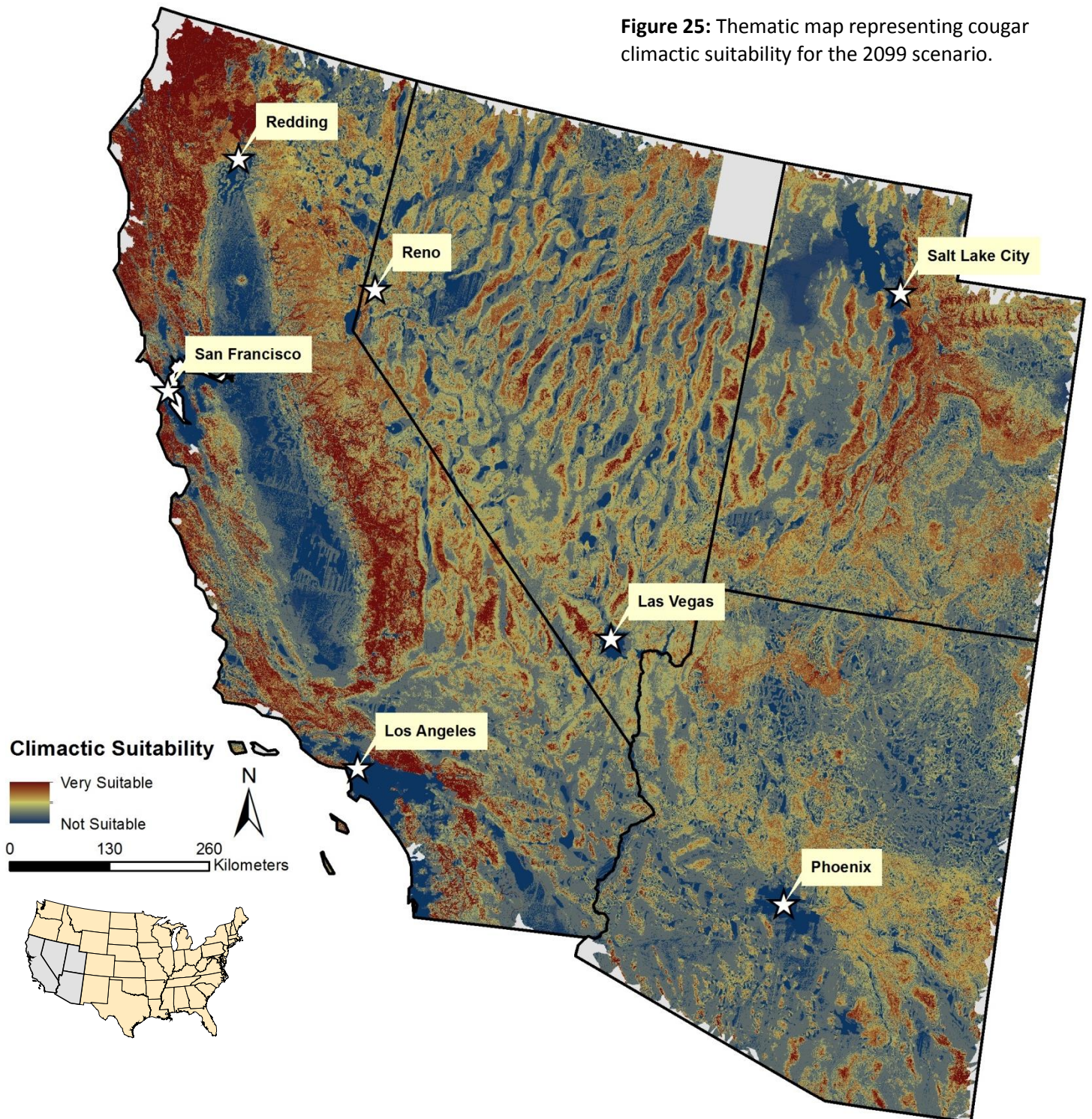


Figure 25: Thematic map representing cougar climactic suitability for the 2099 scenario.



Discussion

The discussion section will be broken down into three sections. Firstly, the model framework will be interpreted by presenting and analyzing a series of model assumptions. Secondly, a brief literature review of climate change management practices will be presented to reach a better understanding of best management practices when managing for climate change stress. Finally, the model results for the three modeled species will be interpreted.

Model Framework:

Before interpreting the results of the model, it is important to understand various aspects of the proposed model framework. All models, regardless of type or format, have their own respective advantages and disadvantages due to the model's framework. A model's framework can be understood through the series of assumptions on which the model is based on. For example, simple economic supply and demand models operate under the assumption that following a change in either supply or demand, the price will either increase or decrease until the market reaches an equilibrium. Analyzing this model without understanding this assumption can create presupposed and inaccurate conclusions that can be misleading. Additionally, especially in regard to ecological projection models, understanding these assumptions is important to understanding model uncertainties that arise due to model framework. Models with unidentified uncertainties can take away from conservation effectiveness as species that are generally modeled to be vulnerable to climate change are also the most vulnerable to bad management decisions based on uncertain models (Schwartz 2012, Uusitalo et al. 2015).

Depending on the model's purpose, the amount and complexity of assumptions varies. Models that have less structure (operate under fewer assumptions) provide more flexibility within model results by allowing users to manipulate model parameters while still remaining within the loose model framework. Conversely, models that are more structured (operate under more assumptions) provide less flexibility within model results by restricting the

ability of users to manipulate model parameters. The proposed model uses the former approach, as the model is designed to operate using a wide range of user created parameters.

Model Assumption #1: Two-period model.

Two-period models track temporal changes in the phenomenon being modeled by comparing model results between two periods. The first period is the current period which represents the phenomenon in the present, while the second period is the future period which represents the phenomenon in its future state. This is called a two-period model because, by the end of the second period, the model has exhausted all possibilities of temporal change between the two periods. Two-period models assume that, following the second period, the 'world ends' and there can no longer be any temporal phenomenon change because the full extent of changes has already occurred. In the proposed model, the current period is the current year (2015), and the future period is whatever projected year is being analyzed up until 2099, which is when the future period ends.

This assumption is a direct result of the Python script used to rank changes in temperature and precipitation to create the CCI. Recall from the methods section that the Python script ranks both temperature and precipitation anomalies on a scale of 0-10 which are then added together to create an overall climate change score between 0 and 20. Pixels that are assigned a 0 have the least amount of climate change and those assigned a 20 have the most amount of climate change.

Ideally, the breakpoints used within the Python script that set the upper and lower bounds for each climate change score would be based on species-specific information related to climatic requirements. For example, if it was known that LOWA cannot exist within an ecosystem past temperature anomalies greater than 7, the threshold for scoring a 10 (which corresponds to the maximum amount of climate change) should be set at an anomaly of 7. When this is rescored by the CCI it will receive a value of 0 which will result in a 100% loss of habitat in the PHSI. However, this type of species-specific information is not known. Instead, the threshold for scoring a 10 in both temperature and precipitation is determined by the largest anomaly value within the study region. Assuming that climate change behaves logically

and becomes successively worse from year to year, the 2099 anomalies will be selected as the threshold for scoring a 10, as 2099 is the last year of the future period and thus is experiencing the highest amount of climate change.

If the same model is used to analyze any year past the future period, 2100 for example, the anomaly values will be above the maximum threshold value set by the Python script and will all receive a score of 20, eventually resulting in a 100% loss of habitat once it is rescored by the CCI and used as a multiplier to create the PHSIs. This exhausts all possibilities of habitat loss (0% in 2015, 100% in 2100). It is important to note that the maximum anomaly values used to create the Python thresholds are averages, and thus not every single pixel in the study region will experience 100% habitat loss beyond the future period as some pixels will have anomaly values below the average. This being said, the logic behind the two-period model assumption within this model framework is valid. Through this explanation, it is clear how the proposed model operates under the assumption of a two-period model, as for no matter what species or study area, the model will always exhaust all possibilities of habitat loss by the end of the future period.

This assumption changes the way model outputs should be interpreted. Because climate change isn't quantified based on species-specific values but rather stretched across the range of anomaly values, pixels that are very suitable may be either overstating or understating their suitability. Using the previous example, if the maximum anomaly in the LOWA study region is 11 degrees but in actuality LOWA cannot survive in an ecosystem with an anomaly greater than 7 degrees, the suitability score will be overstated.

Rather than taking model results at face value, suitability scores given to pixels in the PHSI should be analyzed in relative terms. For example, a pixel that scores very suitable in the 2099 projection may be either overstated or understated, but it can be concluded that the pixel is relatively more suitable than other pixels in lower suitability classes, as it received a higher score. In this manner, the model results can still be accurately interpreted to understand what areas in the study region are climactically more suitable, even though the extent of how suitable the pixel actually is remains a mystery. This type of relative analysis is used in other

scientific fields, such as the use of an index of biological integrity (IBI) to measure the overall health and quality of streams.

When combining the model interpretation in this way with other environmental or biological factors, it is possible to more accurately determine the relative suitability of pixels. For example, cougars prefer habitat far from population densities. This informs the user that very suitable pixels located far from cities are more relatively suitable than pixels closer to such cities. The accuracy of two-period models at predicting temporal trends is further validated by the fact that many two-period economic models such as the New Keynesian and Real Business Cycle models have been used successfully to predict future macroeconomic trends (Gali 2008).

