Assessing the Potential Effects of Climate Change on Species in the Cumberland Piedmont Network of the National Park Service

By,

Christopher Bruno, Phil Hartger, Laura Mendenhall and Emily Myron

Dr. James Clark, Advisor
Rickie White, NatureServe Client
Teresa Leibfreid, National Park Service Client
May 2012

Masters project submitted in partial fulfillment of the
requirements for the Master of Environmental Management degree in
the Nicholas School of the Environment of
Duke University
2012

Abstract

In this study, we evaluate the climate change vulnerability of a subset of key species found in the Cumberland Piedmont Network (CUPN) of the National Park Service (NPS), an ecologically important and diverse region. We developed a list of species of conservation concern (globally and sub-nationally) within each of the fourteen NPS units in the CUPN. Next, we employed NatureServe's Climate Change Vulnerability Index (CCVI) in order to determine which of those species may be most vulnerable to climate change, based on each species' 1) direct exposure to climate change, 2) indirect exposure to climate change, 3) sensitivity, and 4) documented/ modeled response to climate change. CCVI results showed a range of vulnerability scores among taxonomic groups, including high vulnerability for mollusks and low vulnerability for migrant songbirds. Furthermore, we found that species of conservation concern were not necessarily those most vulnerable to climate change.

Additionally, we modeled the current and projected habitat suitability in 2050 and 2080 for four case study species, three that were assessed by the CCVI to be vulnerable to climate change and one assessed to be presumed stable. We used the software package MaxEnt (chosen modeling method of NatureServe) and the program BIOMOD, which produces habitat suitability estimates using a variety of different algorithms. We combined the results produced by MaxEnt and BIOMOD to create an ensemble projection for each species. This shows areas where all models predict future suitable habitat. Finally, we examined which of the NPS Units within the CUPN were in danger of losing vulnerable species populations under the climate change scenarios we chose. These models predict that key species may disappear from some parks with climate change. This information can be incorporated into regional management and prioritization strategies that increase the long term viability of these species, as well as help NPS land managers better understand which species of conservation concern are likely to be most affected by climate change.

Acknowledgements

This work was made possible by many people at Duke University's Nicholas School of the Environment, NatureServe and NPS. We would like to thank our advisor, Dr. Jim Clark, for his continual advice and support throughout the project. We would also like to give a special thanks to our NatureServe clients, Rickie White and Lindsey Smart, as well as our NPS contact, Teresa Leibfreid, for providing us with guidance, direction, and recommendations on all aspects of the project. Thanks also to Dr. Dean Urban, Brenna Forester, John Fay, Kai Zhu, Milo Pyne, Jason McNees, Kurt Helf, Bill Moore, Jonathan Jernigan and all those at Duke, NaturesServe and NPS who contributed to this effort. Finally, we acknowledge our family and friends who have supported us and given us encouragement these past two years.

Table of Contents

List of Tables and Figures

1.0 Introduction

The 2007 report published by the Intergovernmental Panel on Climate Change (IPCC) details research findings that show climate change is having a recognizable impact on global biotic and abiotic systems. The report details major impacts from climate change including rising sea levels, increasing temperatures, and changes in precipitation regimes. All of these major impacts can influence the survival of plant and animal species across the globe (IPCC 2007). Furthermore, the stresses induced by climate change, coupled with habitat loss, may cause unknown changes in the population dynamics and the spatial distributions of species (Halpin 1997). Increasing uncertainty regarding the direct and indirect effects that climate change may have on species, and overall biodiversity, hastens the need for further research and modeling of species' ranges and distributions. We can begin to understand some of these potential effects and their implications for management actions through the use of species habitat suitability models (Franklin 2009). To do this effectively, we must analyze species and habitat distributions at site-specific or sub-regional (ecoregion or state) scales to effectively inform the conservation decisions made by regional policy-makers, academic researchers and land managers (Halpin 1997).

Scientists and decision-makers should account for sensitivity, exposure, and adaptive capacity as the three components of species vulnerability to climate change (Turner II et al. 2003; Berry et al. 2006; Williams et al. 2008; Hansen & Hoffman 2011). Sensitivity refers to the intrinsic characteristics of a species, such as ecological traits, physiological tolerance limits, genetic diversity, and resilience. For example, if a species has a large habitat range and its populations are genetically diverse, then that species has a better chance of persisting given climate change than a species with a restricted habitat range and low genetic diversity. Consequently, resilient species have the best chance to survive and recover from the frequent disturbances that climate change may induce (Williams et al. 2008).

In contrast to sensitivity, exposure relates to the external factors that influence species during climate change. Williams et al. (2008) suggest that exposure refers to the degree to which regional climate change affects an organism based on a species' range or habitat. For example, cave-dwellers may be less exposed to the effects of climate change than other species because cave species live underground and may be buffered from above ground climate (Culver et al. 2003, Hamilton-Smith and Finlayson 2003, Lamoreux 2004). Thus, in the context of species vulnerability, sensitivity refers to intrinsic characteristics of a species while exposure pertains to a species' extrinsic relationship to the surrounding environment.

In the context of climate change, adaptive capacity relates to the idea that humans can manage and minimize the impacts of climate change on a species, and potentially even enhance their viability in an ecosystem (Williams et al. 2008; Dawson et al. 2011; Hansen & Hoffman 2011). Species generally have the ability to adapt through evolutionary changes or ecological responses (Williams et al. 2008), but humans also play a role in contributing to species adaptation because humans manage lands in which species reside. Our study demonstrates the capacity of tools like the Climate Change Vulnerability Index (CCVI) and habitat suitability modeling to inform organizations and government agencies on how climate change might affect certain species.

The objective of this project is to use NatureServe's CCVI, in conjunction with habitat suitability modeling, to assess species' vulnerability to climate change and quantify their potential future habitat ranges within the Cumberland Piedmont Network (CUPN) of the NPS. By combining the CCVI and habitat suitability modeling, our intention is to develop a transparent framework with both non-spatial and spatial components that NatureServe and NPS can employ to inform decision-making for climate change management strategies and policies within the CUPN.

1.1 Climate Change Vulnerability Index

In 2010, NatureServe developed the CCVI to evaluate species that may be vulnerable to the effects of climate change. Previous studies from Nevada (Young et al. 2009), New York (Schlesinger et al. 2011), and West Virginia (Byers & Norris 2011) employed the CCVI to assess species of conservation concern within their respective states. The CCVI is a programmed Microsoft Excel Workbook that is designed to work in concert with NatureServe's Conservation Status Ranks. In order to prevent redundancy, information used to determine a species' Conservation Status Rank is not included in the inputs for the CCVI. The exposure and sensitivity of each species to climate change is evaluated using the CCVI, and the final output is a categorical score representing the species' vulnerability.

Supported by extensive literature in climate science, the CCVI divides species' vulnerability into two primary components: **exposure** and **sensitivity** (Williams et al. 2008). The index further breaks exposure into direct and indirect components. In total, the CCVI contains four sections to score climate change vulnerability: 1) direct exposure to climate change, 2) indirect exposure to climate change, 3) sensitivity, and 4) documented/modeled response to climate change (Figure 1). By including sensitivity and documented/modeled response to climate change, the index moves beyond climate envelope models that limit vulnerability assessments to exposure (Dawson et al. 2011).

Although separate categorically, the four components of the CCVI work in conjunction to produce a final score. For example, species within assessment areas that experience low exposure to temperature and moisture changes will not be highly vulnerable to climate change, even if they are sensitive to its effects. Likewise, a species that displays low sensitivity to climate change within a highly exposed area will produce a similarly low vulnerability score. Conversely, climate change will compound its effects on highly sensitive species within assessment areas that are predicted to undergo drastic temperature and moisture shifts.

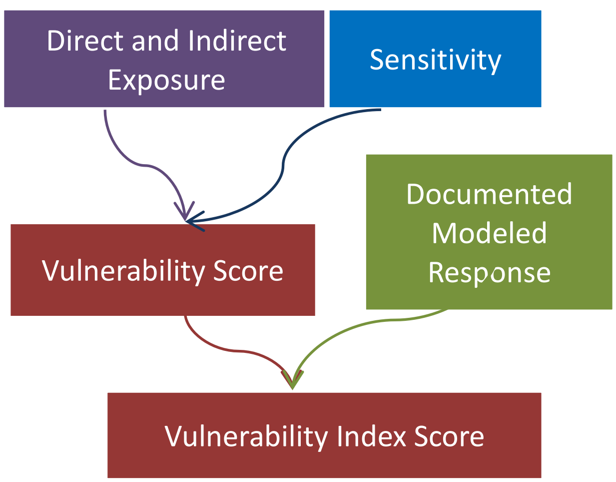


Figure 1. Factors of NatureServe's Climate Change Vulnerability Index (adapted from Young et al. 2010).

1.1.1 Scoring system

The CCVI ranks vulnerability based on a total of twenty factors that are distributed between the four components mentioned above. These factors, discussed further in the Methods section, are scored according to their relative influence on the species' climate change vulnerability. Each factor is assessed categorically and includes the following possible scores on a species' climate change vulnerability: **decrease, somewhat decrease, neutral, somewhat increase, increase, and greatly increase**. Detailed descriptions for each scoring category for each factor are available within the Index.

The information provided in the aforementioned factors combine to yield a numerical sum that is subject to a threshold, then transformed into one of the six climate change vulnerability scores below as outlined by Young et al. (2010) (Table 1).

Table 1. Descriptions and abbreviations for each CCVI score as outlined by Young et al. (2011).

Index Score	Description
Extremely Vulnerable (EV)	Species abundance and/or range within assessment area is extremely likely to decrease or disappear by the year 2050.
Highly Vulnerable (HV)	Species abundance and/or range within the assessment area is likely to decrease by 2050.
Moderately Vulnerable (MV)	Species abundance and/or range likely to decrease moderately by 2050.
Not Vulnerable / Presume Stable (PS)	According to the evidence presented in the CCVI, the species is not expected to change in abundance and/or range within the assessment area by 2050.
Not Vulnerable / Increase Likely (IL)	Species abundance and/or range likely to experience increase within the geographical assessment area by 2050.
Insufficient Evidence (IE)	The species' assessment did not contain adequate information to produce a vulnerability score.

NatureServe developed the Index to work in conjunction with Conservation Status Ranks. Additionally, because vulnerability rankings implicate climate scenarios in the 2050's, species that display the highest vulnerability are not necessarily those that are currently the most threatened. In applying the CCVI to NPS units in the CUPN, the goal of this study is to identify state-listed species of conservation concern (species with a NatureServe Conservation Status "S" Rank of 1 - 3 or a "G" Rank of 1 - 3) that are also vulnerable to the future effects of climate change. From this information, managers can integrate conservation actions into existing programs to address potential negative effects of climate change on key species. From habitat monitoring to fire management to regional planning, confronting the implications of future climate change is the first step to mitigating the effects on susceptible species.

1.2 Habitat Suitability Modeling

Habitat suitability modeling draws inferences from a species' relationship with environmental variables based on observations in environmental space (Pearson 2007). A myriad of habitat suitability modeling approaches exist, including inductive and machine-learning techniques, as well as mechanistic (deductive) approaches (Franklin 2009). For this study, we selected maximum entropy modeling (MaxEnt), generalized linear models (GLM), generalized additive models (GAM), gradient boosting models (GBM), and classification tree analysis (CTA) on the basis of ease of interpretability and widespread use among conservation professionals (Hijmans et al. 2006; Pearson 2007; Guisan & Zimmerman 2000; Thuiller 2003; Phillips 2006).

We compared the projections generated from the maximum entropy approach with those generated from the ensemble approach in order to illustrate the variability among models when attempting to project on future climate space (Buisson et al. 2010; Thuiller 2003).

The onset of anthropogenic climate change (Johns et al. 2003) necessitates *bioclimatic* suitability modeling for the purpose of making projections into future climatic space to guide long-term management protocol (Hijmans et al. 2006). Models are trained on observations in current bioclimatic space and then projected onto bioclimatic surfaces grids derived from general circulation models (GCMs) representing climate change scenarios that vary with Special Report on Emission Scenarios (SRES) (IPCC 2007).

The hierarchy of landscape scale constrains selection of resolution and study extent to sizes for which, for the purposes of this study, macro-climatic factors are the primary factors in determining a species' response to habitat (Levin 1992). Bioclimatic predictor variables correlated most with a species' current distribution are then identified to establish that species' bioclimatic niche (Pearson & Dawson 2003).

The aim of this study was to build bioclimatic suitability models for a selection of species with "Moderately Vulnerable," "Highly Vulnerable," "Extremely Vulnerable", and "Presumed Stable" scores from the CCVI to inform NPS managers where suitable climatic conditions range now, and how these ranges are projected to shift in 2050 and in 2080.

2.0 Study Goals

Our study fulfilled three goals concerning species selection, CCVI analysis, and bioclimatic habitat suitability modeling. The first goal was to select species of conservation concern within the CUPN for climate change vulnerability analysis. We did this by cross-referencing wildlife action plans with state-listed species in each of the fourteen NPS units on which we were focusing. Other notable species, such as keystone species, were also identified as candidates in an effort to include species that may be particularly important for the foundation of certain ecosystems.

The second goal of this project was to use NatureServe's CCVI to assess the vulnerability of a number of species that inhabit the lands of the CUPN. These vulnerability assessments, in concert with the previously established NatureServe Conservation Status Ranks, will add to the current body of research on species' vulnerabilities under climate change scenarios.

The third goal of this study was to develop habitat suitability models based on bioclimatic variables for three species evaluated to be "Moderately," "Highly," or "Extremely Vulnerable" to climate change and one species evaluated to be "Presumed Stable." Habitat suitability models are important for understanding the potential impacts of management actions or environmental change on biodiversity patterns (Franklin 2009). Consequently, the results of this project will serve to inform NPS managers of potential suitable habitat for species under climatic conditions at the present, in 2050, and in 2080.

By documenting the process we have used to address these goals, we hope to create a framework for use by other researchers for future climate change vulnerability assessments. Our paper demonstrates this framework by outlining an integrative process through which NPS and NatureServe can work together to analyze certain species. With these goals in mind, transparency in this research is an important theme for the project. We paid specific attention to documenting the inputs and threshold values used within the CCVI and habitat suitability modeling because the results of this study could have major implications for park managers, policy-makers, researchers, and the general public. The results from this study could serve to guide regional conservation policies and land management practices within the National Park Service's CUPN.

3.0 Methods

3.1 Study Area

NatureServe and NPS are interested in the effects of climate change on species within the CUPN. Geographically, the CUPN spans east to west from Tennessee to North Carolina and north to south from Kentucky to Georgia, excluding the Appalachian Mountains. Fourteen National Park Service units fall within the CUPN (Table 2; Figure 2).

In order to accurately model species within the CUPN, we expanded our study area to include the nine ecoregions that intersect the CUPN (Appendix A: Figure 1), as delineated by The Nature Conservancy (TNC) (ConserveOnline 2009). This larger ecoregional study area was particularly important for modeling because there must be a balance between covering a species' full bioclimatic envelope while still using a geographic area that is ecologically-relevant (Elith et al. 2011). This is especially important when models are used to forecast onto future climatic or new geographic space (Elith et al. 2011). While a large geographic area allows models to discriminate between occupied sites and the rest of the area, localized models perform a more fine-scale discrimination. However, reducing the study area size increases the chance that novel environments will be encountered in future projections (Elith et al. 2011). As we are only interested in projecting distributions within the CUPN, we assume the ecoregional approach will cover the climate within the CUPN and reduce the likelihood of encountering novel environments with climate change *within* the CUPN.

Table 2. Park Abbreviations for parks found within the CUPN. Abbreviations are used throughout this text.