Model Assumption #2: Pixels can only be reduced in suitability.

Because of the way the CCI works as a multiplier or divider, pixels can only lose suitability from year to year. This assumption is important to the model because it restricts the total number of possible pixel changes between suitability categories from 81 to 15 possibilities as outlined in figure 10. Additionally, it allows the results of the model to follow much more logical trends, as pixels in later years will always have lower suitability than pixels in earlier years, which is intuitively logical to the mechanics of modelling climate change. However, this assumption restricts the possibilities of pixels ever regaining lost suitability. Because of the uncertainty of climate change, there may be future years where the increasing temperature and decreasing precipitation due to climate change is less severe than previous years. In this situation, areas may be able to naturally 'recover' from climate change during stretches of time that are less climactically stressful on habitats. However, the model is unable to capture this recovery. Thus, suitability scores from the model output may be slightly misstated, however the overall areas of where climactically suitable exists will still be accurate.

Model Assumption #3: Model outputs are based on existing ecological understandings of species' habitat preferences, and assumes that these preferences will not change.

The model relies on consistency between input parameters of the HSI and PHSI to reduce the third variable problem. The third variable problem is when two variables appear to be correlated to each other but in actuality, there is a third variable that is the real cause of the correlation between the first two variables (Johnson 2001). By keeping ecological habitat preferences constant, eliminating it as a changing third variable, the model can draw a more direct correlation, and thus a more accurate one, between climate change and habitat loss.

This assumption ignores the ability of species to evolve and adapt to their natural environment, which is one of the largest oversights of this model. If a species adapts to live in a completely different habitat, the results of the model, for that species, will be voided.

Model Assumption #4: Climate change is a non-discriminatory stressor.

The model assumes that climate change has an equal impact on all pixels throughout the study region, regardless of geographic location or landcover type. This is obviously not realistic, as it is well understood that climate change puts varying levels of stress on different locations based on their geography and landcover (Pearson 2003). Coastal areas, for example, are under much more threat from climate change than inland areas as they will be exposed to rising sea levels. Additionally, certain landcover types such as riparian zones are much more impacted to climate change because they are very sensitive to small climactic changes. A desert on the other hand, which is already accustomed to higher temperatures, might not experience nearly the same stress from climate change.

Although this assumption is problematic to the ability of the model to represent the real world, it fits in with previous model assumptions. Recall that, since the model framework is two-period, the model results must be interpreted in relative terms. Modelling climate change as a non-discriminatory stressor enhances the ability of the user to do so, as every pixel within the study region is being impacted the same way by climate anomalies. Without this consistency, interpreting the model results in relative terms would be impossible.

Additionally, any information that is lost due to this assumption can be easily accounted for by analyzing the model in the context of conditions that exist outside the model. For example, the model results may show that there is a significant area of climactically suitable cougar habitat along the coast that is optimal for conservation. However, by analyzing the model in context of climate change threats, the user can easily determine that any conservation efforts in this area would be unsuccessful, as there is a high chance that the area may be underwater in the near future.

These four assumptions provide interesting insight into some of the major challenges when modelling the impacts of climate change. Model frameworks must follow a certain amount of logic and reason while climate change is characterized by uncertainty which is inherently illogical. There is a common ground within a model framework that must be met between providing structural logic and the ability to account for uncertainties. This model framework accounts for uncertainty by using a mechanistic approach that incorporates many individual and smaller parameters, such as land cover and canopy cover, to understand and project a complex environmental system. The user has full ability to choose, control, and manipulate parameters which allows the user to reduce uncertainty within the model framework by using the appropriate parameters.

Climate Change Management Strategies

The recent field of climate change management has resulted in a shift in management practices under the understanding that the future will be different from both the past and present. Attempts to maintain or restore past conditions can potentially create landscapes that are more vulnerable to future changes in climate. Thus, climate change management focuses on a portfolio of approaches including both short-term and long-term options focused on ecosystem resistance and resilience that enhance the ability of ecosystems to adapt to changes in local and regional climates (Millar 2007).

Adaptive management options include strategies designed to manage ecosystems so they can better resist the stress of climate change. This is often accomplished by removing

additional stressors such as treatment of currently existing invasive species and unwanted diseases to improve the defense of the ecosystem to environmental changes (Agee and Skinner 2005). Reducing the overall number of stressors on an ecosystem reduces their combined effect, thus indirectly conserving for climate change. Another active adaptive management option involves taking early defense actions at key migration points to block future climate change related invasions or disturbances (Millar 2007). For example, due to environmental changes, the mountain pine beetle found in Canada migrated from its native ecosystem, where it was an endemic species, to a new ecosystem, where it has become an invasive species (Carroll et al. 2006). If this threat was identified previously, the migration of the beetle between ecosystems could have been prevented. This case study shows the importance of combining modelling with environmental and geographical management strategies.

Promoting ecosystem resilience to change is the most commonly suggested management option. A resilient ecosystem is one that not only adjusts to environmental changes but also tends to return towards biological integrity following disturbance, either naturally or with the help of management strategies (Millar 2007). Resilience based strategies are very similar to resistance based strategies but are applied on a broader scale to increase the overall resilience of an ecosystem. An example of this strategy is using surplus seed-banking, intensive management, and replanting during forest revegetation cycles to result in the retention of desired tree species within an ecosystem (Dale 2001).

Additionally, managers can elect to strategically allow ecosystems to respond to change, which intentionally accommodates environmental changes rather than resisting them (Millar 2007). These types of treatments mimic, assist, or enable ongoing natural adaptive processes such as species dispersal and migration, population mortality and colonization, changes in species' dominance and community composition, and changing disturbance regimes (Millar 2007). If this type of management is accomplished correctly, it will help ecosystems avoid unadaptable rapid environmental changes by providing a gradient along-which successful climatic transition is possible. Strategies that promote ecosystem response to change include assisted migration, encouraging genetic diversity, and refugia.

The majority of species cope with environmental changes through migration. However, some species, such as plants, cannot migrate quickly enough to remain in their desired climatic envelope. Assisted migration is a tool that managers can utilize to help slow-migrating species migrate along expected climatic gradients (Parker et al. 2005). Assisted migration can be complemented by promoting connectedness through landscapes by limiting anthropological barriers that interrupt climatic gradients. Landscapes that are well connected facilitate migration patterns as species can more easily move shift from one location to another (Millar 2007).

Genetic diversity is extremely characteristic to the ability of an ecosystem to cope with environmental changes (Elmqvist 2003). Especially in forest ecosystems, current guidelines that determine genetic diversity best management practices were created under the assumption of constant and unchanging environmental conditions (Betancourt et al. 2004). Many conservation biologists have suggested that these guidelines should be loosened in order to allow ecosystems to reach higher levels of genetic diversity (Betancourt et al. 2004).

Finally, a refugium is an area in which a population of organisms can survive through a period of unfavorable conditions (Petit 2003). Refugia are environments that are more buffered against climate change than others due to a high diversity of climatic conditions, compounding topographic variables that provide climate regulation, and higher levels of genetic diversity (Keppel et al. 2011). Refugia can either extend over a large geographical extent, providing refuge for multiple species, or can be very small (micro-refugia) and centered around niche environments containing certain keystone resources and specific environmental and ecological conditions. Refugia are traditionally based off of previous refugia that were historically utilized by species to survive long periods of glaciation. Much attention within climate change management strategies has been focused on identifying past refugia in order to preserve them as refuges against current anthropogenic driven climate change. However, as the past is no longer a good indicator of the future it is important to predict new refugia that can be targeted for management.

LOWA:

The LOWA is a long-distance neotropical migratory bird primarily found summering in large, old-growth deciduous forests throughout the eastern, central, and northeastern contiguous United States (Robinson 1995). This medium-sized warbler with a white underside with dark stripes and a dark back is a specialist species that has found its environmental niche within the hilly streams and riverbeds that it prefers for habitat. As such, this species of songbird is extremely reliant on first and second order streams for food, protection, and nesting (Wilcove et al 1986). LOWA are most typically found nesting and foraging in healthy riparian zones with steep banks and good canopy cover (Environment Canada 2012). Because the riparian zones on which LOWA rely on for their habitat are so sensitive to climate change, LOWA are a good indicator species of climate change impacts and can help us obtain a greater understanding of how future climate change will affect other riparian zone specialist bird species.

Of birds, migratory birds have experienced the most impact from global climate change. Unlike other species of birds, migratory birds often face unique challenges because they live in separate locations, sometimes thousands of miles apart, during the summer and winter seasons (Crick 2004). Every year, when neotropical migratory birds return to the Northeast U.S. to breed, they come back to a slightly climatically different habitat. These year-to-year changes may not individually have any major impacts, but, over time, they pose serious threats to migratory bird populations (Visser and Both 2005). Studies have already shown that many migratory bird species are shifting their summering range northward to find their preferred climatic range, resulting in significant habitat loss or increased stress due to new threats or predators (Walther et al. 2002). Additionally, for some species, changing environmental indicators are disrupting the biological clocks that birds rely on to properly time their migrations, resulting in species that miss their migratory window and thus arrive on their breeding grounds pre- or post- peak season.

One of the proposed strategies to reduce the stresses of climate change on migratory specialists such as the LOWA is to enhance the migratory corridors that they utilize during their migration. Providing suitable habitat that can be used as stop-over points is extremely important for the success of long-distance migrants as it provides these birds a suitable location

to restore their energy supplies before finishing their migration. A great example of such location within Pennsylvania is Presque Isle, which is an ecologically unique peninsula that rests on the south shore of Lake Erie which acts as a barrier disrupting northbound migration. Presque Isle meets the needs of over 320 species of birds that rely on the ecological area as a stop-over point (McWilliams 2000).

The study region analyzed during the model is within the northern most section of the LOWA's breeding range (Figure 26). Assuming that habitat ranges of migratory birds continues to move northward, the study region will, in the future, be located towards the middle of

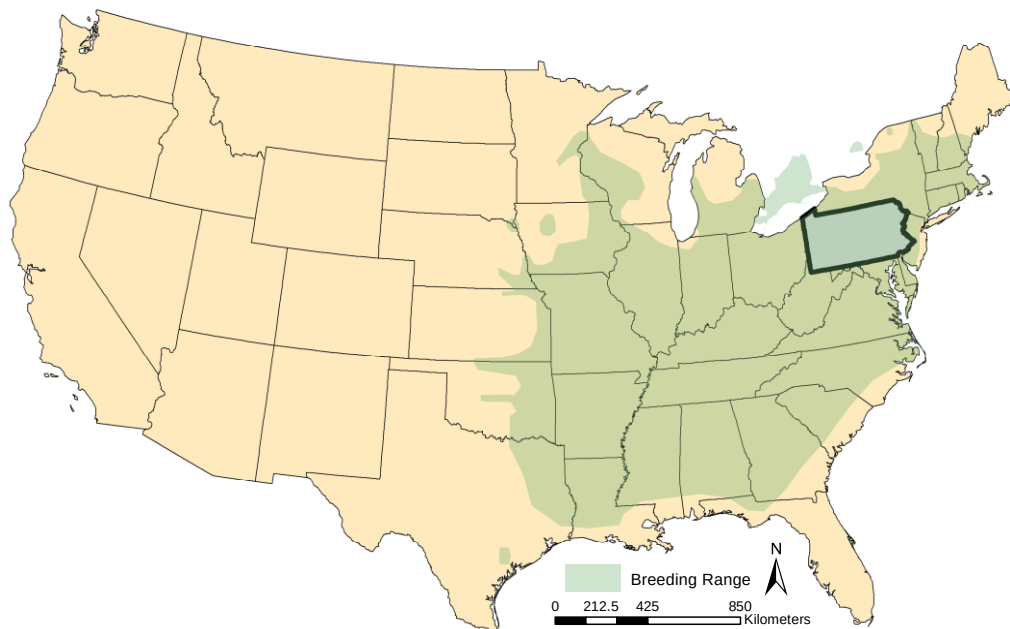


Figure 26: LOWA breeding range with respect to study region.

LOWA's breeding range. Maintaining areas of suitable habitat within the study region is extremely important to provide LOWA with additional stop-over points that assist in migrations and provide habitat corridors that the species can utilize to travel throughout their range. When managing habitat areas for climate change, it makes the most sense to focus management efforts in areas that are most climactically suitable rather than those that are not. Thus, the output from the model can be used to identify the areas that are climactically suitable and give conservation biologists an idea of where LOWA management practices should occur.

The largest concentration of climactically suitable pixels was found in the Susquehannock National Forest and surrounding areas. Subsets of the area (Figure 27) show that there is a significant amount of climactically suitable areas located in stream riparian zones. As distance from streams increase, the climactic suitability of pixels decreases. This makes intuitive sense when compared with the ecological properties of LOWA, as they are extremely reliant on streams for both food and nesting. The importance of riparian zones in

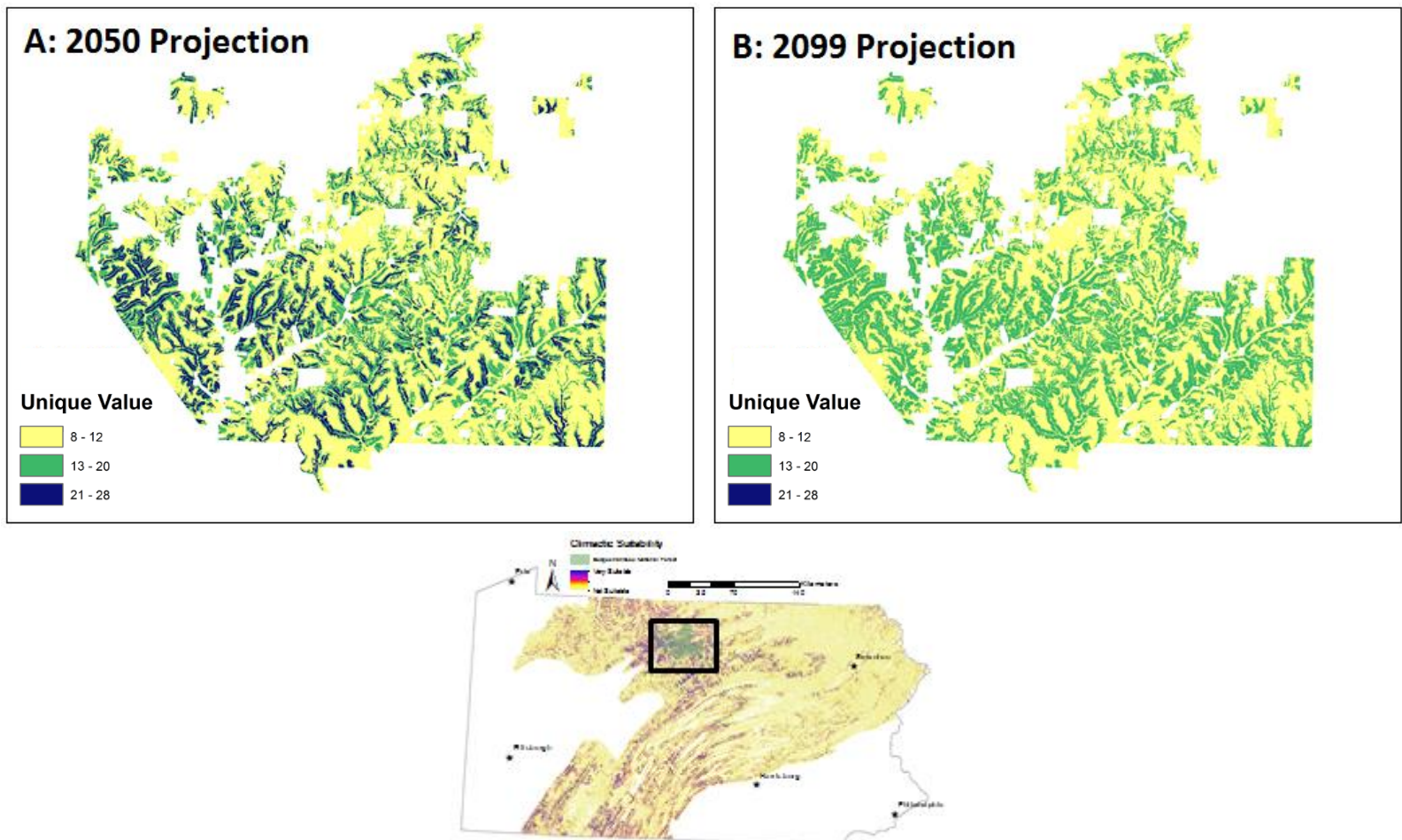


Figure 27: LOWA subsets of the Susquehannock National Forest. Unique values correspond to those from figures 9 and 10.

determining climactic suitability is indicative that promoting resilience within riparian zones to changing environmental conditions is paramount to managing populations of LOWA. Thus, management strategies such as revegetation assistance to keep riparian zones in permanent vegetation could be useful approaches for conservation.

In order to create a meaningful management plan, research must be completed on a much finer scale within individual riparian zones to assess different areas for variables that the GIS cannot capture such as micro-topographies and micro-climates. However, the GIS model presents a starting point upon which researchers can easily determine which areas should be selected for finer evaluation. Once individual riparian zones are selected they can be targeted for revegetation management to create connected migratory pathway that LOWA can utilize as their range shifts northward.

Eastern Gray Squirrel:

The eastern gray squirrel is a type of tree squirrel native to the eastern United States but has since been introduced to parts of Canada and many European regions (Huynh et al 2010). This species is a generalist species which can live in a wide variety of natural and urban landscapes. Eastern gray squirrels are reliant on dense patches of trees for defense from predators and for nesting and can be commonly found inhabiting large areas of mature, dense woodland ecosystems that are preferably 40 hectares or larger (Lawniczak 2002).

Although considered a pest species in many areas where it has been introduced due to lacking a natural predator, the eastern gray squirrel is an ecologically important species within its domestic range. Eastern gray squirrels are an important predator of seeds and have been shown to increase seed dispersal of trees by burying seed hoards for storage (Lawniczak 2002). Additionally, they are key components of a forest's food chain as they not only eat small animals such as birds and insects but also are common prey for larger keystone predators such as foxes, bobcats, grey wolves, coyotes, and birds of prey.