Park Name	Abbreviation
Abraham Lincoln National Historic Site	ABLI
Carl Sandburg Home National Historic Site	CARL
Chickamauga and Chattanooga National Military Park	CHCH
Cowpens National Battlefield	COWP
Cumberland Gap National Historic Park	CUGA
Fort Donelson National Battlefield	FODO
Guilford Courthouse National Military Park	GUCO
Kings Mountain National Military Park	KIMO
Little River Canyon National Park	LIRI
Mammoth Cave National Park	MACA
Ninety Six National Historic Site	NISI
Russel Cave National Monument	RUCA
Shiloh National Military Park	SHIL
Stones River National Battlefield	STRI

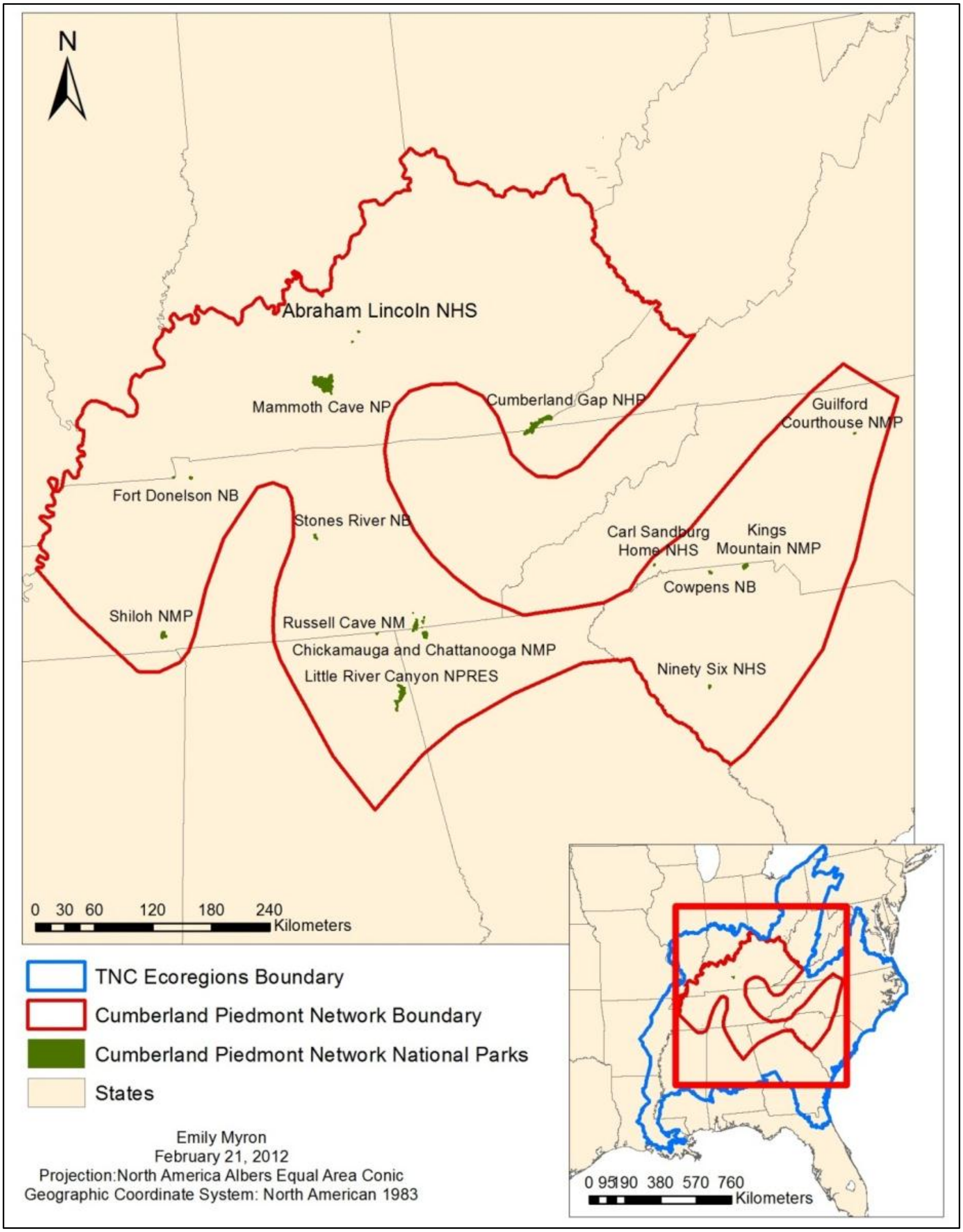


Figure 2. Cumberland Piedmont Network (CUPN) of National Parks. Fourteen National Park Service units fall within the CUPN. The larger area for which we are modeling is delineated in blue and includes the nine TNC ecoregions that intersect the CUPN.

3.2 Climate Change Vulnerability Index

3.2.1 Species selection

Species were selected as candidates for CCVI runs using a document obtained from the NPS that details species present in each CUPN NPS unit (NPS 2011). We restricted the initial list to vertebrates and vascular plants, but subsequently added thirteen non-vertebrate species from the NPS document to represent other taxonomic groups. We cross-referenced vertebrate species in the fourteen NPS units of the CUPN with "Species of Greatest Conservation Need," as enumerated in each state's Wildlife Action Plan. The list was then narrowed using a conservation status threshold, similar to methods in the West Virginia climate change vulnerability study by Byers and Norris (2011). Critically imperiled and vulnerable species, on either state or global scales (NatureServe Conservation Status Ranks S1-S3, G1-G3), were included as final candidate species for the CCVI.

The final list contained 153 species individuals[1] that met the initial criteria that we set for our list. Our final list 1) spanned seven taxonomic groups, 2) included both state and global species of conservation in the CUPN, and 3) included organisms that contained adequate information for assessment (Table 3). The final list represented species that have been documented in twelve of the fourteen NPS units in the CUPN. We completed the CCVI for each candidate species in each unit in which it occurs because some units are predicted to experience different levels of exposure to temperature and moisture changes.

Table 3. Taxonomic breakdown of the final CCVI candidate species.

Taxonomic Group	# of species individuals
Amphibians	4
Birds	98
Fish	6
Mollusks	13
Mammals	19
Reptiles	1
Vascular plants	12

[1] The term "species individuals" represents the individual CCVI runs done for the same species in multiple parks. A species that fulfilled the above criteria for multiple parks requires separate runs for each park due to differing degrees of exposure. It is therefore possible, though unlikely, for one species to produce disparate climate change vulnerability rankings in different parks. Any discrepancies in Index ranking would therefore be attributed to spatial heterogeneity of exposure, as the species' sensitivity would be identical.

3.2.2 Procuring Species Information & Resources

We used NatureServe Explorer[2] to gather species information for the CCVI. Other resources included the USDA Plants Database[3] and the U.S. Forest Service Atlas of Change[4] (Matthews et al. 2011). Peer-reviewed literature on species' traits, adaptations, and management filled information gaps where necessary. During this process, many species were eliminated from consideration due to a dearth of available information on important environmental attributes. This was particularly notable for rare plant species that exhibited low element occurrences.

3.2.3 Preliminary inputs

Prior to entering species' factors, the CCVI tool includes a section for entering background information. The species name, taxonomic group, NatureServe Conservation Status Ranks (global and state rankings), geographic assessment area, and relation of that assessment area to the species' overall range are included in the background information. Additionally, this section allows the user to input whether or not the species is an obligate of caves or aquatic groundwater systems (Young et al. 2010).

3.2.4 Section A. Direct exposure to local climate change

Direct exposure divides future changes in temperature and moisture predictions into five and six levels of exposure, respectively (Appendix B: Table 1) We used a medium A1B emissions scenario of an ensemble average of sixteen global circulation models (GCMs) to assess the species' exposure to climate change (available for download through TNC's Climate Wizard[5]). We examined the predicted moisture and temperature changes for each of the fourteen CUPN units, recording the results in a "Park Attributes" spreadsheet to expedite future CCVI runs (Appendix B: Table 2).

3.2.5 Section B. Indirect exposure to climate change

Indirect exposure to climate change includes factors that are governed by changes in climate but that are not climatic changes in themselves (Appendix B: Table 1). This category broadens spatial considerations beyond the assessment area to the surrounding geographic region

[2] Available at http://www.natureserve.org/explorer/
[3] Available at http://plants.usda.gov/java/
[4] Available at http://www.nrs.fs.fed.us/atlas/bird/index.html
[5] Available at http://www.climatewizard.org/

at the landscape scale. Factors in this section include exposure to sea level rise, distribution of natural and anthropogenic barriers, and the impact of land use resulting from human response to climate change. We used National Land Use Land Cover data (NLCD 2006) to evaluate the surrounding developments and potential barriers to dispersal for each park unit region. It is important to note that, for this study, no coastal areas were evaluated; this resulted in neutral rankings for exposure to sea level rise for all species in this assessment. This section requires completion of at least three factors for sufficient evidence of assessment (Young et al. 2010).

3.2.6 Section C. Sensitivity

The sensitivity component contains species-specific factors that are scored according to their effect on the species' climate change vulnerability (Appendix B: Table 1). Sensitivity represents the ability of the species to adapt in light of climate change effects, notably the effects of temperature and moisture. This component includes variables related to ecophysiological traits, life-history characteristics, interspecific interactions, microhabitat characteristics, phenological considerations, and genetic factors. Specific factors include physiological hydrologic niche, dietary versatility, and dependence on a disturbance regime likely to be impacted by climate change. Again, we gathered information on these species from NatureServe Explorer and extensive peer-reviewed literature. Sensitivity expands the vulnerability assessment to ecological considerations, in addition to climatic factors. In total, the sensitivity component includes fifteen species' attributes that influence vulnerability, although the CCVI requires at least ten responses in this category to yield an Index score (Young et al 2010).

3.2.7 Section D. Documented or modeled response to climate change

The final section of the CCVI depicts the species' documented or modeled response to climate change. Containing only four factors, this optional component allows the user to include information on the species' recent response to climate change events and range shifts that may occur with future climate change scenarios. In consideration of these range shifts, the Index also accounts for the degree of the shift and location of protected areas within the modeled future habitat, according to peer-reviewed literature. For this study, we used the U.S. Forest Service's Atlas of Change to obtain information on the modeled future habitat of many birds and several tree species (Matthews et al. 2011).

3.2.8 Confidence in Species Information

After calculating the species' vulnerability score, the CCVI computes a level of confidence in each score. The confidence output is generated through use of a Monte Carlo simulation, running 1,000 iterations to recalculate the Index score. The simulation assumes that each box in a checked factor is equally likely to be checked in each run (Young et al. 2010). The CCVI generates a simple histogram based on the results of this statistical simulation (Figure 3).

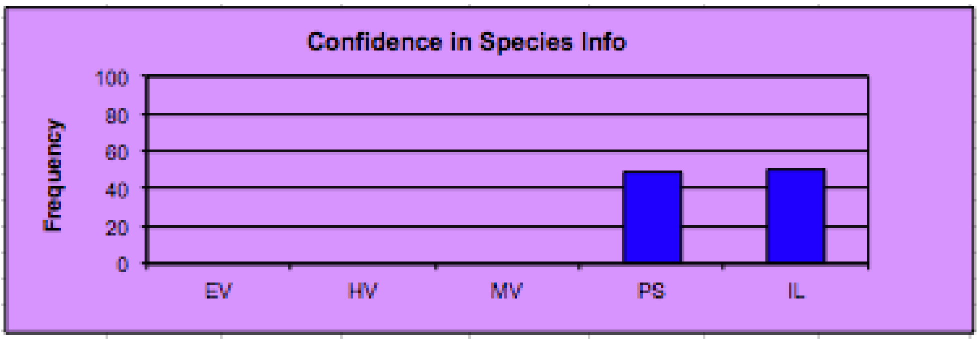


Figure 3. Example of a confidence output in the vulnerability index score, generated through a Monte Carlo simulation (Young et al. 2010). EV = Extremely Vulnerable, HV = Highly Vulnerable, MV = Moderately Vulnerable, PS = Presumed Stable, IL = Increase Likely

3.3 Habitat Suitability Modeling Data

3.3.1 Species Occurrence Data

After completing each CCVI assessment, we explored the available data for all species that were classified as "Moderately Vulnerable," "Highly Vulnerable," or "Extremely Vulnerable." We chose species to model based on several criteria. First, we chose species with available, reliable occurrence data within our study area. Second, we chose species for which we could encompass their presumed full climatic envelope in the model (for example, species bounded by the Gulf of Mexico were excluded because we had no way of knowing their true climatic boundary) (Elith et al. 2011). Finally, we incorporated client interest and a desire to model species from a variety of taxonomic groups into our decision. This resulted in four species – an amphibian, two plants, and a mammal (Table 4). The mammal species was actually ranked as "Presumed Stable" in the CCVI; however, we included it in order to explore modeling outputs for a variety of taxonomic groups.

In order to model potential climate effects on suitable habitat for species, we first needed to obtain precise locations at which species are currently present. We were able to obtain Natural Heritage Program source feature data through NatureServe for some species in Alabama, Georgia, North Carolina, South Carolina, and Tennessee (Table 4) (for the Tennessee data, occurrences were marked as polygons, so we found the centroid and used that point as an occurrence point). We restricted the data to observations occurring after 1975 to avoid issues associated with modeling occurrence data and environmental data that are separated by a significant amount of time (Anderson & Martinez-Meyer 2004).

Because these data were incomplete, both in terms of a species' full geographic range and their range within the ecoregional study area, we augmented these data with occurrence data from the Global Biodiversity Information Facility (GBIF)[6] (Table 4). GBIF provides a free and open access source of biodiversity data, shared by a wide range of institutions (including museums, non-profit organizations, and academic institutions). Species for which we did not obtain Natural Heritage Program data, we used only GBIF occurrence data. We screened the GBIF data for only those observations after 1975 to be consistent with the Natural Heritage Program source features' temporal range. There was no overlap between the Natural Heritage Program occurrence data and the occurrence data obtained through GBIF.

[6] Available at http://data.gbif.org/welcome.htm

Table 4. Species modeled and their respective sources of data. "NHP" refers to state Natural Heritage Program source feature data. "GBIF" refers to Global Biodiversity Information Facility (2011). All occurrence points were collected between 1975 and 2011.

Species	Common Name	Data Sources	CCVI Rating	Number of Occurrences*
Aneides aeneus	Green Salamander	NHP (AL, GA, NC, SC, TN); GBIF[7]	Moderately Vulnerable	392
Scutellaria montana	Large-flowered Skullcap	NHP (TN only**); GBIF[8]	Moderately Vulnerable	168
Sorex longirostris	Southeastern Shrew	NHP (AL, GA, NC, SC, TN); GBIF[9]	Presumed Stable	138
Plantago cordata	Heartleaf Plantain	NHP (TN), GBIF[10]	Highly Vulnerable	31

*This refers to the number of occurrences actually used to create the models for each species.
**These data were received as polygons. We calculated the centroid of each and used that point as the presence record.

3.3.2 Environmental Variables

We used nineteen bioclimatic variable surfaces based on current conditions (1950-2000) (Table 5) and downscaled each of them to a one square kilometer resolution (WORLDCLIM database[11]; Hijmans et al. 2005). We used these same nineteen bioclimatic variables for 2050 and 2080 scenarios based on the Hadley CM3 GCM and SRES A1B (Johns et al. 2003; Matthews et al. 2011; Iverson et al. 2008). These variables were downscaled using the Delta method (Ramirez-Villegas et al. 2010).

[7] Biodiversity occurrence data published by: Alabama Museum of Natural History, Arctos, California Academy of Sciences, Cornell Museum of Vertebrates, Los Angeles County Museum of Natural History, National Museum of Natural History, Royal Ontario Museum, San Diego Natural History Museum, Staatliches Museum, Sternberg Museum of Natural History, and University of Alberta. (*Accessed through GBIF Data Portal, data.gbif.org, 2012-02-12).*

[8] Biodiversity occurrence data published by: USDA Plants. (*Accessed through GBIF Data Portal, data.gbif.org, 2012-02-12).*

[9] Biodiversity occurrence data published by: Arctos, California Academy of Sciences, Cornell Museum of Vertebrates, Michigan State University Museum, Santa Barbara Museum of Natural History and University of Kansas Biodiversity Research Center. (*Accessed through GBIF Data Portal, data.gbif.org, 2012-02-12).*

[10] Biodiversity occurrence data published by: The New York Botanical Garden, University of Alabama Biodiversity and Systematics, and USDA Plants. (*Accessed through GBIF Data Portal, data.gbif.org, 2012-03-30).*

[11] Available at http://www.worldclim.org/

Table 5. WORLDCLIM bioclimatic variables used in analysis and their abbreviations.

Variable Abbreviation	Bioclimatic Variable
BIO1	Annual Mean Temperature
BIO2	Mean Diurnal Range (Mean of monthly (max temp - min temp))
BIO3	Isothermality (BIO2/BIO7) (* 100)
BIO4	Temperature Seasonality (standard deviation *100)
BIO5	Max Temperature of Warmest Month
BIO6	Min Temperature of Coldest Month
BIO7	Temperature Annual Range (BIO5-BIO6)
BIO8	Mean Temperature of Wettest Quarter
BIO9	Mean Temperature of Driest Quarter
BIO10	Mean Temperature of Warmest Quarter
BIO11	Mean Temperature of Coldest Quarter
BIO12	Annual Precipitation
BIO13	Precipitation of Wettest Month
BIO14	Precipitation of Driest Month
BIO15	Precipitation Seasonality (Coefficient of Variation)
BIO16	Precipitation of Wettest Quarter
BIO17	Precipitation of Driest Quarter
BIO18	Precipitation of Warmest Quarter
BIO19	Precipitation of Coldest Quarter

We calculated a topographic relative moisture index (TRMI) to characterize site moisture using a USGS National Elevation Dataset digital elevation model (Parker 1982) downloaded from the National Hydrography Dataset website[12]. Site moisture is a supplement to bioclimatic conditions, and is arguably a more direct component of bioclimatic niches for vegetation (Lookingbill & Urban 2005). This variable is not a proxy for other bioclimatic variables (e.g. as elevation is a proxy for temperature) and, thus, can be used when projecting the model onto future climate space. Additionally, we utilized the USDA Natural Resource Conservation Service (NRCS) soils data[13] as a variable when modeling the plants.

[12] Available at http://www.horizon-systems.com/nhdplus/
[13] Available at http://soils.usda.gov/

3.4 Habitat Suitability Modeling Analyses

3.4.1 Selection of Variables for Modeling

We chose variables for each species' model based on exploratory data analysis and life history knowledge gleaned from the CCVI process. We calculated Pearson correlations between environmental variables and species presence/absence and retained the top ten variables with the highest correlation coefficients and/or any variables that were found to have ecological significance (even if correlation was not high, as was the case for TRMI in the Green salamander model) (Appendix C). We then parsed pairs of highly correlated variables (correlation coefficient > 0.07; p-value < 0.05) so that the remaining variables retained the most unique information (Table 6) (The R Foundation for Statistical Computing, 2011; Goslee & Urban, 2007).

Table 6. Variables chosen for use in each species' models (abbreviations defined in Table 5).