Studies have shown that an increase in the frequency, severity, and duration of heat stress (higher temperatures, lower precipitation) is threatening forest composition throughout the world (Allen et al 2010). Most notably, this increase in heat stress can potentially cause increases in tree mortality rates due to outbreaks of wildfire and insect plagues. Allen et al (2010) has found evidence that forests have already become more vulnerable to high-risk factors due to climate change. Increases in tree mortality within ecosystems that contain the eastern gray squirrel will have severe implications on the ability of the species to successfully

reproduce and hide from predators, resulting in potential local population decline. The loss of eastern gray squirrels within tree ecosystems will result in a loss of the natural ecosystem services they provide to the forest.

Even with the loss of their natural habitat, overall populations of eastern gray squirrels will remain relatively high in the face of climate change because they can also live in urban environments. Eastern gray squirrels have been recorded living in areas of high urbanization in concentrations of 1.08 squirrels per hectare (Williamson 1983). This number will only raise as future urbanization increases the available urban habitat to the species. However, it should be noted that from an ecological standpoint, eastern gray squirrels that live within urban environments are significantly less ecologically important than squirrels that live in the wild. Squirrels in urban environments do not act as prey for major keystone predators nor contribute largely to seed dispersal of trees, but are rather considered as pests due to their increased aggression and overabundance (Parker 2008). Thus, from a conservation standpoint, it is important to conserve eastern gray squirrels in the wild.

From the model results, there is a clear trend in movement of climactically suitable pixels towards the north-west corner of the study region. However, the change between the 2050 and 2099 projection is very extreme which suggests that there must be significant changes in suitability between 2050 and 2099. To get a better understanding of how climactic suitability transitions from what is seen in 2050 to 2099, another iteration of the model was completed for 2075 (Figure 28).

When the 2075 model output is included, there is a clear trend forming where pixels located in the southern portion of the

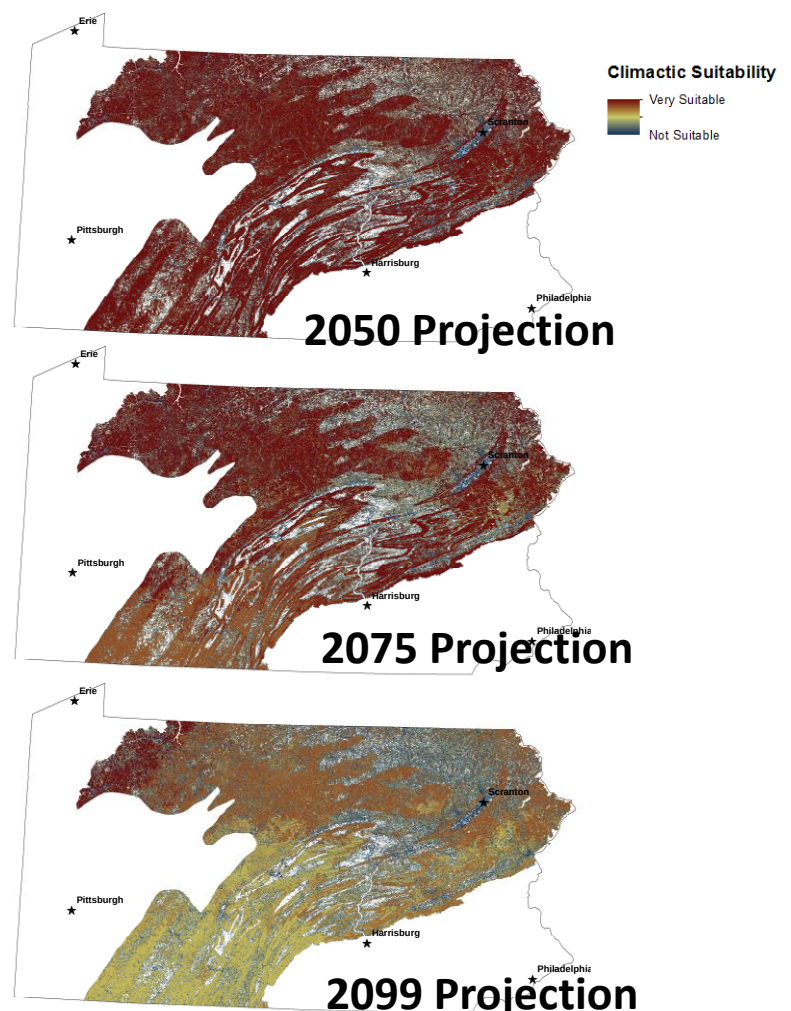


Figure 28: Comparison of all three squirrel projections.

study region are losing suitability, eventually isolating the pixels with the most suitability in the northwest corner of the region. Because eastern gray squirrels are generalists which easily adapt to changing environmental conditions, the results of this model with respect to eastern gray squirrel conservation is fairly limited. However, the model results can still provide useful information for the overall conservation of the region by analyzing the variables that went into the model: land cover, canopy cover, and forest size.

The trends in suitability loss throughout the study region are driven by the degradation of these input variables due to climate change. Areas located in the south of the study region that were once characterized by large deciduous forests with high canopy cover, over time, have lost many of their deciduous trees due to climate change induced tree mortality, resulting in lower canopy cover and a smaller forest area. When moving through the projections, it is clear to see how this trend continues northward. The trends seen in the model results can be used to understand how climate change is affecting species that rely on the same habitat parameters as eastern grey squirrels but are more impacted by environmental changes, such as the little brown bat, the American black bear, the while-tailed deer, the northern goshawk, the timber rattlesnake, and the red-cheeked salamander.

By the 2099 projection, the only significant area containing large deciduous forests with high canopy cover is the north-western corner of the study region. Because of the exemplary climactic suitability in the north-west part of the study region, this area could be researched more to determine whether or not it would be a suitable location for a refugium. If, upon further site-specific research, the area is found to have the necessary topological and environmental conditions required for a refugium, further conservation efforts could be focused on the area to maintain its biological integrity. Additionally, assisted migration could be utilized to move appropriate slowly-migrating species (such as salamanders and rattlesnakes, from the previous list), into the refugium. The earlier this is done the better, as it will allow the introduced species to breed with any existing species in the area to promote genetic diversity.

The eastern gray squirrel model is an example of why the model results should be analyzed in context of larger ecological and biological variables. When analyzed in this fashion,

model iterations can often produce unintended results that can still be useful for conservation purposes.

Cougar:

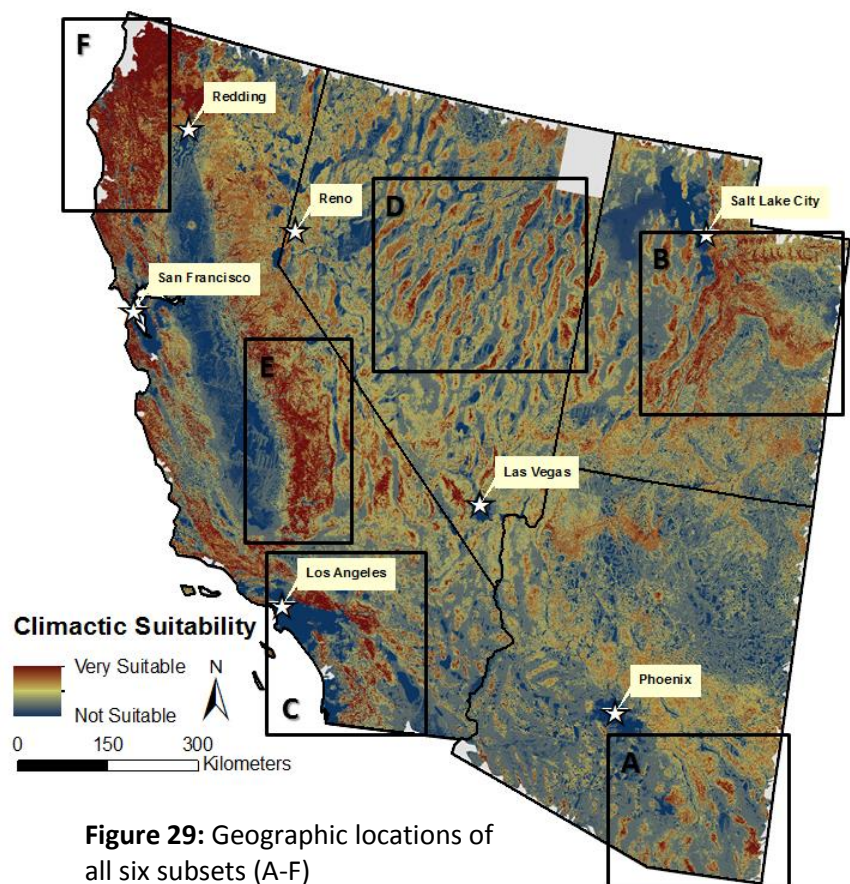
The cougar is a large, predatory wildcat native to North and South America that functions as a keystone species by providing population control for prey populations such as deer, mice, squirrels, and raccoons. Cougars persist in a wide range of ecosystems, including swamps and marshes, deserts, and large mountain ranges such as the Rock Mountains and the Sierra Nevadas (Dickson and Beier 2002). Regardless of habitat type, cougars are reliant on sloped topography for both hunting and nursing cubs. The cougar once inhabited the full extent of North America but has since been relegated to habitats in the western states and southern Florida due to persecution by both sport hunters and farmers protecting their livestock (Dickson and Beier 2002). Additionally, cougar populations have been declining due to habitat loss, habitat fragmentation, and automobile accidents (Sweanor et al. 2002).

The extreme stress put on cougar populations through anthropogenic activities is problematic when managing the species for climate change. Assisted migration northward along connected landscape corridors is problematic as cougar habitat is already extremely fragmented by anthropogenic land use changes. Thus, the best management strategy is to maintain current cougar habitats. Additionally, cougars are K-selected species characterized by long gestation periods, significant time spent rearing offspring, and production of fewer offspring. As a result, genetic changes within cougar populations occurs much slowly (Carpenter and McCullough 1980). This reduces the ability of cougars to genetically adapt to changing environments. Because of this, facilitating genetic diversity within cougar populations is one of the keys to their conservation. In order to understand genetic diversity within cougar populations, it is important to understand their population dynamics (Sweanor et al. 2002).

Cougars are solitary hunters that exist in metapopulations. A metapopulation is a group of subpopulations that are separated by space but consist of the same species (Levins 1969). These spatially separated populations interact as individuals move from one population to

another (Jannsen et al. 1997). Subpopulations exist within patches of suitable habitat that are surrounded by habitat fragmentation. Each subpopulation is exposed to different environmental conditions, anthropogenic pressures, and predator-prey dynamics (Sweanor et al. 2002). Subpopulations of cougars are reliant on immigration of cougars from other subpopulations to maintain genetic diversity. This is especially important in small cougar subpopulations, as genetic diversity is already very low (Sweanor et al. 2002). Additionally, a large and healthy cougar subpopulation can provide enough immigration to support several surrounding subpopulations. Rather than conserving cougars throughout their entire range, focusing on maintaining several healthy cougar subpopulations is a conservation method that could result in maintaining the overall genetic diversity and health of the larger metapopulation. The model results can be used to identify areas which could best support large cougar subpopulations.

The model results can be analyzed by looking closer at specific subsets of the study region that contain significant amount of suitable cougar habitat that could potentially support large cougar subpopulations (Figure 29). However, it is important to note that an area that registers as suitable in the model output is not necessarily a suitable area due to variables existing outside of the model framework.



Subset A:

Subset A is located in the southwest corner of the study region, just southwest of Phoenix, AZ, and is made up of two large habitat islands (labeled A and B) surrounded by smaller areas of high suitability (Figure 30). Although island A is the largest and most suitable habitat island in this area, it is located very far from the majority of suitable habitat within the

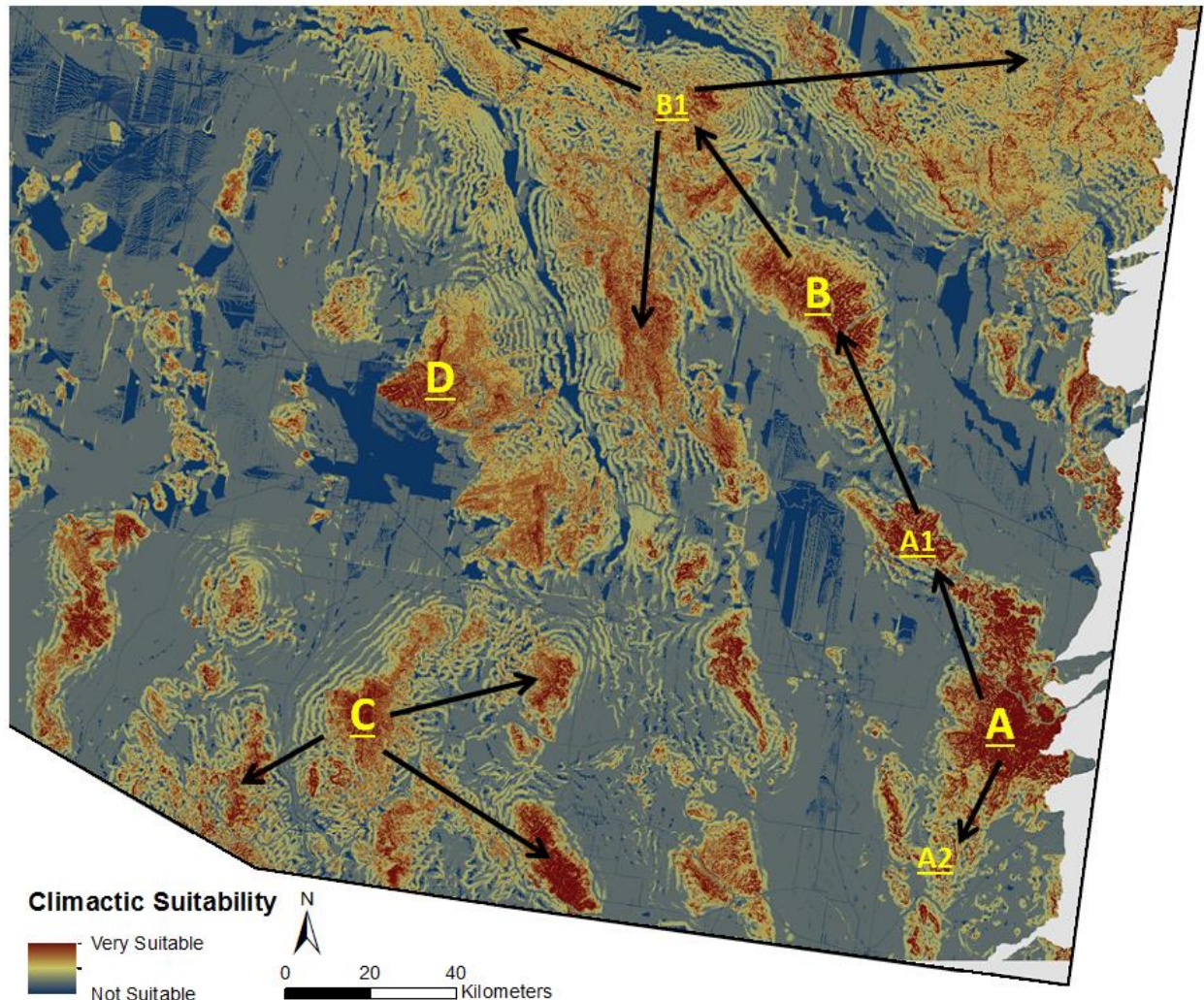


Figure 30: Subset A with labelled habitat corridors between habitat islands.

subset, thus making it a less optimal location for establishment of a subpopulation with the intention of boosting genetic diversity within the region.

However, subset A is very far from population densities and linked closely with islands A1 and A2. If maintained, a cougar population in A could travel through clusters A1 and B to reach the rest of the suitable habitat within the subset. The corridor from A1 to B is fragmented by a highway that passes through the clusters, but this problem could be avoided by constructing a habitat corridor to assist cougars in crossing into B. This strategy of managing cougar populations in A and B with a habitat corridor between A1 and B could provide enough connectivity between suitable areas for cougars to utilize.

Habitat island C is centrally located within the south section of the subset and can facilitate cougar movement to the surrounding three habitat clusters as shown. Island D, on the other hand, contains many very suitable pixels but is at risk of future anthropogenic threats from urbanization of the nearby city. Phoenix is just to the north west of the subset, which is important to note because any further urbanization to the east or south could cut off this corner of habitat from the rest of the range.

Subset B:

Subset B is located in the northeast corner of the study region, just south of Salt Lake City, UT, and is made up of one large, centrally located cluster of suitable habitat (A) that branches off in three directions according to the arrows (Figure 30).

All three branches contain a significant amount of suitable habitat, with the bottom two branches characterized by optimal slope and remoteness from population density and the top branch containing many forested and sloped riparian zones that are optimal for cougar hunting and movement. Because the three branches are very well connected, ensuring that cougars in this area have effective habitat corridors is not an issue. However, urbanization from Salt Lake City (which is the 12th fastest growing city in the country) greatly threatens the main habitat cluster within this subset.

To protect this cluster, preventative measures should be taken to prevent urbanization from spreading past the red wedges shown in Figure 31. Doing so will require either policy or