Species	Variables Used in Modeling
Green Salamander	BIO5, BIO9, BIO12, BIO17, BIO19, TRMI
Large-Flowered Skullcap	BIO8, BIO14, BIO16, BIO17, TRMI, Soils
Southeastern Shrew	BIO6, BIO8, BIO9, BIO14, BIO17, TRMI
Heartleaf Plantain	BIO7, BIO8, BIO14, BIO17, BIO18, TRMI, Soils

3.4.2 Maximum Entropy Modeling (MaxEnt)

Maximum entropy modeling (using the program, MaxEnt) is a relatively new approach to species distribution modeling that has quickly become a favorite method for conservation practitioners including GIS analysts at NatureServe (Smart, NatureServe, pers. comm. 2012). MaxEnt is a discriminative modeling technique, meaning it fits species occurrences relative to available habitat in a model as loosely as possible, with the single constraint that the mean of the function for each variable must be the same as the mean of the observed data (Elith et al. 2011). When compared to other "presence-only" methods, such as Genetic Algorithm for Ruleset Prediction (GARP), MaxEnt consistently outperforms in terms of predictive ability, interpretable output, and accuracy using small datasets (Phillips et al. 2004; Phillips et al. 2006). For this analysis, we used MaxEnt, Version 3.3.3k (Philips et al. 2004, 2006)[14].

As actual species absence data were not available, we generated 10,000 random points using ArcGISv10 within the ecoregion study area to be used both as the background points in

[14] Available at http://www.cs.princeton.edu/~schapire/maxent/

MaxEnt, and as pseudo-absence points for the models in BIOMOD. In MaxEnt, each model was built based on the environmental conditions at each of the occurrence points within the ecoregion study area contrasted with the environmental conditions of the background of pseudo-absences. We projected each model onto the study area using the species-specific bioclimatic variables of interest (Table 6). We generated projections for the current range, the range in 2050, and the range in 2080.

For each analysis, we trained each model using 70% of the data and tested each model using 30% of the data (withheld initially) (Thuiller 2003), with a default regularization parameter of 1. Additionally, we jackknifed the predictors in the model, meaning that, for each variable, a model was created including that variable and a model was created that included all but that variable. This technique allows us to assess the relative explanatory power of each variable.

We imported the resulting habitat probability maps into ArcGISv10. This allowed us to look at a continuous surface of habitat suitability over the study area. Finally, we used the conventional MaxEnt threshold that balances training omission, predicted area, and threshold value to threshold this probability surface. This produced a binary map of predicted "habitat" and "not habitat" for the current, 2050, and 2080 projections.

3.4.3 BIOMOD Ensemble Forecasting Approach

We used the program BIOMOD (Thuiller 2003) within R statistical software (The R Foundation for Statistical Computing 2011) to build additional bioclimatic suitability models to supplement the maximum entropy model using an ensemble forecasting approach. We chose to use four of the most widely-used, easily-implemented and interpretable models according to recent habitat suitability modeling literature (Buisson et al. 2000; Hijmans et al. 2006; Guisan and Zimmerman 2000; Phillips 2006; Thuiller 2003; Pearson 2007; Elith et al. 2006; Austin 2002; Elith et al. 2008).. These models include the generalized linear model (GLM), the generalized additive model (GAM), classification tree analysis (CTA), and the general boosting model (GBM).

We implemented the following procedure for constructing these models: (1) We used approximately 10,000 randomly-generated pseudo-absence points (to signify background/random climatic habitat) and species presence points constrained by nine TNC ecoregions, (2) We trained each of the models on 70% of the data and tested each of the models using 30% of the data (withheld initially) (Thuiller 2003), (3) We used linear predictor terms and an automatic stepwise procedure to generate the GLM, (4) We used 50-fold cross validation to guide the CTA classification scheme, (5) We used an automatic stepwise procedure to generate the GAM, (6) We used 5-fold cross validation to guide GBM construction.

We assessed model performance using sensitivity scores produced from running the models using the test data. Sensitivity is an indication of the model's ability to correctly identify actual occurrence points as suitable habitat as the result of model performance and not the result of random chance (Araújo et al. 2005; Phillips et al. 2009).

We calculated a mean across all five model probability surfaces (GLM, CTA, GAM, GBM, and MaxEnt) to generate an ensemble average for the 2050 and 2080 projections – the first ensemble approach. Receiver operator characteristic (ROC) curves guided our choice of where to set a probability threshold to convert probability surfaces into binary form. We used these thresholds to project suitable bioclimatic habitat in binary form on 2050 and 2080 climatic conditions across our study area. We then added each of the binary surfaces together with the MaxEnt binary output to show areas of model agreement – the second ensemble approach.

4.0 Results

4.1 Climate Change Vulnerability Index

Out of the 153 total species individuals[15] assessed in this study, approximately 30% were determined to be either "Extremely Vulnerable" (EV), "Highly Vulnerable" (HV), or "Moderately Vulnerable" (MV) (Figure 4). The remaining 70% of species individuals, many of which were birds, were considered "Presumed Stable" (PS) or "Increase Likely" (IL) (Figure 4).

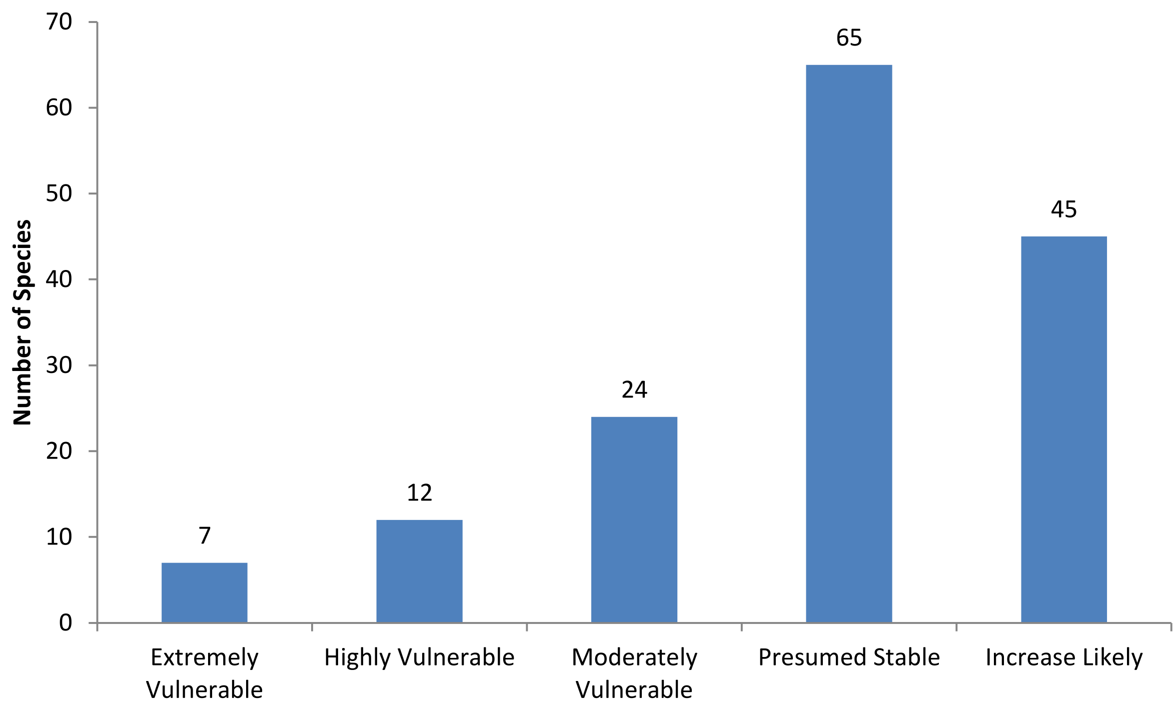


Figure 4. Number of species individuals from the CUPN study area within each vulnerability category.

Mollusks, amphibians, mammals, and plants were the most vulnerable taxonomic groups. All mollusks assessed were determined to be vulnerable, with over 50% of them deemed EV (Figure 5). Similarly, over 50% of species individuals within the amphibian, mammalian, and plant groups were indexed as MV or HV (Figure 5). Figure 5 also illustrates that over 90% of the birds were presumed stable or would likely increase, with the exception of *Picoides borealis* (red-cockaded woodpecker), *Wilsonia canadensis* (Canada warbler), and *Junco hyemalis* (dark-

[15] As mentioned in the Methods section, the term "species individuals" represents the individual CCVI runs done for the same species in multiple parks. A species that fulfilled the above criteria for multiple parks requires separate runs for each park due to differing degrees of exposure. It is therefore possible, though unlikely, for one species to produce disparate climate change vulnerability rankings in different parks. Any discrepancies in Index ranking would therefore be attributed to spatial heterogeneity of exposure, as the species' sensitivity would be identical.

eyed junco).

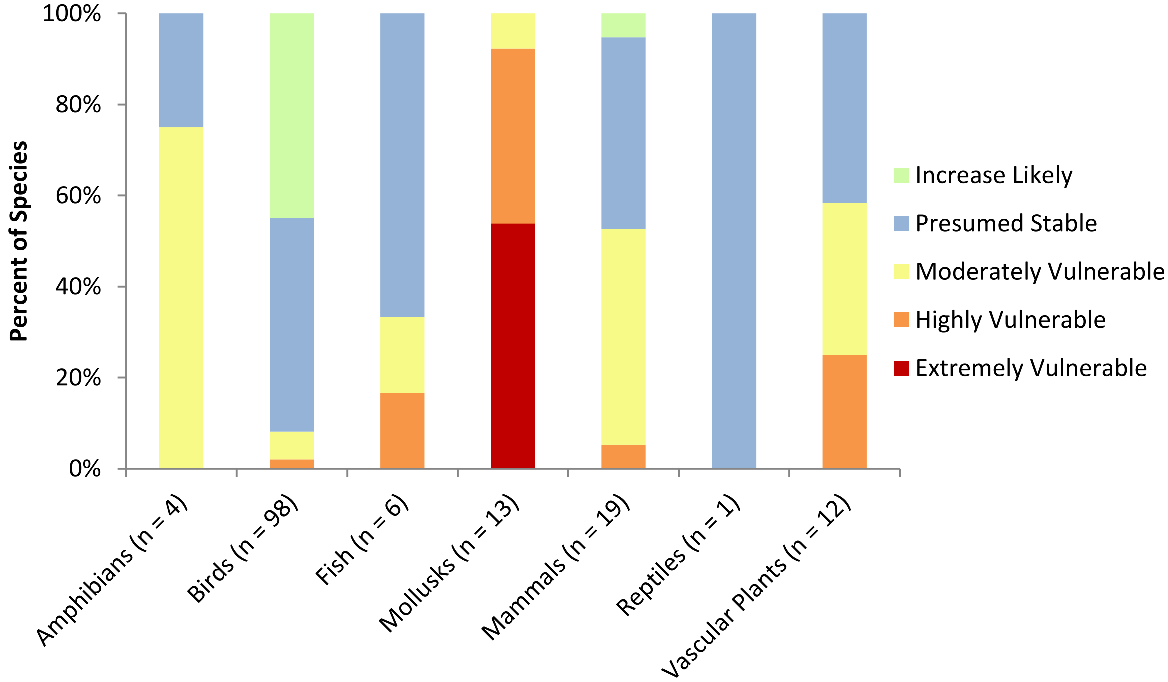
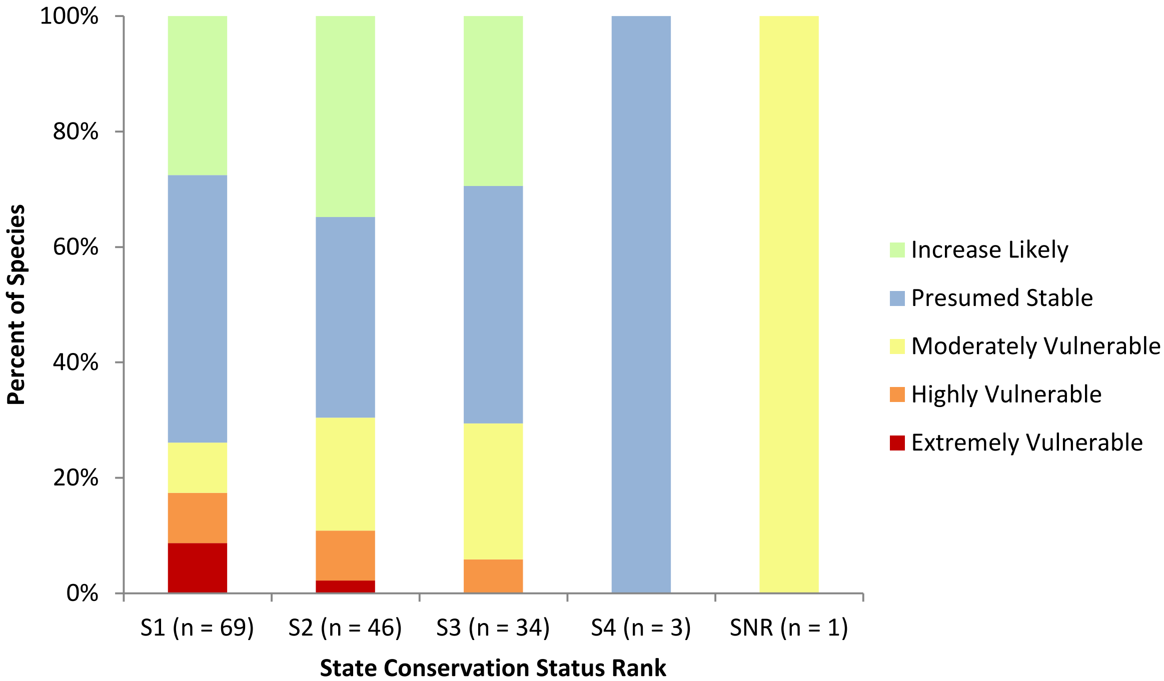


Figure 5. Percent of species individuals from the eight taxonomic groups that fall within each vulnerability category. Note that "n" represents the number of individuals evaluated using the CCVI. The same species could have been evaluated multiple times if it resided in multiple park units. For example, if the same species resided in two different parks, we ran that species through the CCVI twice, changing park attributes accordingly.

Climate change vulnerability and conservation status are not directly related to each other, but comparing species' CCVI scores to their Conservation Status Ranks yields some interesting results. When considering each of the S1, S2, and S3 state conservation statuses, just over 25% of species individuals were assessed as EV, HV, or MV (Figure 6a). S1 species are considered critically imperiled sub-nationally, and S3 species are considered vulnerable. Since we focused mostly on species with ranks from S1 to S3 (i.e. species of great conservation concern), it is interesting to observe that approximately 75% of those species individuals are of high conservation concern but were assessed as PS or IL in response to climate change (Figure 6a). In contrast to the state ranks, many species individuals with global conservations ranks of G1, G2, and G3 were classified into a vulnerability category. Approximately 100% of G1, 40% of G2 and 65% of G3 species individuals were found to be vulnerable (Figure 6b). Figure 6b also illustrates that a majority of species in the G4 and G5 ranks were PS or IL with climate change.

a.



b.

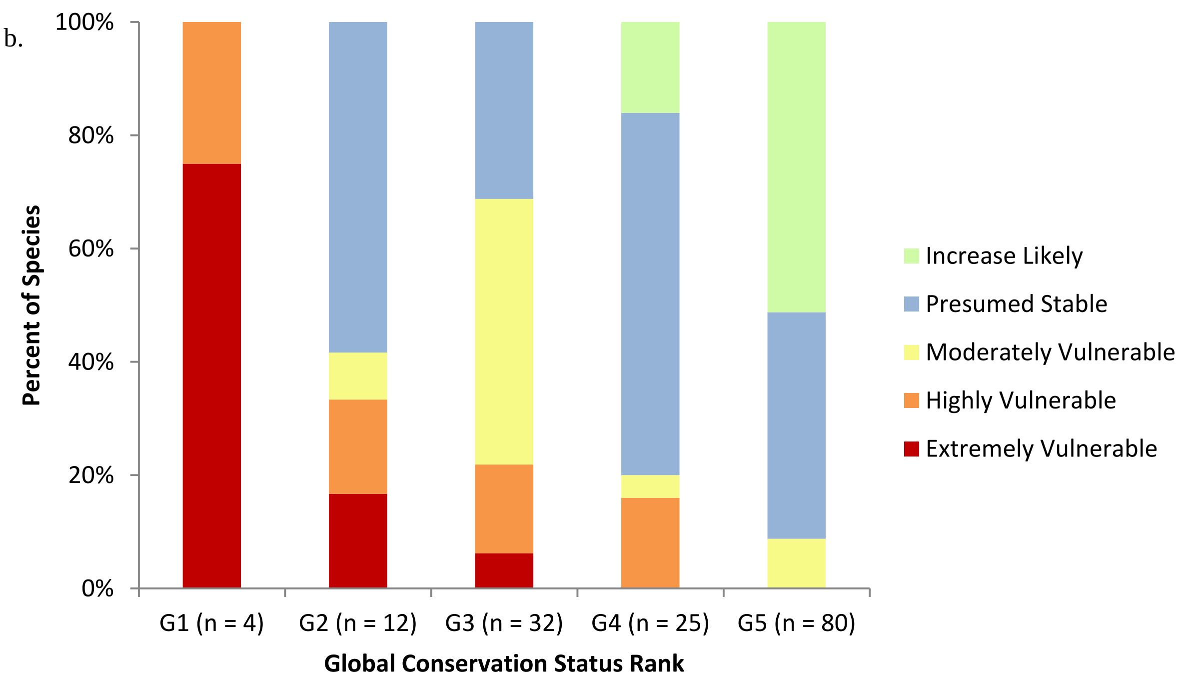


Figure 6. Percent of species individuals from rounded state (a.) and global (b.) conservation rankings that fall within each vulnerability category. If two rankings existed, we rounded to the more imperiled status to keep a conservative ranking. Note that "n" represents the number of individuals evaluated using the CCVI. The same species could have been evaluated multiple times if it resided in multiple NPS units. For example, if the same species resided in two different parks, we ran that species through the CCVI twice, changing park attributes accordingly. Only breeding statuses were used when rounding state conservation rankings for birds.

4.1.1 Taxonomic Groups

Amphibians

Although amphibians comprised only four CCVI runs, three of these runs produced a MV ranking (Table 5). The green salamander (*Aneides aeneus*), present in three separate parks, accounted for all three of these rankings. The Tennessee cave salamander (*Gyrinophilus palleucus*) was PS in Cumberland Gap National Historic Park. Factors that contributed to the MV ranking of the green salamander included limited dispersal ability, physiological hydrologic niche, and physical habitat requirements. The green salamander shows narrow habitat specificity, using damp rock outcrops for laying eggs and residence (Wilson 2003).

Table 7. CCVI scores and global (G) and state (S) Conservation Status Ranks for amphibians in specific NPS units within the CUPN.

Species	G-Rank	S-Rank	Index	Park
Green Salamander (*Aneides aeneus*)	G3G4	S3	Moderately Vulnerable	CARL
Green Salamander (*Aneides aeneus*)	G3G4	S3	Moderately Vulnerable	LIRI
Green Salamander (*Aneides aeneus*)	G3G4	S3	Moderately Vulnerable	RUCA
Tennessee Cave Salamander (*Gyrinophilus palleucus*)	G2	S2	Presumed Stable	CUGA

Birds

Avian species represented the taxonomic group with the highest abundance of CCVI candidate species. Birds also contained the highest proportion of species with Index scores of PS or IL, with only eight MV to HV individuals out of 98 total assessments. The Red-Cockaded Woodpecker (*Picoides borealis*), a prominent species of conservation concern, displayed the highest vulnerability of all the bird species assessed. Causal factors included intensive forest management practices that neglect old-growth pine forests and increased efforts of fire suppression over the past several decades (Ligon et al. 1986). Further, this species has relatively short dispersal ranges to suitable habitat (Walters 1990). Factors important in promoting the vulnerability of the Canada warbler (*Wilsonia canadensis*) and dark-eyed junco (*Junco hyemalis*) include physiological hydrological niche space and modeled future habitat, respectively (American Ornithologists' Union 1998). In many regions, the Canada warbler habitat is localized to swamps, bogs, or forested wetlands (Miller 1999). The dark-eyed junco showed significant decreases in modeled future habitat that contributed heavily to its MV Index ranking (Matthews et al. 2011)

Long-distance dispersal capacity and a broad historical hydrological niche accounted, in part, for the substantial list of PS and IL individuals. Many long-distance migrants easily overcome both anthropogenic and natural barriers, resulting in a near ubiquitous "Neutral" ranking for the factors considering the effect of barriers on climate change vulnerability. The fact that these species live in diverse areas over the course of a single year necessitates a certain degree of ecological adaptability, including a wide dietary and habitat breadth. These factors weighed heavily in producing the abundance of PS and IL avian individuals.

Table 8. CCVI scores and global (G) and state (S) Conservation Status Ranks for birds in specific NPS units within the CUPN.

Species	G-Rank	S-Rank	Index	Park
Red-Cockaded Woodpecker (*Picoides borealis*)	G3	S2	Highly Vulnerable	CHCH
Red-Cockaded Woodpecker (*Picoides borealis*)	G3	S1	Highly Vulnerable	CUGA
Canada Warbler (*Wilsonia canadensi*)	G5	S3B	Moderately Vulnerable	ABLI
Canada Warbler (*Wilsonia canadensi*)	G5	S3B	Moderately Vulnerable	CUGA
Canada Warbler (*Wilsonia canadensi*)	G5	S3B	Moderately Vulnerable	MACA
Dark-eyed Junco (*Junco hyemalis*)	G5	S2S3B,S5N	Moderately Vulnerable	ABLI
Dark-eyed Junco (*Junco hyemalis*)	G5	S2S3B,S5N	Moderately Vulnerable	CUGA
Dark-eyed Junco (*Junco hyemalis*)	G5	S2S3B,S5N	Moderately Vulnerable	MACA
Bachman's Sparrow (*Aimophilia astivalis*)	G3	S2	Presumed Stable	CHCH
Bachman's Sparrow (*Aimophilia astivalis*)	G3	S1/S2b	Presumed Stable	CUGA
Bachman's Sparrow (*Aimophilia astivalis*)	G3	S1b	Presumed Stable	MACA
Bald Eagle (*Haliaeetus leucocephalus*)	G5	S2S3B,S3N	Presumed Stable	CUGA
Bald Eagle (*Haliaeetus leucocephalus*)	G5	S3B	Presumed Stable	LIRI
Bald Eagle (*Haliaeetus leucocephalus*)	G5	S2B,S2S3N	Presumed Stable	MACA
Bald Eagle (*Haliaeetus leucocephalus*)	G5	S3B	Presumed Stable	RUCA
Bank Swallow (*Riparia riparia*)	G5	S3B	Presumed Stable	MACA
Blackburnian Warbler (*Dendroica fusca*)	G5	S1S2B	Presumed Stable	ABLI
Blackburnian Warbler (*Dendroica fusca*)	G5	S1S2B	Presumed Stable	CUGA
Blackburnian Warbler (*Dendroica fusca*)	G5	S1S2B	Presumed Stable	MACA
Black-crowned Night-heron (*Nycticorax nycticorax*)	G5	S1S2B	Presumed Stable	MACA
Blue-winged Teal (*Anas discors*)	G5	S1,S2B	Presumed Stable	MACA
Brown Creeper (*Certhia americana*)	G5	S1S2B,S4S5N	Presumed Stable	ABLI
Brown Creeper (*Certhia americana*)	G5	S1S2B,S4S5N	Presumed Stable	CUGA
Brown Creeper (*Certhia americana*)	G5	S1S2B,S4S5N	Presumed Stable	MACA
Cerulean Warbler (*Dendroica cerulea*)	G4	S1	Presumed Stable	CHCH
Cerulean Warbler (*Dendroica cerulea*)	G4	S3B	Presumed Stable	CHCH
Cerulean Warbler (*Dendroica cerulea*)	G4	S3B	Presumed Stable	CUGA
Cerulean Warbler (*Dendroica cerulea*)	G4	S3B	Presumed Stable	FODO

Cerulean Warbler (*Dendroica cerulea*)	G4	S3B	Presumed Stable	SHIL
Cerulean Warbler (*Dendroica cerulea*)	G4	S3B	Presumed Stable	STRI
Common Moorhen (*Gallinula chloropus*)	G5	S1S2B	Presumed Stable	MACA
Common Moorhen (*Gallinula chloropus*)	G5	S1S2B	Presumed Stable	MACA
Common Raven (*Corvus corax*)	G5	S1,S2	Presumed Stable	CUGA
Golden Eagle (*Aquila chrysaetos*)	G5	S1	Presumed Stable	CUGA
Golden-crowned Kinglet (*Regulus satrapa*)	G5	S2B,S5N	Presumed Stable	CUGA
Henslow's Sparrow (*Ammodramus hanslowii*)	G4	S3B	Presumed Stable	MACA
Hooded Merganser (*Lophodytes cucullatus*)	G5	S1S2B,S3S4N	Presumed Stable	MACA
Magnolia Warbler (*Dendroica magnolia*)	G5	S1S2B	Presumed Stable	CUGA
Northern Harrier (*Circus cyaneus*)	G5	S1S2B,S3N	Presumed Stable	ABLI
Northern Harrier (*Circus cyaneus*)	G5	S1S2B,S3N	Presumed Stable	CUGA
Northern Harrier (*Circus cyaneus*)	G5	S1S2B,S3N	Presumed Stable	MACA
Northern Saw-whet Owl (*Aegolius acadicus*)	G5	S1	Presumed Stable	CUGA
Northern Saw-whet Owl (*Aegolius acadicus*)	G5	S1B, S2N	Presumed Stable	CUGA
Peregrine Falcon (*Falco peregrinus*)	G4	S1b,S1n,S2n	Presumed Stable	CUGA
Peregrine Falcon (*Falco peregrinus*)	G4	S1n	Presumed Stable	FODO
Pied-billed Grebe (*Podilymbus podiceps*)	G4	S1b, S4N	Presumed Stable	MACA
Rose-breasted Grosbeak (*Pheucticus ludovicianus*)	G4	S2S4B	Presumed Stable	ABLI
Rose-breasted Grosbeak (*Pheucticus ludovicianus*)	G4	S2S4B	Presumed Stable	CUGA
Rose-breasted Grosbeak (*Pheucticus ludovicianus*)	G4	S2S4B	Presumed Stable	MACA
Savannah Sparrow (*Passerculus sandwichensis*)	G5	S2S3B,S2S3N	Presumed Stable	MACA
Sedge Wren (*Cistorthorus platensis*)	G5	S3B	Presumed Stable	MACA
Swainson's Warbler (*Limnothlypis swainsonii*)	G4	S2B	Presumed Stable	CUGA
Vesper Sparrow (*Pooecetes gramineus*)	G5	S1B, S4N	Presumed Stable	CHCH
Vesper Sparrow (*Pooecetes gramineus*)	G5	S1B	Presumed Stable	MACA
American Coot (*Fulica americana*)	G5	S1B	Increase Likely	MACA
Bewick's Wren (*Thryomanes bewickii*)	G5	S1	Increase Likely	CHCH
Bewick's Wren (*Thryomanes bewickii*)	G5	S3B	Increase Likely	MACA
Bewick's Wren (*Thryomanes bewickii*)	G5	S1	Increase Likely	STRI
Cooper's Hawk (*Accipiter cooperii*)	G5	S3B, S4N	Increase Likely	LIRI
Cooper's Hawk (*Accipiter cooperii*)	G5	S3B, S4N	Increase Likely	RUCA
Golden-winged Warbler (*Vermivora chrysoptera*)	G5	S2B	Increase Likely	ABLI
Golden-winged Warbler (*Vermivora chrysoptera*)	G4	S1	Increase Likely	CHCH
Golden-winged Warbler (*Vermivora chrysoptera*)	G5	S2B	Increase Likely	CUGA
Golden-winged Warbler (*Vermivora chrysoptera*)	G5	S2B	Increase Likely	MACA
Great Egret (*Ardea alba*)	G5	S2B,S3N	Increase Likely	CHCH
Great Egret (*Ardea alba*)	G5	S2B,S3N	Increase Likely	FODO

Great Egret (*Ardea alba*)	G5	S2B,S3N	Increase Likely	SHIL
King Rail (*Rallus elegans*)	G4	S1B	Increase Likely	MACA
Lark Sparrow (*Chondestes grammacus*)	G5	S2S3B	Increase Likely	ABLI
Least Flycatcher (*Epidonax minimus*)	G5	S1B	Increase Likely	ABLI
Least Flycatcher (*Epidonax minimus*)	G5	S1B	Increase Likely	CUGA
Least Flycatcher (*Epidonax minimus*)	G5	S1B	Increase Likely	MACA
Little Blue Heron (*Egretta caerulea*)	G5	S2B,S3N	Increase Likely	FODO
Little Blue Heron (*Egretta caerulea*)	G5	S1B	Increase Likely	MACA
Little Blue Heron (*Egretta caerulea*)	G5	S2B,S3N	Increase Likely	SHIL
Mississippi Kite (*Ictinia mississippiensis*)	G5	S2S3	Increase Likely	FODO
Olive-sided Flycatcher (*Contopus cooperi*)	G4	S1	Increase Likely	CHCH
Olive-sided Flycatcher (*Contopus cooperi*)	G4	S1	Increase Likely	CUGA
Osprey (*Pandion haliaetus*)	G5	S2S3B	Increase Likely	ABLI
Osprey (*Pandion haliaetus*)	G5	S2S3B	Increase Likely	CUGA
Osprey (*Pandion haliaetus*)	G5	S2S3B	Increase Likely	MACA
Red-Breasted Nuthatch (*Sitta canadensis*)	G5	S1B	Increase Likely	ABLI
Red-Breasted Nuthatch (*Sitta canadensis*)	G5	S1B	Increase Likely	CUGA
Red-Breasted Nuthatch (*Sitta canadensis*)	G5	S1B	Increase Likely	MACA
Sharp-Shinned Hawk (*Accipiter striatus*)	G5	S3B, S4N	Increase Likely	ABLI
Sharp-Shinned Hawk (*Accipiter striatus*)	G5	S3B	Increase Likely	CHCH
Sharp-Shinned Hawk (*Accipiter striatus*)	G5	S3B	Increase Likely	CUGA
Sharp-Shinned Hawk (*Accipiter striatus*)	G5	S3B	Increase Likely	FODO
Sharp-Shinned Hawk (*Accipiter striatus*)	G5	S3B, S4N	Increase Likely	MACA
Sharp-Shinned Hawk (*Accipiter striatus*)	G5	S3B	Increase Likely	SHIL
Sharp-Shinned Hawk (*Accipiter striatus*)	G5	S3B	Increase Likely	STRI
Snowy Egret (*Egretta thula*)	G5	S2B,S3N	Increase Likely	SHIL
Winter Wren (*Troglodytes troglodytes*)	G5	S2B,S4N	Increase Likely	CUGA
Yellow-bellied Sapsucker (*Sphyrapicus varius*)	G5	S1B, S4N	Increase Likely	CHCH
Yellow-bellied Sapsucker (*Sphyrapicus varius*)	G5	S1B, S4N	Increase Likely	CUGA
Yellow-bellied Sapsucker (*Sphyrapicus varius*)	G5	S1B, S4N	Increase Likely	FODO
Yellow-bellied Sapsucker (*Sphyrapicus varius*)	G5	S1B, S4N	Increase Likely	SHIL
Yellow-bellied Sapsucker (*Sphyrapicus varius*)	G5	S1B, S4N	Increase Likely	STRI

Fish

A total of six at-risk fish were assessed in this study, two of which resulted in vulnerable index scores (MV and HV) (Table 7). Geographic isolation and anthropogenic barriers were important factors in limiting the dispersal of both the Southern cavefish (*Typhlichthys subterraneus*) and the Carolina darter (*Etheostoma collis*). Particular barriers for dispersal include developments, dams, and areas experiencing poor water quality. For the cavefish, pollution and groundwater pollution in caves puts the species in further risk of anthropogenic effects in addition to climate change (Boschung and Mayden 2004). All four other fish species assessed were PS, with increased dispersal ability playing an important role in neutralizing vulnerability.

Table 9. CCVI scores and global (G) and state (S) Conservation Status Ranks for fish in specific NPS units within the CUPN.

Species	G-Rank	S-Rank	Index	Park
Southern Cavefish (*Typhlichthys subterraneus*)	G4	S2S3	Highly Vulnerable	MACA
Carolina Darter (*Etheostoma collis*)	G3	SNR	Moderately Vulnerable	KIMO
Blue Shiner (*Cyprinella caerulea*)	G2	S1	Presumed Stable	LIRI
Mountain Blackside Dace (*Phoxinus cumberlandensis*)	G2	S1S2	Presumed Stable	CUGA
Spotted Darter (*Etheostoma maculatum*)	G2	S2	Presumed Stable	MACA
Western Sand Darter (*Ammocrypta clara*)	G3	S1	Presumed Stable	CUGA

Mammals

Out of the nineteen mammals run through the CCVI, 12 produced MV to HV rankings (Table 8). Out of these twelve, ten were bat species. For the bats, the physical habitat (i.e. caves), anthropogenic barriers, susceptibility to disturbance, and diet were factors that resulted in their vulnerability. Physiological hydrological niche contributed to vulnerability for the gray myotis (*Myotis grisescens*), as the species procures food near riparian areas that are negatively affected by insecticides and pesticides (Northern Prairie Wildlife Research Center 2006). For Rafinesque's big-eared bat (*Corynorhinus rafinesquii*), the species' intolerance of natural and anthropogenic disturbance events at their roosting sites contributed to its MV and HV Index scores (Harvey 1991). Not all bats were vulnerable, however, as the Eastern small-footed myotis (*Myotis leibii*) and the Indiana bat (*Myotis sodalist*) both received PS Index scores. Interestingly, the Eastern spotted skunk (*Spilogale putorius*) was the only non-bird species assessed as IL, due in large part to its dietary behavior as an opportunistic omnivore (Caire et al. 1989). The remaining four CCVI runs on non-bat species yielded PS scores.

Table 10. CCVI scores and global (G) and state (S) Conservation Status Ranks for mammals in specific NPS units within the CUPN.