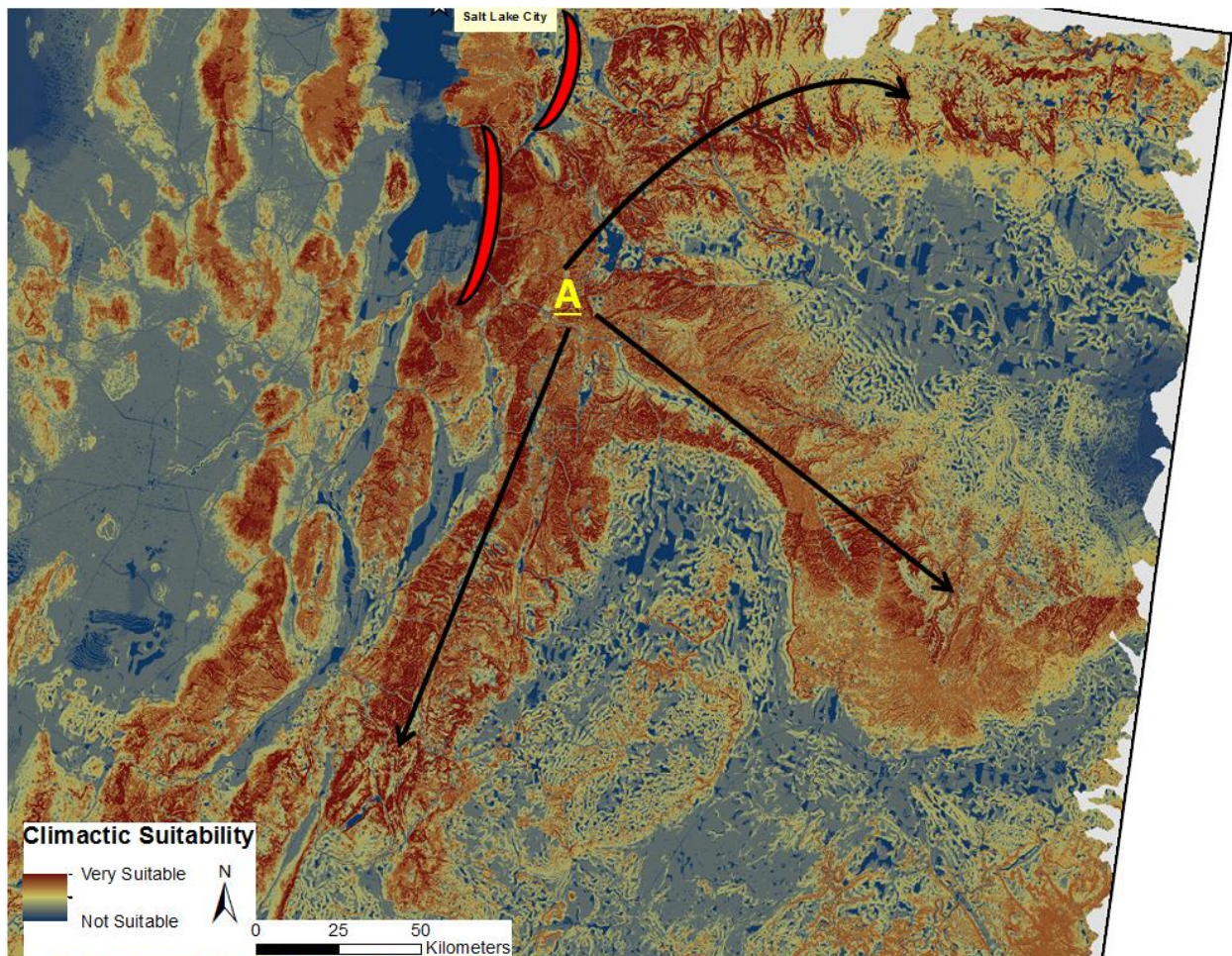


Figure 31: Subset B with labelled habitat corridors between habitat islands. Red wedges represent areas where urbanization should be prevented.

zoning changes within the city that prevent urbanization from interfering with any existing suitable cougar habitat. Protecting the large and centralized cluster of suitable habitat is extremely important for cougar conservation in this area, as any fragmentation of the central cluster can break off the three branches from each other and prevent cougar immigrations and recruitment. The habitat clusters on the west side of the subset should not be managed at all, as they are already too fragmented to support viable cougar subpopulations.

Subset C:

Subset C is located in the southern-middle portion of the study region in the areas surrounding Los Angeles, CA and consists of three large habitat islands located around the perimeter of Los Angeles (Figure 32). Cluster A, although being ranked as very suitable, is

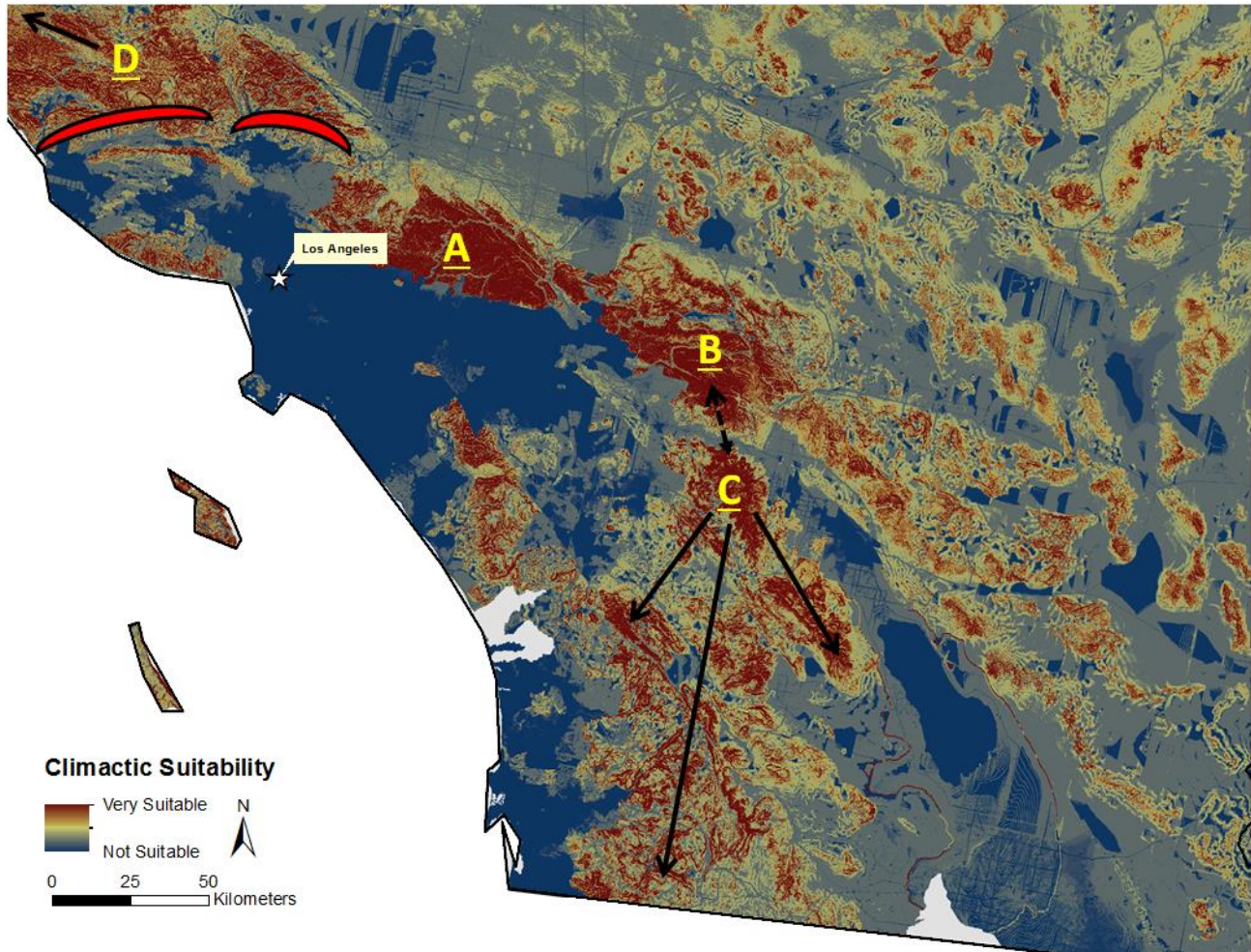


Figure 32: Subset C with labelled habitat corridors between habitat islands. Red wedges represent areas where urbanization should be prevented.

surrounded on all sides by extensive urban sprawl and thus is almost completely isolated from surrounding suitable habitats, making it a location that is not suitable for cougar management. Cluster B is slightly more preferable than Cluster A as it is partially surrounded by other areas of cougar suitability. However, these areas are quite small and relatively disconnected from each other, so it is questionable whether or not the surrounding areas will be suitable enough in the future to support sub populations of cougars. Cluster C is more preferable for conservation than both clusters A and B because cougars will be able to move into the surrounding habitat

clusters to the south. With the exception of a few roads and small towns, the area located south of cluster C is relatively free of urbanization but is threatened by the expansion of San Diego, located in the southwest corner of the state. Clusters B and C are relatively close together and could be connected by a habitat corridor to allow cougars to surpass the highway separating the two clusters.

Cluster D is the most suitable cluster for conservation because it is the least surrounded by urbanization, excluding the few roads that connect Los Angeles to central California. This cluster also extends northward past the subset along the coastline. Preserving this habitat cluster will be important in maintaining range connectedness throughout the state of California.

The clusters within this subset are the most anthropologically threatened clusters within the study region due to the extreme urbanization threat presented by the city of Los Angeles. Any management efforts in this area would need to be backed up with restrictions on urbanization into cougar habitat to maintain suitability within the large clusters. If cluster D is conserved, preventative measures should be taken to prevent urbanization from spreading past the red wedges.