Species	G-Rank	S-Rank	Index	Park
Rafinesque's Big-eared Bat (*Corynorhinus rafinesquii*)	G3G4	S3	Highly Vulnerable	MACA
Rafinesque's Big-eared Bat (*Corynorhinus rafinesquii*)	G3G4	S3	Moderately Vulnerable	CUGA
Rafinesque's Big-eared Bat (*Corynorhinus rafinesquii*)	G3G4	S3	Moderately Vulnerable	SHIL
Southeastern myotis (*Myotis austroriparius*)	G3G4	S1S2	Moderately Vulnerable	MACA
Gray Myotis (*Myotis grisescens*)	G3	S1S2	Moderately Vulnerable	CHCH
Gray Myotis (*Myotis grisescens*)	G3	S1S2	Moderately Vulnerable	CUGA
Gray Myotis (*Myotis grisescens*)	G3	S1S2	Moderately Vulnerable	FODO
Gray Myotis (*Myotis grisescens*)	G3	S2	Moderately Vulnerable	LIRI
Gray Myotis (*Myotis grisescens*)	G3	S2	Moderately Vulnerable	MACA
Gray Myotis (*Myotis grisescens*)	G3	S2	Moderately Vulnerable	SHIL
Eastern Spotted Skunk (*Spilogale putorius*)	G5	S2S3	Increase Likely	CUGA
Southeastern Shrew (*Sorex longirostris*)	G5	S4	Presumed Stable	SHIL
Southeastern Shrew (*Sorex longirostris*)	G5	S4	Presumed Stable	STRI
Southeastern Shrew (*Sorex longirostris*)	G5	S4	Presumed Stable	CHCH
Eastern Small-footed Myotis (*Myotis leibii*)	G3	S2	Presumed Stable	CUGA
Eastern Small-footed Myotis (*Myotis leibii*)	G3	S2	Presumed Stable	MACA
Indiana Bat (*Myotis sodalis*)	G2	S1S2	Presumed Stable	CUGA
Indiana Bat (*Myotis sodalis*)	G2	S1S2	Presumed Stable	MACA
Allegheny Woodrat (*Neotoma magister*)	G3G4	S3	Presumed Stable	CUGA

Mollusks

All thirteen mollusk species evaluated with the CCVI were classified in one of the vulnerability categories (MV, HV, or EV) (Table 11). Factors that tended to increase mollusk vulnerability to climate change included natural and anthropogenic barriers along with dispersal and movement due to the sessile behavior of mollusks. Mollusks also rely on fish for larvae dispersal, and species such as clubshell (*Pleurobema clava*) and the northern riffshell (*Epioblasma torulosa rangiana*) are particularly vulnerable because they rely on only a few fish hosts. The presence of a dam and lock system on the Green River in Mammoth Cave National Park contributes to the barriers and river impoundment that makes these species vulnerable (Harmon 2006). Furthermore, physiological thermal niche and disturbance also factored into mollusk vulnerability, as mollusks generally require cool water temperatures and good water quality to survive – traits that might change if temperature, extreme weather events, and other disturbances increase with climate change. Pocketbook (*Lampsilis ovate*) was the only species to be MV because it has more generalized habitat requirements and adapts well to impounded rivers.

Table 11. CCVI scores and global (G) and state (S) Conservation Status Ranks for mollusks in specific NPS units within the CUPN.

Species	G-Rank	S-Rank	Index	Park
Snuffbox (*Epioblasma triquetra*)	G3	S1	Extremely Vulnerable	MACA
Ring Pink (*Obovaria restusa*)	G1	S1	Extremely Vulnerable	MACA
Rough Pigtoe (*Pleurobema plenum*)	G1	S1	Extremely Vulnerable	MACA
Northern Riffleshell (*Epioblasma torulosa rangiana*)	G2T2	S1	Extremely Vulnerable	MACA
Kentucky Creekshell (*Villosa ortmanni*)	G2	S2	Extremely Vulnerable	MACA
Clubshell (*Pleurobema clava*)	G1G2	S1	Extremely Vulnerable	MACA
Spectaclecase (*Cumberlandia monodonta*)	G3	S1	Extremely Vulnerable	MACA
Pyramid Pigtoe (*Pleurobema rubrum*)	G2G3	S1	Highly Vulnerable	MACA
Sheepnose (*Plethobasus cyphyus*)	G3	S1	Highly Vulnerable	MACA
Pink Mucket (*Lampsilis abrupta*)	G2	S1	Highly Vulnerable	MACA
Fanshell (*Cyprogenia stegaria*)	G1	S1	Highly Vulnerable	MACA
Longsolid (*Fusconaia subrotunda*)	G3	S3S4	Highly Vulnerable	MACA
Pocketbook (*Lampsilis ovata*)	G5	S1	Moderately Vulnerable	MACA

Reptiles

The pine snake (*Pituophis melanoleucus*) was the only reptilian candidate species in the CUPN assessed (Table 11). With habitat preferences for dry, sandy shrubland and well-drained open pine forests that are likely to remain stable with the onset of climate change, this species assessment generated a PS Index rating. The ecology of this species, however, remains relatively unknown compared to other species of reptile (Burger 1990). Because of the small sample of at-risk reptiles, this species should not be considered representative of all reptiles in the CUPN.

Table 12. CCVI scores and global (G) and state (S) Conservation Status Ranks for reptiles in specific NPS units within the CUPN.

Species	G-Rank	S-Rank	Index	Park
Pine Snake (*Pituophis melanoleucus*)	G4	S3S4	Presumed Stable	NISI

Plants

Just over half the twelve plants run through the CCVI yielded MV to HV CCVI scores. The abundance and range of butternut (*Juglans cinerea*), a HV species, has suffered heavily in recent years due to the infliction of the fungus known as butternut canker disease (*Sirococcus clavigignenti-juglandacearum*) (Skilling 1992). Heartleaf plantain also received an HV ranking. The plant has limited dispersal ability and is susceptible to changes in water quality resulting from agricultural activities (NatureServe 2011). Another species, the large-flower skullcap (*Scuttellaria montana*), received a MV ranking due to its narrow environmental specificity, which includes poor competitive ability and sensitivity to specific light regimes. Additionally, this plant has displayed a high susceptibility to disturbance in its rocky habitat. Skullcap may also benefit from fire, although often does poorly in early successional systems (Collins 1976). Anthropogenic barriers, including agriculture and intensive timber management, act as effective barriers to the dispersal of many of the plants in old-growth forests. Other factors playing prominent roles in the vulnerability rankings of these plants include competition with exotic invasive species, adverse effects of disturbance, and narrow physiological hydrological niche.

Table 13. CCVI scores and global and state conservation status ranks for plants in specific National Parks within the Cumberland Piedmont Network.

Species	G-Rank	S-Rank	Index	Park
Butternut (*Juglans cinerea*)	G4	S2S3	Highly Vulnerable	MACA
Butternut (*Juglans cinerea*)	G4	S2S3	Highly Vulnerable	STRI
Heartleaf Plantain (*Plantago cordata*)	G4	S1	Highly Vulnerable	CHCH
Butternut (*Juglans cinerea*)	G4	S2S3	Moderately Vulnerable	CUGA
Cutleaf Meadow-Parsnip (*Thaspium pinnatifidum*)	G2G3	S1	Moderately Vulnerable	CHCH
Cypress-Knee Sedge (*Carex decomposita*)	G3G4	S2	Moderately Vulnerable	MACA
Large-flower Skullcap (*Scutellaria montana*)	G3	S2	Moderately Vulnerable	CHCH
Bearded Skeletongrass (*Gymnopogon ambiguus*)	G4	S2S3	Presumed Stable	MACA
French's Shootingstar (*Dodecatheon frenchii*)	G3	S3	Presumed Stable	MACA
Ill-scented Wakerobin (*Trillium rugelii*)	G3	S2	Presumed Stable	FODO
Oglethorpe's Oak (*Quercus oglethorpensis*)	G3	S3	Presumed Stable	NISI
Traveler's Delight (*Apios priceana*)	G2	S2	Presumed Stable	FODO

4.2 Habitat Suitability Modeling

4.2.1 Aneides *aeneus* (Green Salamander)

MaxEnt

The current, 2050, and 2080 green salamander habitat projections are generated from the same model; therefore, all projections have the same ROC curves, variable weights, and thresholds. This model has a training area under the curve (AUC) of 0.961 and a test data AUC of 0.944. However, it is important to note that, because MaxEnt does not use true absences, the ROC curve produced is based on sensitivity and the proportion of background cases predicted to be "habitat." Thus, it is not what is considered to be a true ROC curve and cannot be compared to the ROC curves of other models. Additionally, because our geographic extent was larger than the green salamander's current range, the AUC may be inflated because the model may be predicting non-habitat well at the expense of correctly predicting habitat (Smart, NatureServe, pers. comm. 2012)

Therefore, we looked at the sensitivity of the model (true positive rate) to assess model performance. For this model, the sensitivity is 0.975 for the training data and 0.957 for the test data (based on a threshold of 0.026 habitat probability). Therefore, the model correctly predicts suitable conditions for the green salamander that encompass 97.5% of the occurrences for the training run and 95.7% of the occurrences for the test run (30% of the original presence points were held back to test the model).

In this model, precipitation in the driest quarter has the largest relative contribution of all the variables (Table 14). Additionally, based on the results of jack-knifing, both precipitation in the driest quarter and annual precipitation are very important variables (Appendix D: Figure 1). These two variables had the highest gain when a model was constructed using each alone, which means that these variables contain unique information with high predictive power. Conversely, TRMI appears to be the least important predictor in this model, both in terms of percent contribution and gain in jackknifing.

Table 14. Estimates of relative contribution of each variable in the training model for the green salamander (*Aneides aeneus*).

Environmental Variables Used in Modeling	Percent Contribution
Precipitation Driest Quarter (BIO17)	54.2
Annual Precipitation (BIO2)	26.4
Max Temperature Warmest Month (BIO5)	10.4
Precipitation Coldest Quarter (BIO19)	6.9
Mean Temperature Driest Quarter (BIO9)	2
TRMI	0

The predicted area of suitable habitat (based on a threshold of 0.026 habitat probability) decreases substantially between the present and 2080 (Figures 7 and 8). The range of suitable habitat contracts in the future and shifts out of the CUPN into the southern Appalachian Mountains. It is worth reiterating that this model's projections reflect habitat areas that are *climatically* suitable. This does not necessarily coincide with the species' realized niche due to other important variables such as biotic interactions and microhabitat conditions.

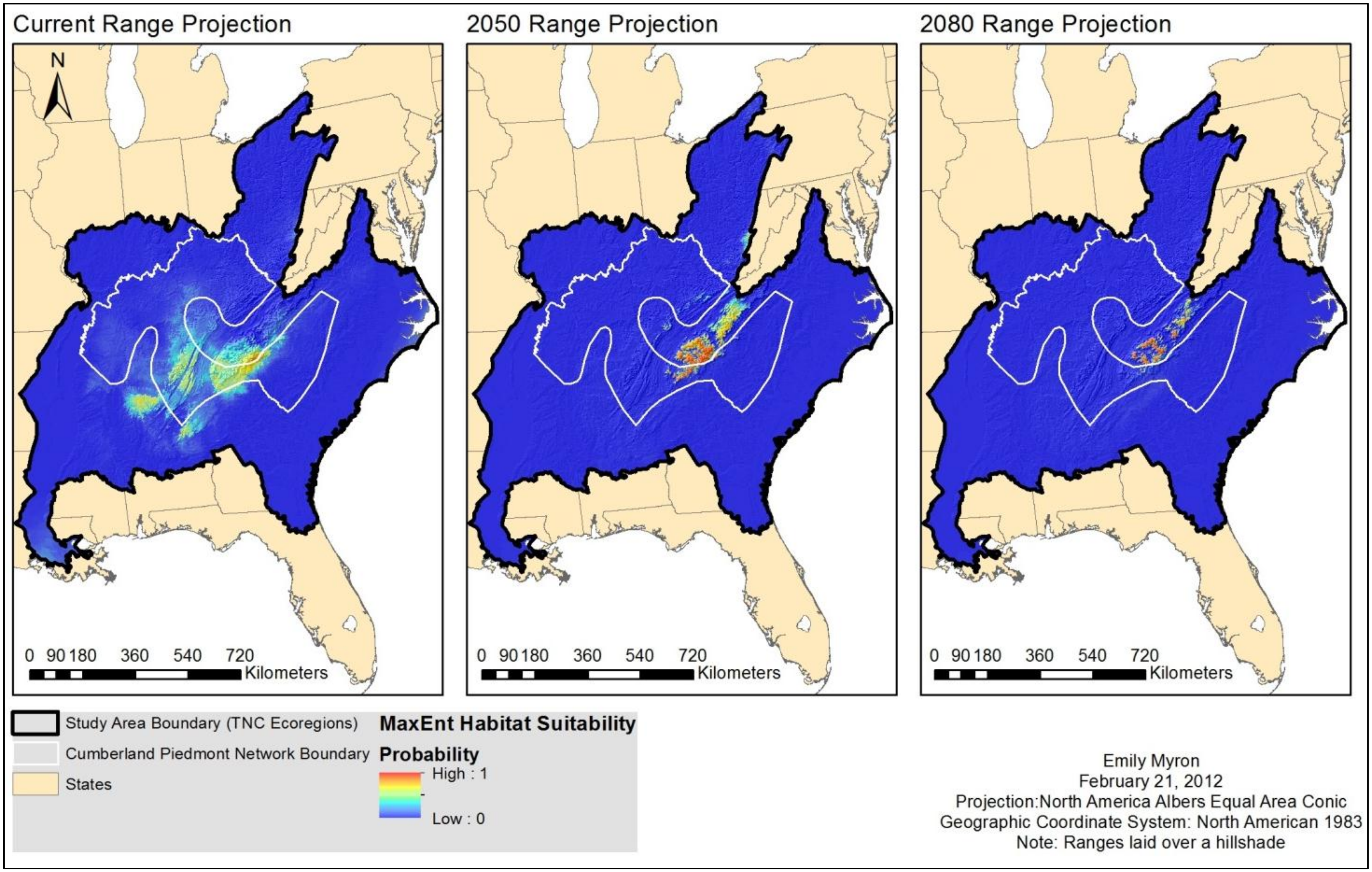


Figure 7. MaxEnt habitat suitability surface for the green salamander (*Aneides aeneus*). Red indicates a high probability of suitable habitat.

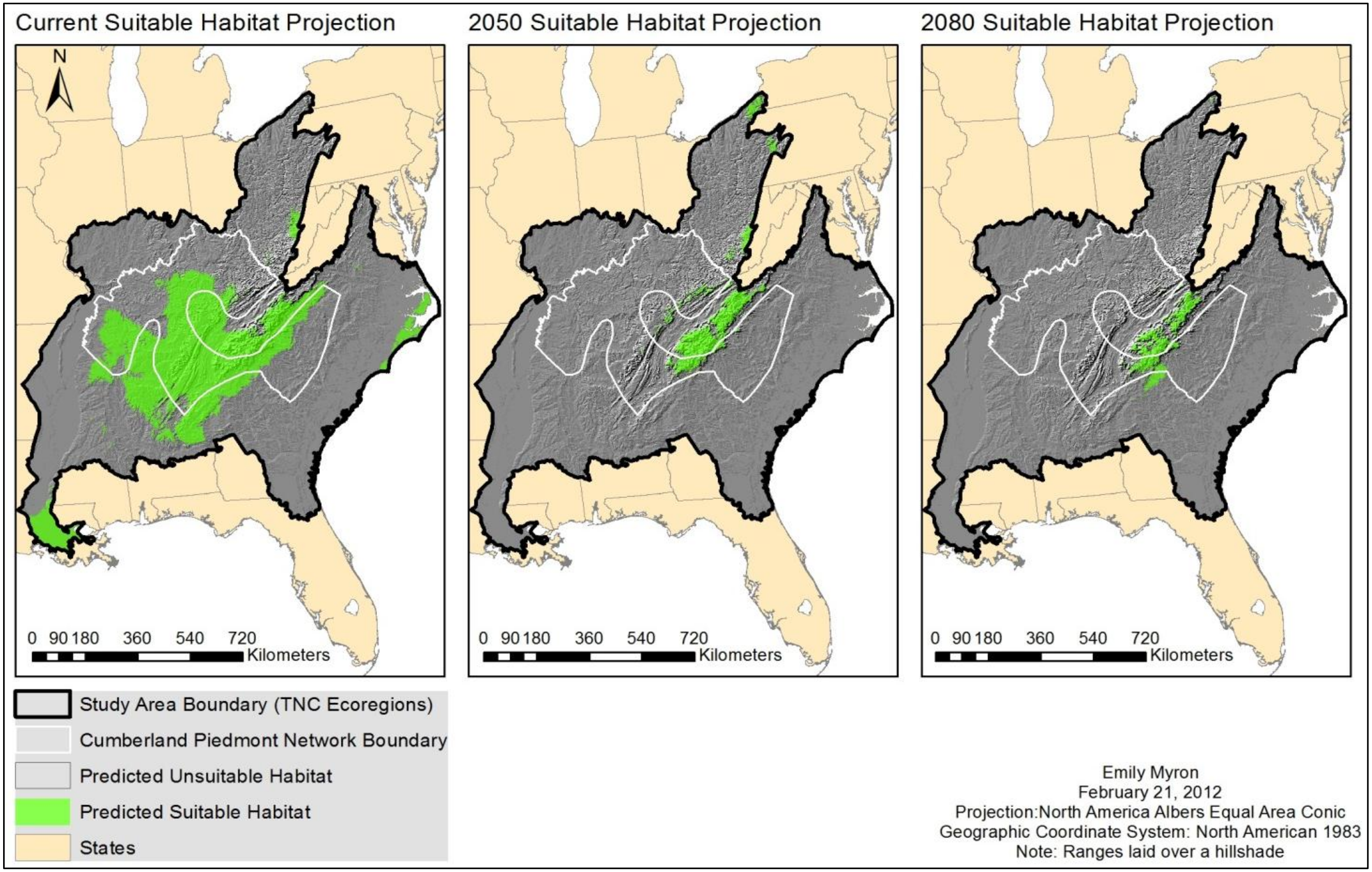


Figure 8. MaxEnt habitat suitability projections for the green salamander (*Aneides aeneus*). Binary predictions based on a threshold of 0.026 to balance training omission, predicted area and threshold value.