Subset D:

Subset D is located in central Nevada, just east of Reno, NV, and contains the highest concentration of habitat islands in the study region (Figure 33). The habitat clusters are forested, hilly regions that are separated by stretches of desert and barren land with limited roads and farms. Although not the most suitable in terms of continuity

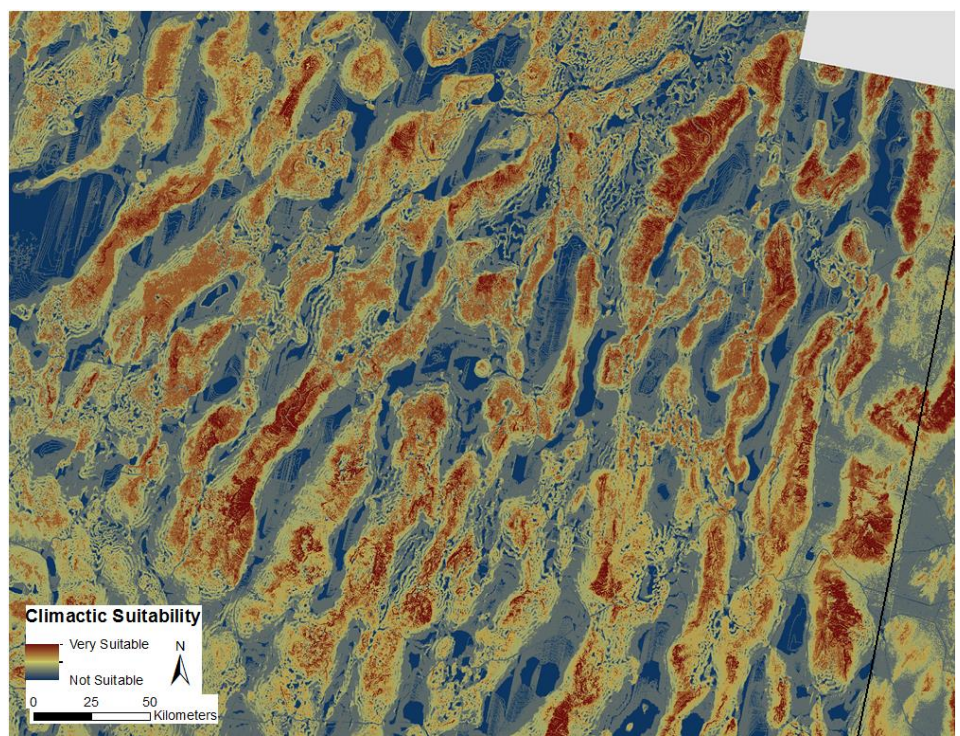


Figure 33: Subset D.

between clusters, the area within this subset is the most important area for cougar conservation within the study region because it forms a ladder of habitat clusters that connects habitat islands from central and southern California to Utah. If these clusters are allowed to degrade until they cannot fully support cougar subpopulations, there will be a large gap that isolates California from the rest of the cougar's natural range, resulting in a severe loss in individual migration and genetic flow within the metapopulation. Conservation tactics to preserve the connectedness of the clusters will include minimizing fragmentation between clusters and maintaining the area within the clusters to promote suitable cougar habitat.

Subset E:

Subset E is located along the California-Nevada border and contains one very large habitat cluster (A) that is located throughout the Sierra Nevada range, stretching from Inyo National Forest in the south to Yosemite National Park in the north (Figure 34).

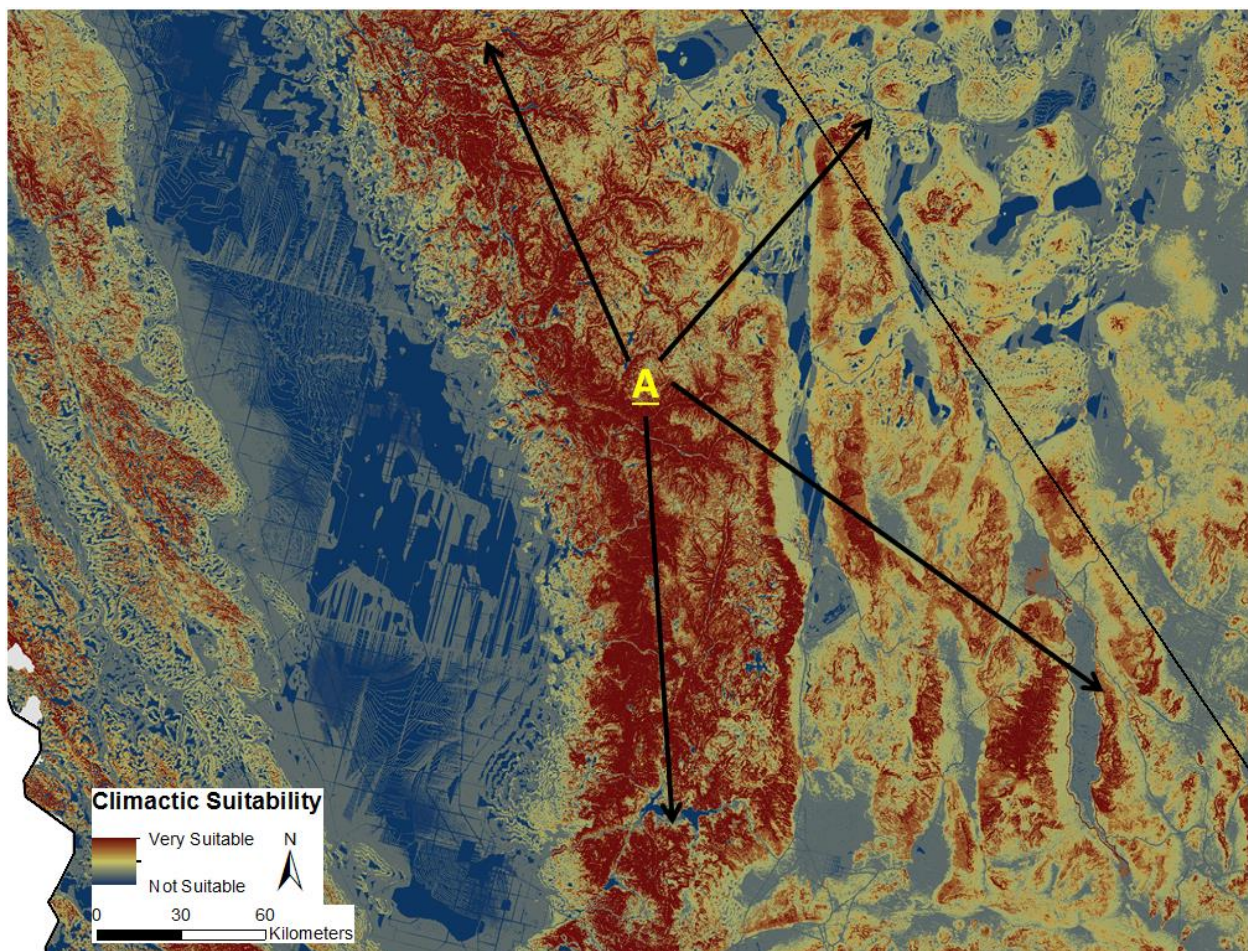


Figure 34: Subset E with labelled habitat corridors between habitat islands.

Cluster A within this subset is the second most suitable area for cougar habitat in the study region due to the amount of continuous suitable habitat. Additionally, this area is made up of many federally protected lands such as Sequoia National Park, Kings Canyon National Park, Inyo National, and Yosemite National Park. The southern Sierra Nevadas are slightly more suitable than the northern due to higher slopes, which allows cougars to hunt more successfully. The large section of not suitable habitat to the west of cluster A is the central valley, which is an expansive agricultural region that stretches across central California. Due to the pre-existing conservation status of the mountain range, cluster A is under relatively little threat from expansion of farmland out of the valley and into the mountains.

The suitable habitat islands on the west side of the subset are an extension of cluster D in subset C and continue north past this subset. These habitat islands are currently under less protection than cluster A and provide an important habitat corridor that allows cougars to move north along the coast of California. Thus, protecting this area from anthropologic threats is important for preserving connected landscapes that facilitate cougar immigration.

Subset F:

Subset F is located in the northwest corner of the study region, just west of Redding, CA, and contains the largest contiguous cluster of suitable cougar habitat (Figure 35). Because this area is already projected to be very suitable for cougar habitat, and due to its size and distance from urbanization, very little conservation efforts will be required in this area to support large cougar populations. This area of the study region connects habitat clusters in California to other habitat clusters in Oregon, allowing cougars to move northward beyond the state boundary. Additionally, due to its size and suitability, this

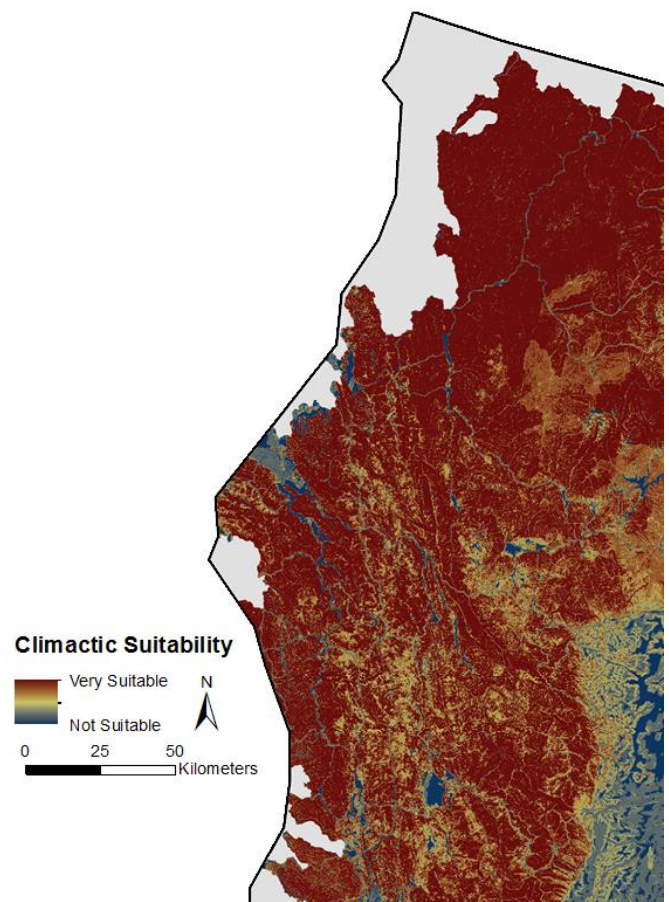


Figure 35: Subset F.

cluster will play an important role in cougar research in the future.