MaxEnt handles novel combinations of bioclimatic variables by restricting the predictions to the range of combinations used to train the model (Phillips[16]). MaxEnt calls this 'clamping,' and we have less confidence in the predictions in areas that have been clamped because we cannot predict how species will respond to novel climate conditions. This is crucial to note because some areas of high clamping coincide heavily with those areas predicted to be green salamander habitat in 2080 (Figure 9; full clamping maps can be found in Appendix D: Figure 2); therefore, predictions in these areas likely less certain.

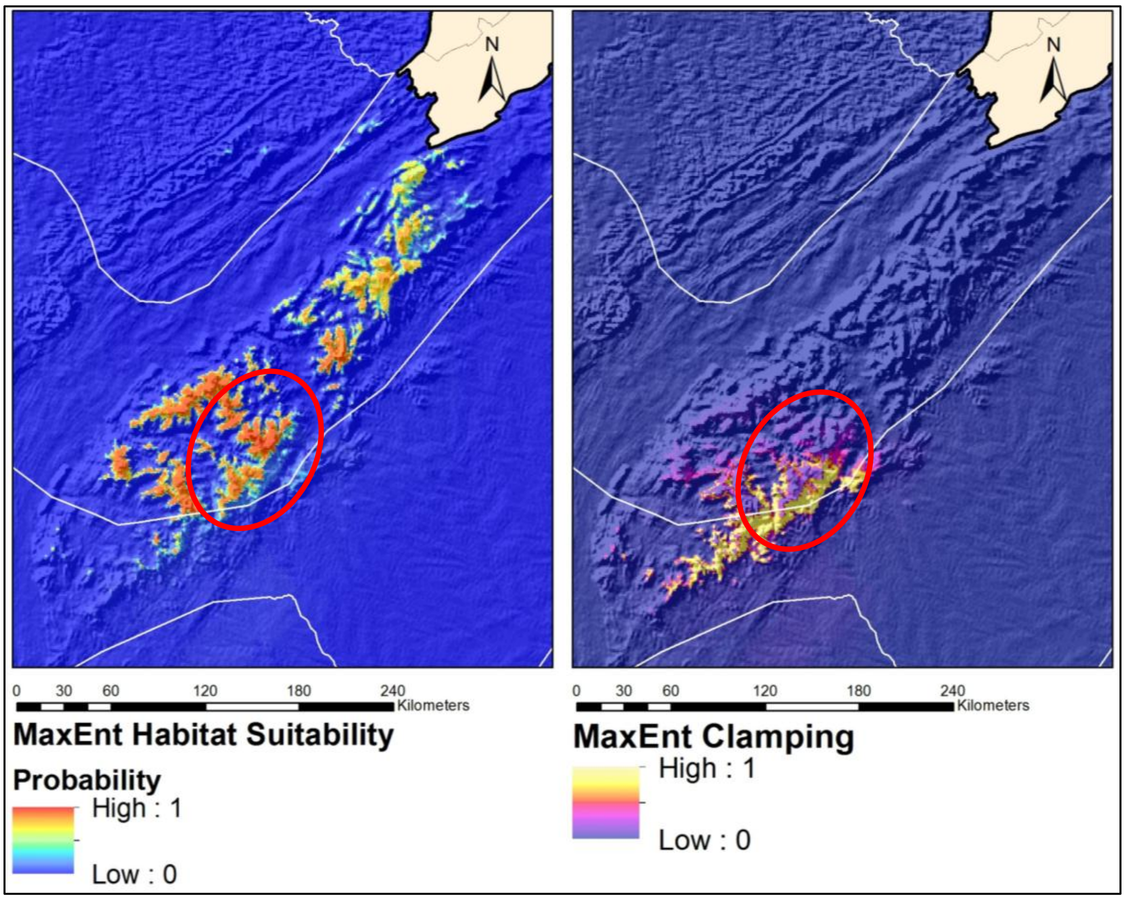


Figure 9. Predicted green salamander habitat suitability in 2080 and areas of clamping. The red circles indicate an example of where an area of high clamping (uncertainty due to novel climatic conditions) and high habitat probability coincide; we are less confident in these habitat predictions than those in areas of less clamping.

Biomod Ensemble

Each of the five models selected precipitation of driest quarter as the most important predictor variable and eliminated TRMI from consideration (Table 14 and Appendix E). This confirms our exploratory data analysis, which assigned the highest correlation coefficient (P-

[16] A Brief Tutorial on Maxent. Available at http://www.cs.princeton.edu/~schapire/maxent/

value < 0.05) to precipitation of driest quarter and one of the lowest correlation coefficents (p-value < 0.05) to TRMI (Appendix C: Figure 2).

The sensitivity score is an indicator of a good model when using species occurrence points and pseudo-absence (as opposed to true absence points) because it quantifies how well the model classified true species occurrence points as suitable habitat (Table 15). Each of our models performed well given this scoring method (Table 15).

The first ensemble approach, the ensemble average, shows a probability surface constrained around the southern Appalachian Mountains (Figure 10). The second ensemble approach, the areas of binary habitat agreement, illustrates the vast discrepancies between the different modeling techniques (Figure 11). The GLM is the least constrained of the models because the automatic stepwise regression resulted in the elimination of two environmental variables from the final model (to achieve parsimony). The rest of the models in the ensemble retained all five of the original environmental variables; however the differences are still marked. Suitable climatic range reaches into southern Louisiana for some of the models, but is constrained to the southern Appalachian region in other models.

Table 15: Sensitivity scores for test data for each of the 5 models in the ensemble for the green salamander (*Aneides aeneus*).

Model	Sensitivity Score
CTA	91.071
GAM	89.286
GBM	89.796
GLM	87.5
MaxEnt	95.7

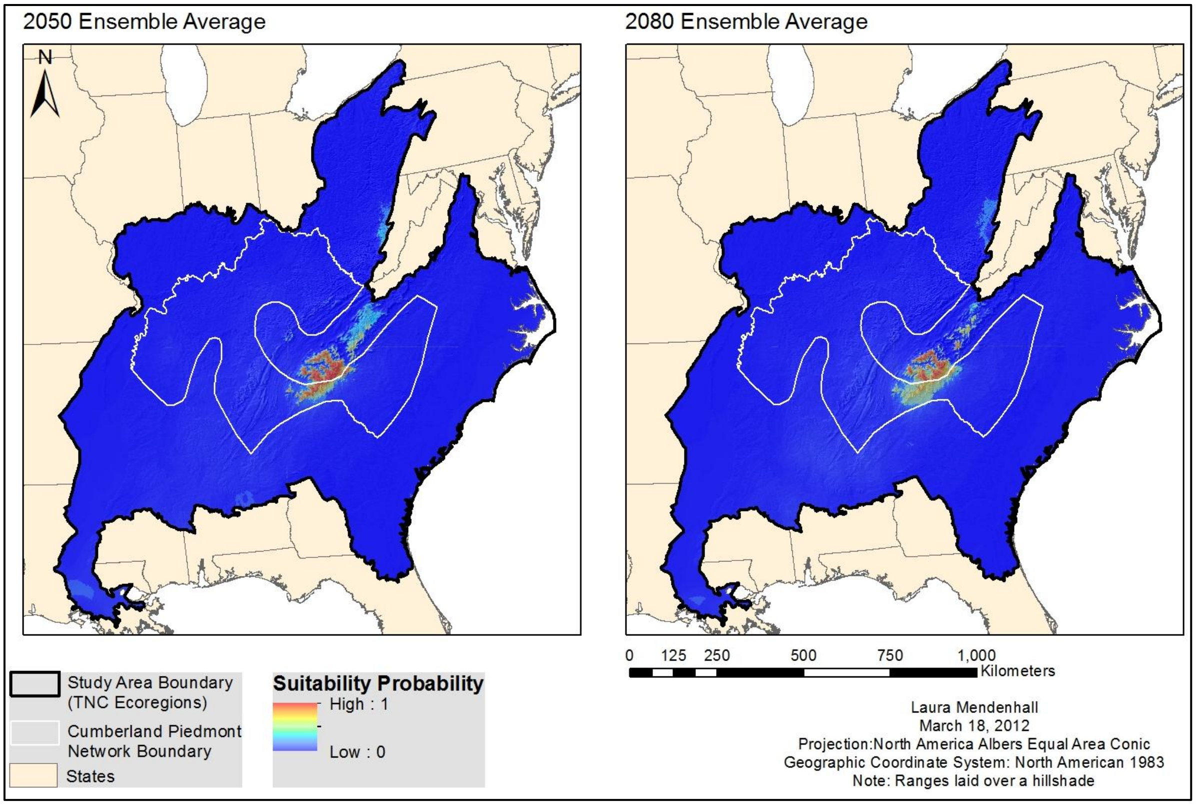


Figure 10. Mean taken across the probability surfaces all 5 models of the ensemble. Red indicates high probability of climatic suitability for the green salamander (*Aneides aeneus*).

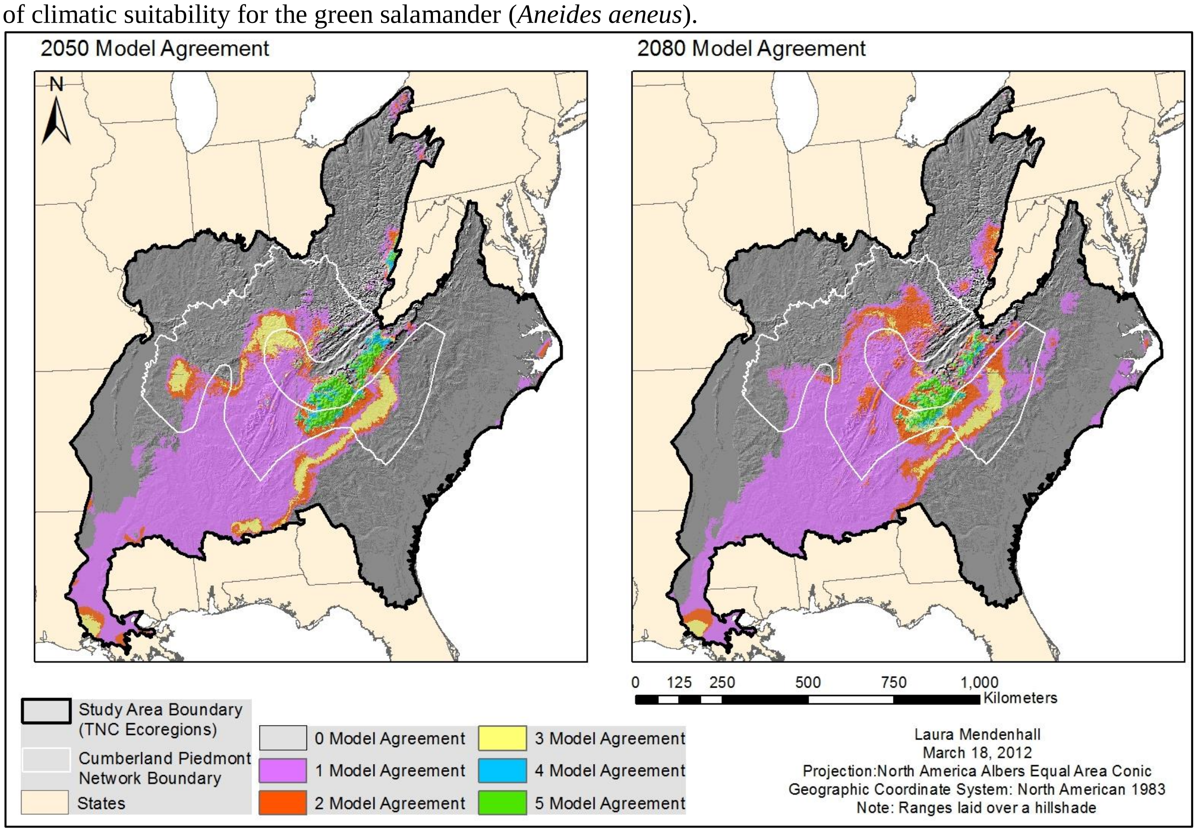


Figure 11. Areas of agreement for MaxEnt, CTA, GLM, GAM, GBM models. Green areas indicate consensus across all five models for suitable green salamander (*Aneides aeneus*) habitat.

Summary

Currently, NPS records cite the green salamander in two Park Service units (LIRI and CARL), with potential presence in a third Park Service unit (RUCA). MaxEnt predicts suitable habitat in all of these Park Service units (Table 16). However, MaxEnt noticeably over-predicts current salamander suitable habitat when compared to where the salamander is actually presumed present (Table 16).

Overlaying the binary predictions of each model algorithm allows us to compare which CUPN units may contain suitable green salamander habitat in the future. MaxEnt and the ensemble consensus (using all five models) show rather compatible results with respect to future habitat predictions (Table 16). Both techniques predict that LIRI and RUCA will lose their habitat (and potential habitat, respectively). MaxEnt predicts that suitable habitat will remain in CARL through 2080, but the ensemble consensus does not show this result. Interestingly, both techniques predict suitable habitat in CUGA, at least into 2050; however, the green salamander is not currently found in this NPS unit.

These differences are also reflected in the total predicted area of salamander habitat within the CUPN using MaxEnt (based on a threshold of 0.026) and the ensemble. The ensemble consensus for 2050 and 2080 contains about half as much suitable habitat than the respective MaxEnt predictions (Table 17). However, both methods show a substantial decrease in suitable habitat within the CUPN between now and 2080.

Table 16. Results of MaxEnt and ensemble model output (consensus of all 5 models) for each park within the CUPN. An "X" means that suitable green salamander habitat was predicted to be within that park. This does not reflect the amount of suitable habitat within each park. (Key to Park abbreviations can be found in Table 2).

		MaxEnt			Ensemble Consensus	
National Park	**NPS Records**	**Current**	**2050**	**2080**	**2050**	**2080**
ABLI		X				
CARL	X	X	X	X		
CHCH		X				
COWP		X				
CUGA		X	X	X	X	
FODO						
GUCO						
KIMO		X				
LIRI	X	X				
MACA		X				
NISI						
RUCA	X	X				
SHIL						
STRI						

Table 17. Predicted area of suitable habitat for the green salamander within the CUPN.

	Suitable Habitat Area (km^2)	
Projection	**MaxEnt**	**Ensemble Consensus**
Current	109,978	n/a
2050	7,274	4,164
2080	5,326	2,852

4.2.2 *Scutellaria montana* (Large Flowered Skullcap)

MaxEnt

The large-flowered skullcap model has a training area under the curve (AUC) of 0.990 and a test data AUC of 0.990. Again, MaxEnt does not produce a true ROC curve and may have inflated AUC values. Therefore, as with the green salamander, it is more beneficial to look at model sensitivity than model AUC. This model had a true positive rate of 1 for both the training and test data. This means that it correctly predicts skullcap presences 100% of the time given the data we used to train and test the model.

In this model, mean temperature in the wettest quarter has the largest relative contribution of all the variables (Table 18). Additionally, based on the results of jack-knifing, both mean temperature in the wettest quarter and soils are very important variables (Appendix D: Figure 3). These two variables had the highest gain when a model was constructed using each alone, meaning that these variables contain unique information with high predictive power. Conversely, precipitation in the driest quarter appears to be the least important predictor in this model in terms of percent contribution (Table 18), and TRMI appears least important in terms of gain in jack-knifing (Appendix D: Figure3).

By 2080, there is very little suitable habitat left for the skullcap (Figures 12 and 13). Even in areas that may be habitat based on our threshold (Figure 13), the probability of bioclimatic suitability in those areas is very low (almost indistinguishable from zero habitat probability on the probability surface) (Figure 12).Very little clamping occurred in the projection of this model; therefore, we do not expect novel combinations of climatic variables to highly influence our habitat probability projections. (Appendix D: Figure 4).

Table 18. Estimates of relative contribution of each variable in the training model the green salamander within the CUPN.