The overall lesson learned from interpreting the six cougar subsets is that conservation efforts should not always occur in the areas within the model output that are the most climactically suitable. Instead, the model results should be combined with other biological, ecological, and geographical knowledge to determine where conservation efforts will be the most efficient in providing relief.

Validity:

Rather than going through the lengthy and clunky process of backcasting, model validity was tested by comparing model results to current literature on climate change impacts. The LOWA model results showed how patches of very suitable habitat in riparian zones decreased over time due to the shrinking or degradation of riparian zones. Studies have found that heat stress induced by climate change puts extreme stress on riparian zones and can lead to shrinking and degradation of riparian zones in boreal, arid, and semi-arid forests (Nilsson et al. 2012, Perry et al. 2011, Warheit 2011). Although the forest systems in Pennsylvania do not fall into any of those categories, it is easy to understand how the riparian zone threats being faced in the three aforementioned types of forest can be applied to those found in the study region.

The eastern gray squirrel results showed an overall shift of very suitable habitat towards the north-west corner of the study region. Examination of the fossil record has shown that eastern squirrels shifted their range westward in response to late Quaternary climate change (Graham et al. 1996). Although using methods of the past to predict the future was looked down upon in an earlier section, this evidence is a very strong indicator that the model results are correct in showing a westward shift in the range of the eastern gray squirrel. Additionally, climate envelope models have been used to forecast how tree composition in the northeast U.S. will change due to climate change impacts. The results show a large increase in black oak and white oak and decreases in every other tree species as shown in Figure 36 (Perschel et al. 2007, Frumhoff et al. 2007, Rustad 2012, Melilo et al. 2014).

Although there are large percentage increases in oak trees, there are currently very few oak trees in the northeast, so the numerical increase in oaks is not as large. The majority of current preferential oak habitat is located in the southern portion of Pennsylvania and projected to expand northward due to oak's ability to withstand drought conditions (Figure 37). However, oaks are very slow growing and will not be able to fully replenish the large amount of trees that will be quickly decreasing in numbers due to increased mortality from heat stress (Perschel et al. 2007, Frumhoff et al. 2007, Rustad 2012, Melilo et al. 2014). As trees start to die throughout the study region and oaks slowly expand their range north, the areas in the north of the study region that are characterized by larger forest sizes will increase in relative suitability. Conversely, the areas in the south of the study region will decrease in relative suitability due to decreasing canopy cover and forest size. This trend mirrors the model results.

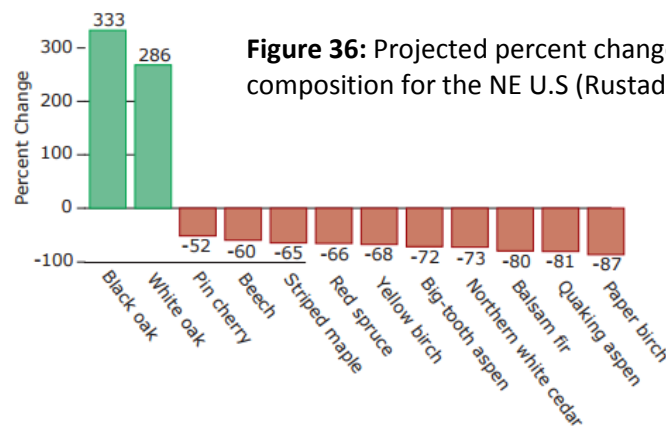


Figure 36: Projected percent change in tree composition for the NE U.S (Rustad 2012).

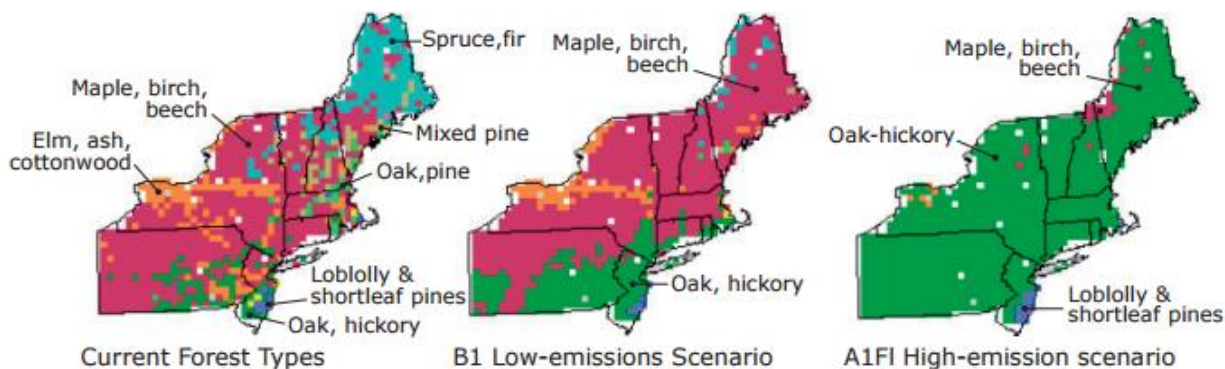


Figure 37: Projected changes in suitable tree habitat by species for the 2099 projection (Rustad 2012).

The cougar results showed an overall decrease in very suitable pixels throughout the study region with the formation of very suitable habitat islands throughout the study region. Studies have found that heat stress from climate change will degrade western forest

and wetlands, which are preferential habitat for cougars (Warheit 2011, Adger 2007, Karl 2009). Additionally, studies have shown that factors that contribute to habitat fragmentation can result in cougar habitat islands throughout the western U.S. (Beier 1995, Crooks 2002). This confirms the appearance of habitat islands within the model results. Unfortunately, there is a very small amount of literature on the impact of climate change on cougars, and thus the cougar results model is hard to prove valid.

Future Research:

Conservation science strives to inform management decisions and ecological projection models provide an interesting avenue to do so (Schwartz 1997). Every model, regardless of model framework, operates most optimally when used for certain applications. Testing a model in a wider range of scenarios can allow the modeler to determine the range of applications for which the model predictions are valid and can be used to inform management decisions (Guisan and Zimmerman 2000).

Some deductions on the model's application range can be made from the current model results. For example, the LOWA analysis likely overestimates the amount of habitat in later projection years due to the two-period model framework that results in large habitat losses in later projection years. Extreme losses of habitat in the 2099 projection is seen only in the LOWA model results, which suggests that the two-period model framework is unsuitable, especially in later projection years, for mapping habitat change in specialist species. Perhaps the large amount of habitat loss is due to the harsher CCI used when modelling specialist species. If specialist niche properties of a species are already accounted for in the ecological input parameters that model habitat preference, then assigning a harsher CCI will result in double-counting. Regardless of the cause of the problem, it is clear that the model in its current form is unsuitable for informing management decisions on specialist species. Iterations on different species that are ecologically different can improve the model's ability to create positive conservation outcomes by better identifying the suitable range of applications.

The largest source of uncertainty, which can result in misguided conservation and management decisions, is from uncertainty in model outputs induced by uncertainty in model

inputs (Uusitalo et al. 2015). This is more problematic in deterministic model approaches than other formats, as deterministic models use many individual inputs to explain a larger phenomenon. Any uncertainty within input data will carry through to the model output and be compounded. When working with a mechanistic ecological projection model, the breadth and accuracy of the biological and ecological information on the species being modeled is one of the largest components in determining whether or not the model outputs can be used to create positive conservation outcomes (Fielding and Bell 1997, Austin 2002). Reducing the ecological and biological knowledge gap will allow more species to be modelled, enhancing the ability of all models to be applied to wider applications.

Knowledge of climate change processes is also required to produce accurate model results when determining the effects of climate change on habitats, as climate change data is a required model input. An increased understanding of climate change will allow better models to be created that better estimate year to year changes in climate variables (Stainforth et al. 2005, Tebaldi et al. 2005, Gosling et al. 2011). This will also allow models to provide more accurate results with less uncertainty.

Conclusion

The model framework proposed in this project successfully accomplished the goal of improving on current ecological projection models by creating a GIS-based mechanistic model that is easy to use, easily manipulated by the user, used in both small and large scale study regions while maintaining a high spatial resolution, applicable to any species, and functions as a decision support tool that can aid in conservation of species vulnerable to climate change impacts. Final results were analyzed for validity by comparing model outputs to current and relevant literature on climate change impacts and sources of uncertainty were addressed within the model framework assumptions. Although all the goals of the project were fulfilled and model outputs were proven to be valid, there is still much future research that must be performed to better understand the model framework and its range of suitable applications. However, the proposed model framework provides an important first step in creating ecological projection models that can anticipate the effects and project the impacts of climate change in a world where our past is no longer a clear guide to our future.

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