Environmental Variables Used in Modeling	Percent Contribution
Mean Temperature Wettest Quarter (BIO8)	87
Soils	9.6
Precipitation Wettest Quarter (BIO16)	1.8
Precipitation Driest Month (BIO14)	1.2
TRMI	0.4
Precipitation Driest Quarter (BIO17)	0.1

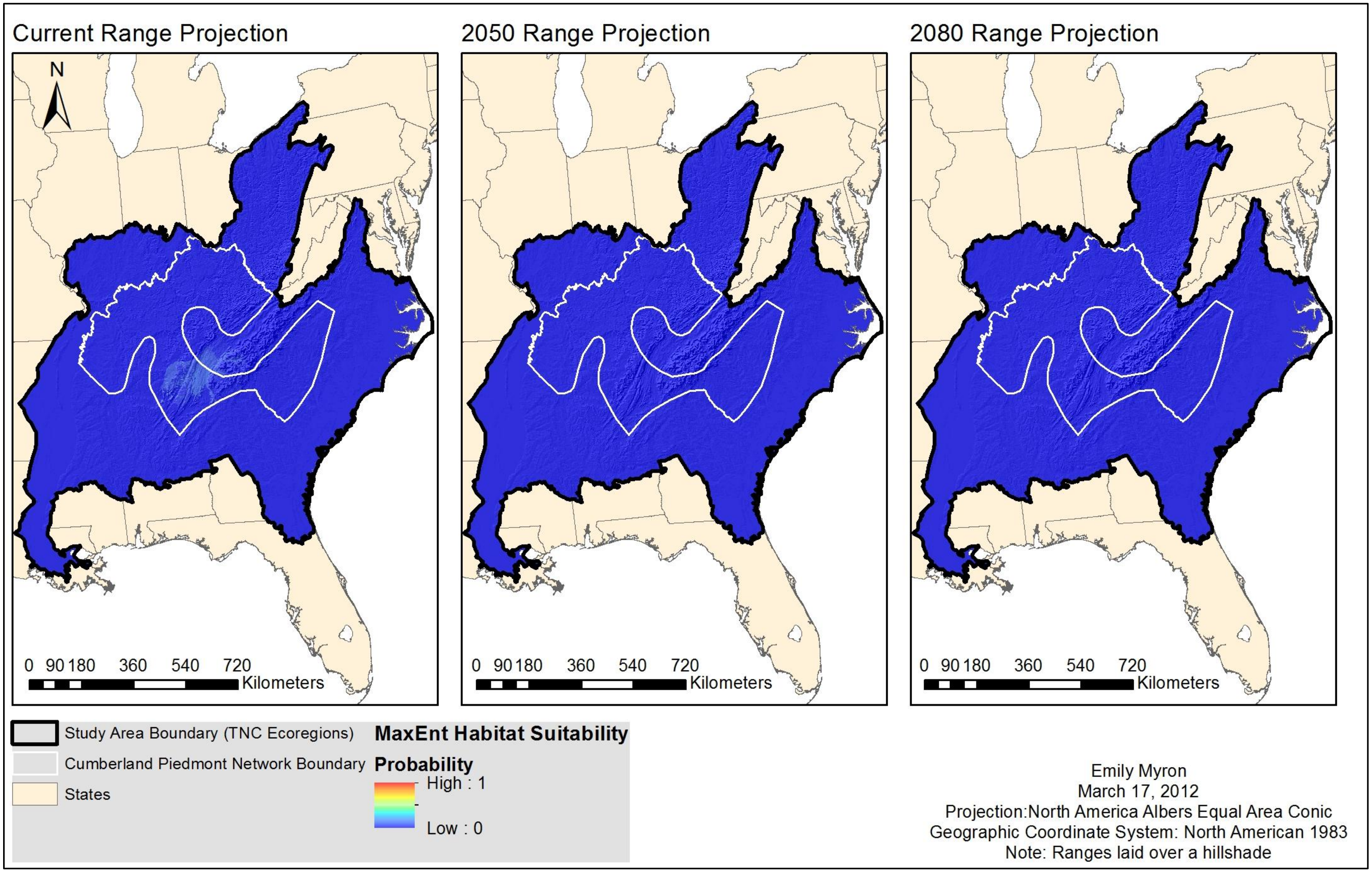


Figure 12. MaxEnt habitat suitability surface for large-flowered skullcap (*Scutellaria montana*). Red indicates high probability of climatic suitability.

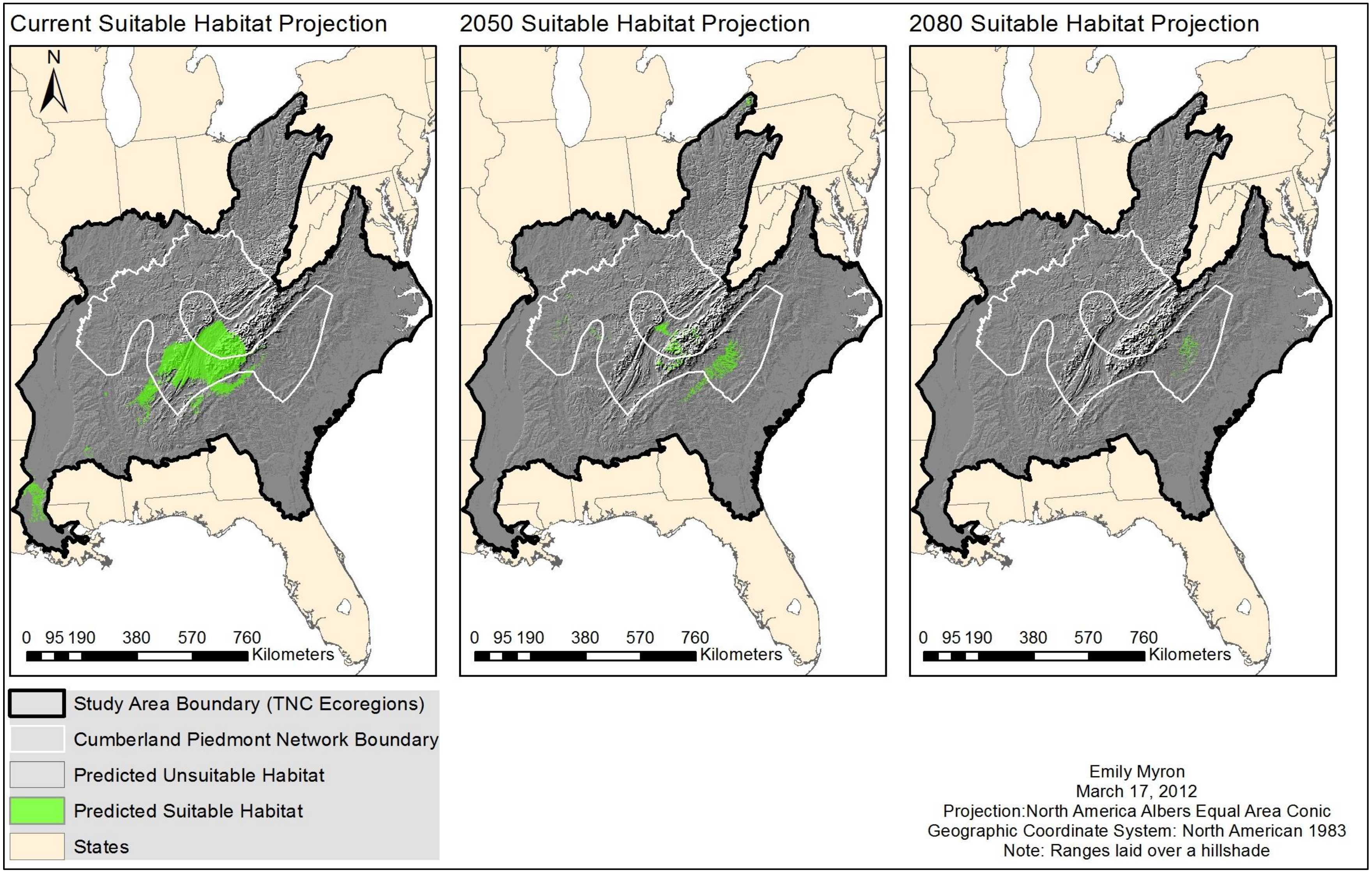


Figure 13. MaxEnt habitat suitability projections for large-flowered skullcap (*Scutellaria montana*). Binary predictions based on a threshold of 0.002 to balance training omission, predicted area and threshold value.

Biomod Ensemble

Four out of five models selected mean temperature of wettest quarter as the most important predictor variable (GAM is the exception) (Table 18 and Appendix E: Figure 4). The GLM eliminated soil from consideration (Appendix E: Figure 3). This confirms our exploratory data analysis which suggested mean temperature of wettest quarter was the highest correlated (p-value < 0.05) with species presence while soil was not significantly correlated (Appendix C: Figure 3). The sensitivity scores are relatively comparable, so the confidence across model performance is good (Table 19).

Both of the ensemble approaches show significant range contraction within our study area (Figures 14 and 15). The model agreement approach shows no areas where all five of the models within our ensemble agree. The mean across all five models resulted in no areas predicted with a high probability of suitable conditions.

Table 19: Sensitivity scores for each of the 5 models used in the ensemble for large-flowered skullcap (*Scutellaria montana*).

Model	Sensitivity Score
CTA	98.214
GAM	98.214
GBM	98.81
GLM	96.429
MaxEnt	100

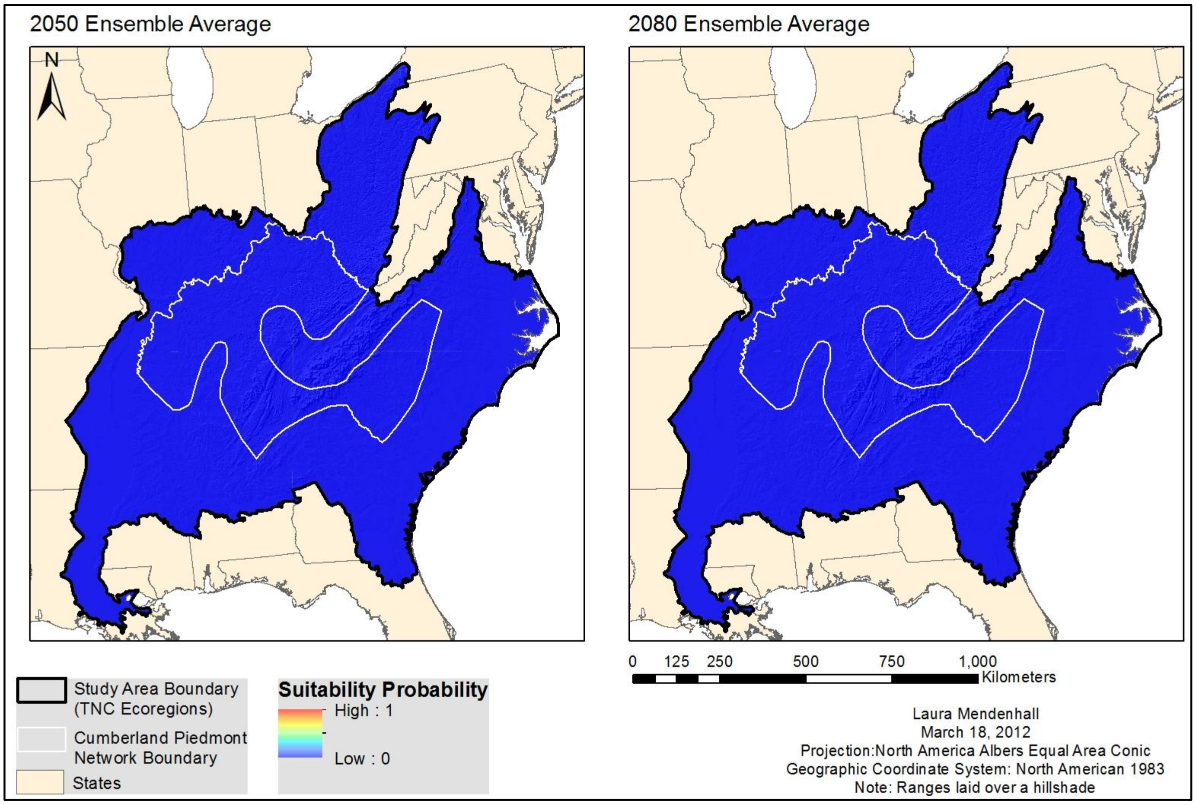


Figure 14. Mean taken across the probability surfaces of all five models. Red areas indicate high climatic suitability for large-flowered skullcap (*Scutellaria montana*).

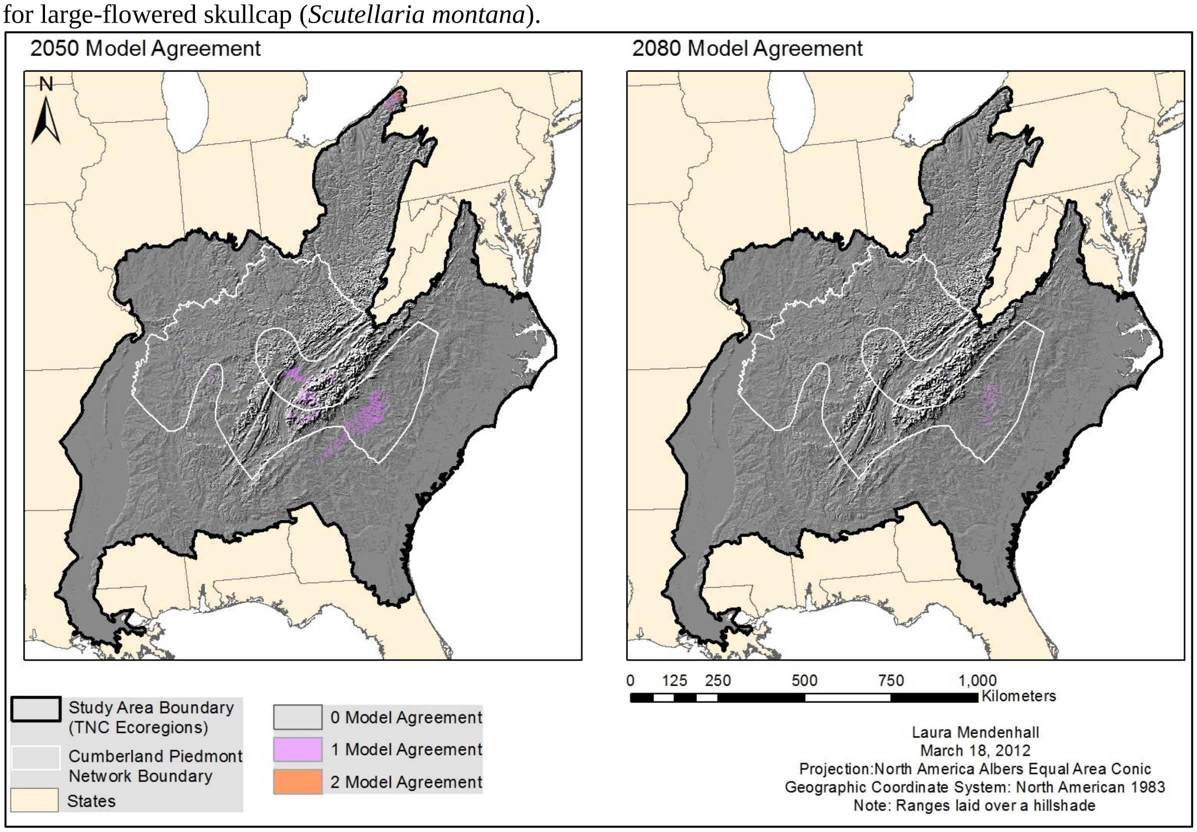


Figure 15. Ensemble of MaxEnt, CRT, GLM, GAM, GBM models for large-flowered skullcap. The highest consensus was only between two models, shown in orange (*Scutellaria montana*).

Summary

Currently, NPS records indicate the large-flower skullcap occurs in one CUPN unit, CHCH, which is confirmed by our MaxEnt projection (Table 20). However, the bioclimatic range of this species is likely to shift. In the 2050 and 2080 predictions, the suitable skullcap habitat is only found in KIMO, which is much farther to the east than CHCH, where this species is currently found (Table 20).

The ensemble consensus shows there is nowhere within the CUPN units all five suitability models agree upon suitable skullcap habitat in the future (Table 20). In fact, the highest consensus was between two models, the area of which is at the very northernmost portion of the CUPN (Figure 14). The predicted area of suitable habitat within the CUPN based on the MaxEnt model (based on a threshold of 0.002 habitat probability) decreases substantially between the present and 2080 (Table 21). This raises concerns as to whether any parks will contain suitable skullcap habitat in the future.

Table 20. Results of MaxEnt and ensemble model output (consensus of all 5 models) for each park within the CUPN. An "X" means that suitable large flowered skullcap habitat was predicted to be within that park. This does not reflect the amount of suitable habitat within each park. (Key to Park abbreviations can be found in Table 2).

		MaxEnt			Ensemble Consensus	
National Park	**NPS Records**	**Current**	**2050**	**2080**	**2050**	**2080**
ABLI						
CARL						
CHCH	X	X				
COWP						
CUGA						
FODO						
GUCO						
KIMO			X	X		
LIRI		X				
MACA						
NISI						
RUCA		X				
SHIL						
STRI						

Table 21. Predicted area of suitable habitat within the CUPN for large-flowered skullcap (*Scutellaria montana*).

	Suitable Habitat Area (km^2)	
Projection	**MaxEnt**	**Ensemble Consensus**
Current	29,252	n/a
2050	6,670	0
2080	1,606	0

4.2.3 *Sorex longirostris* (Southeastern Shrew)

MaxEnt

The southeastern shrew model has a training AUC of 0.951 and a test data AUC of 0.826. In terms of model sensitivity, this model had a true positive rate of 0.99 for the training data and 0.805 for the test data. This means that it correctly predicted only 80.5% of the occurrence points used in the test run.

In this model, minimum temperature in the coldest month, mean temperature in the wettest quarter, and mean temperature in the driest quarter had the largest relative contributions of all the variables (Table 22). According to the jack-knifing, these three variables also had the highest relative gain, revealing that they are the most important variables in terms of predicting suitable habitat (Appendix D: Figure 5). Conversely, TRMI is the least important variable, both in terms of percent contribution (Table 22) and in terms of gain in jack-knifing (Appendix D: Figure 5).

The southeastern shrew's suitable habitat noticeably shifts northward and eastward into the southern Appalachian Mountains by 2050 and 2080 (Figures 16 and 17). MaxEnt over-predicts the shrew's current suitable habitat in the binary prediction (Figure 17). The range then contracts in future projections. Very little clamping occurred in the projection of this model; therefore, we do not expect novel combinations of climatic variables to highly influence our habitat probability projections (Appendix D: Figure 6).

Table 22. Estimates of relative contribution of each variable in the training model for the southeastern shrew (*Sorex Longirostis*).

Environmental Variables Used in Modeling	Percent Contribution
Min Temperature Coldest Month (BIO6)	34.4
Mean Temperature Wettest Quarter (BIO8)	33.8
Mean Temperature Driest Quarter (BIO9)	27.5
Precipitation Driest Quarter (BIO17)	2.4
TRMI	0.9
Precipitation Driest Month (BIO14)	0.9

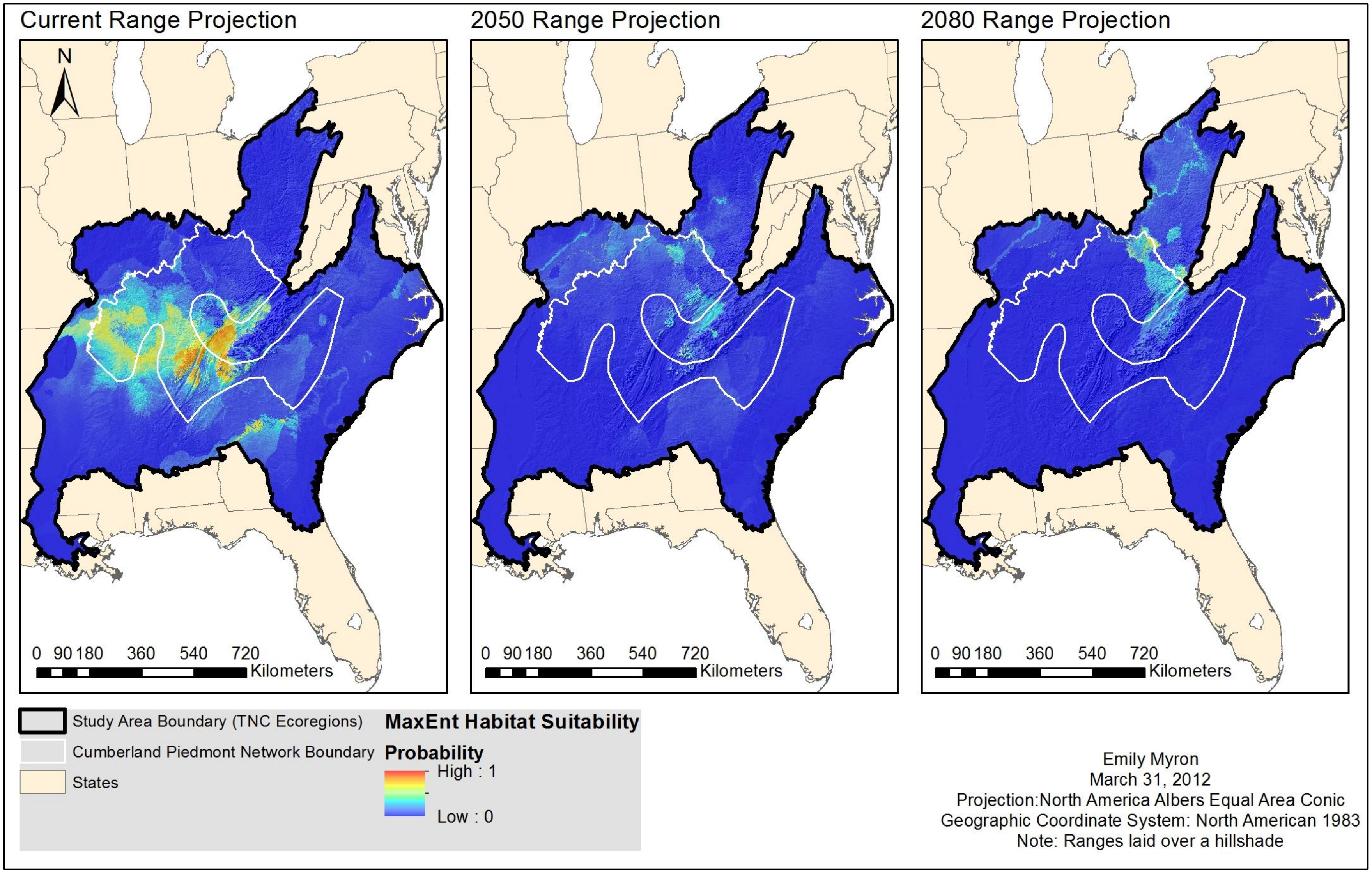


Figure 16. MaxEnt habitat suitability surface for the southeastern shrew (*Sorex longirostis*). Red indicates high probability of climatic suitability.

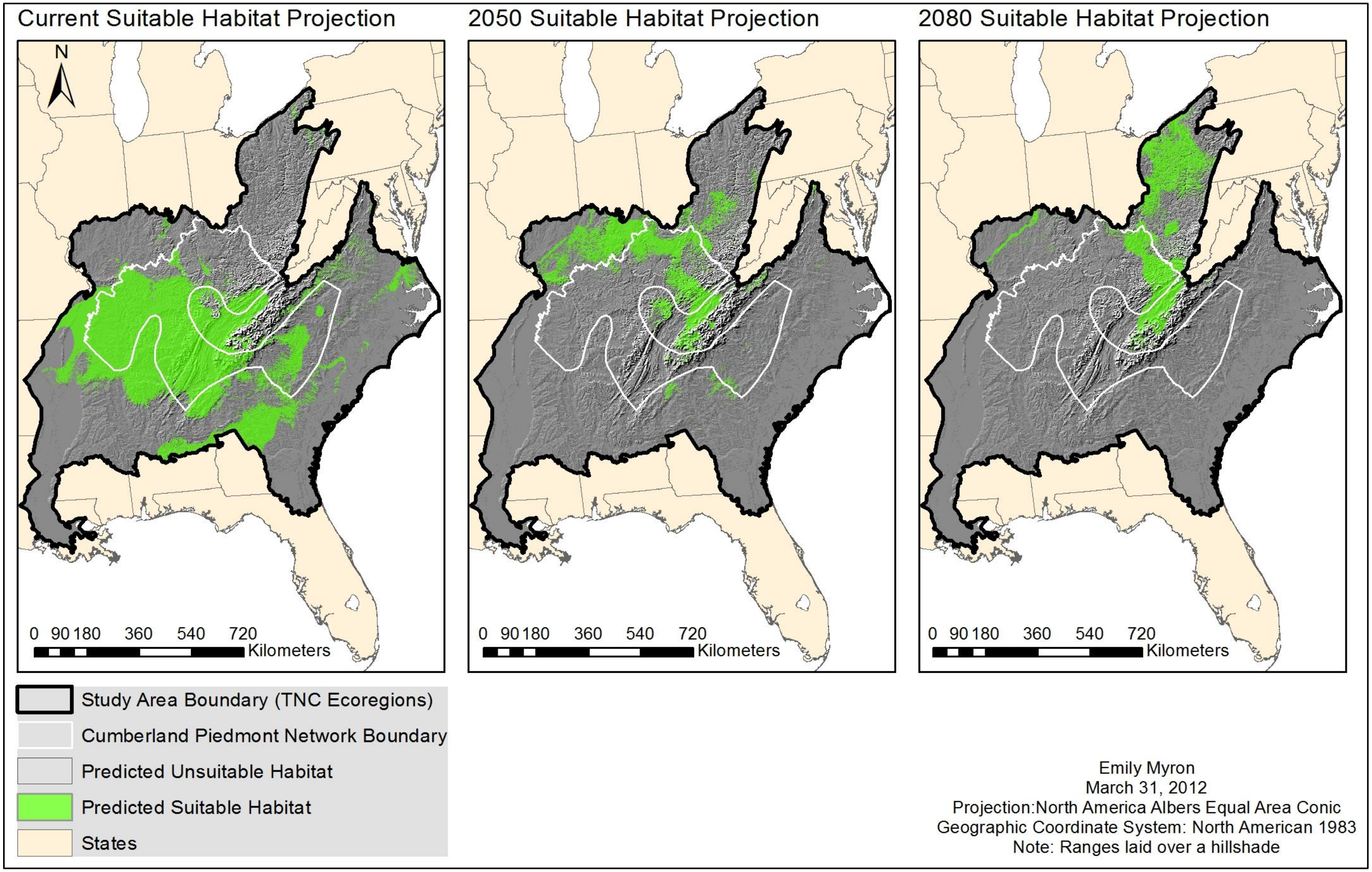


Figure 17. MaxEnt habitat suitability projections for southeastern shrew (*Sorex longirostis*). Binary predictions based on a threshold of 0.080 to balance training omission, predicted area and threshold value.

Biomod Ensemble

Three out of the five models selected mean temperature in the wettest quarter as the most important predictor variable (Appendix E: figure 6). MaxEnt and GAM are the exceptions, having selected minimum temperature in the coldest month as the most important predictor variable (Table 22 and Appendix E). The GLM eliminated precipitation in the driest month and precipitation in the driest quarter from consideration (Appendix E: Figure 5). Exploratory data analysis revealed mean temperature in the wettest quarter to have the highest correlation (p-value < 0.05) with species presence (Appendex C: Figure 4).

The sensitivity scores range greatly, showing confidence should vary across model projections (Table 23). CTA had the worst sensitivity score in the ensemble.

Both of the ensemble approaches show significant range contraction within our study area (Figures 18 and 19). The mean across all five models resulted in no areas predicted as having a high probability of containing suitable habitat (Figure 18). The model agreement approach shows no areas where all five of the models within the ensemble agree (Figure 19). The 2050 projection show areas where, at most, four model projections overlap. Each of the five models is represented, but projections are not nested as they were with green salamander. The 2080 projection shows areas where, at most, three models overlap. CTA is not included in this projection because conversion to binary resulted in no suitable areas for 2080.

Table 23: Sensitivity scores for each of the 5 models used in the ensemble for the southeastern shrew (*Sorex longirostis*).

Model	Sensitivity Score
CTA	33.333
GAM	83.333
GBM	87.344
GLM	74.608
MaxEnt	80.5

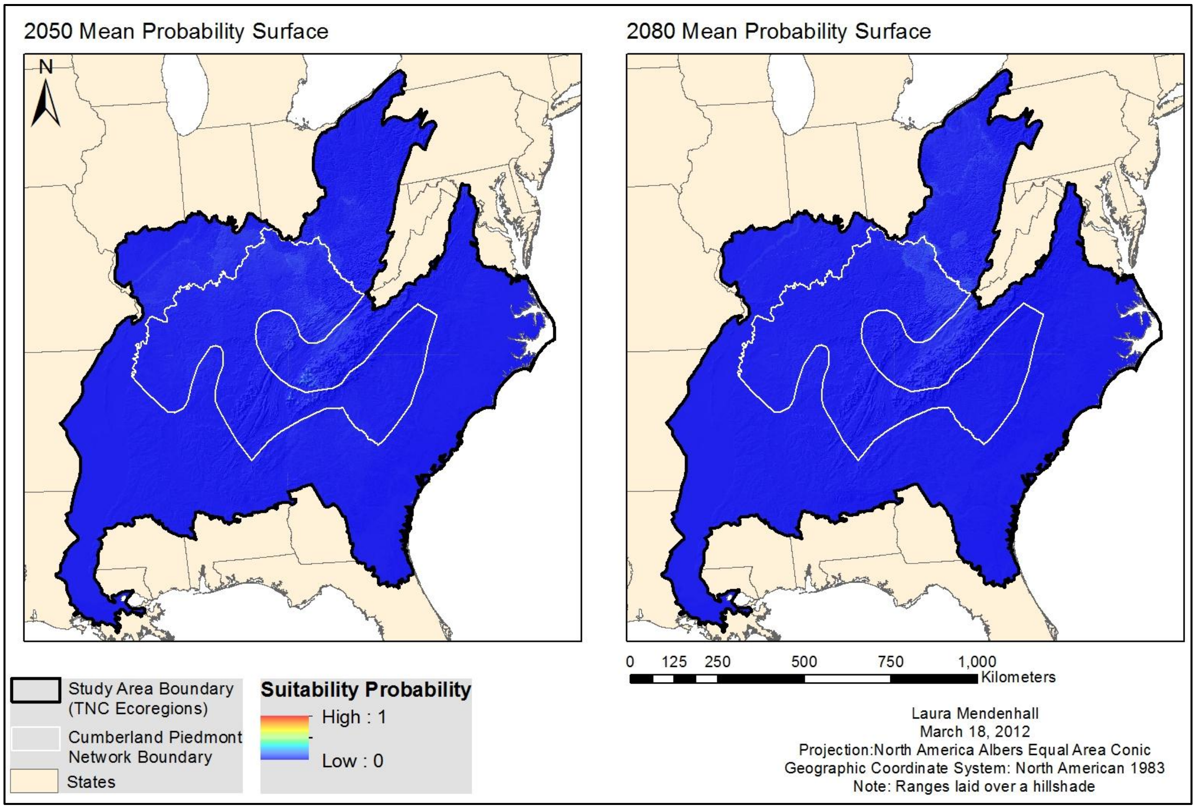


Figure 18. Mean taken across the probability surfaces of all five models. Red areas indicates high climatic suitability for the southeastern shrew (*Sorex longirostis*).

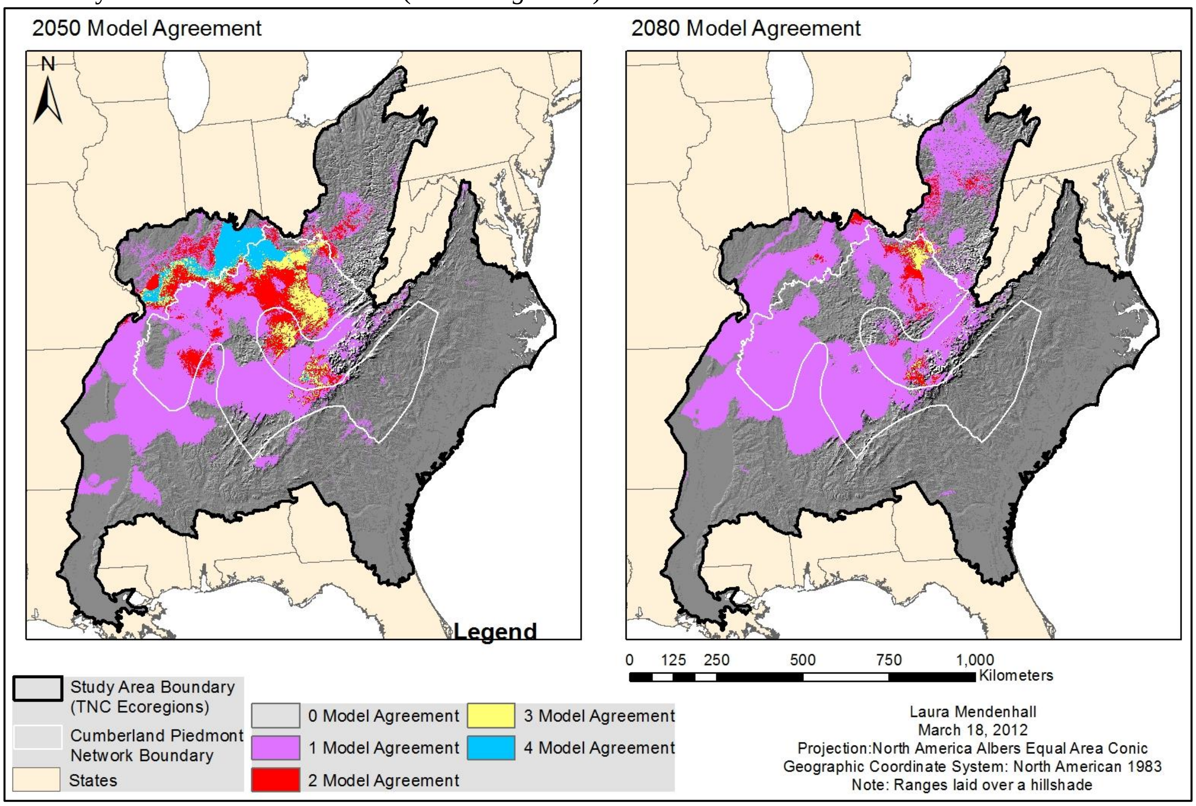


Figure 19. Ensemble of MaxEnt, CTA, GLM, GAM, GBM models for the southeastern shrew (*Sorex longirostis*) (CTA is omitted from the 2080 prediction).

Summary

NPS records indicate the southeastern shrew is presumed present in three CUPN NPS units (CHCH, SHIL, and STRI), which is confirmed by our MaxEnt projection (Table 24). However, MaxEnt over-predicts the number of park service units the shrew is currently found in (eleven rather than three). As the range of this species shifts northward in the future, MaxEnt predicts suitable habitat to remain in one Park Service unit, CUGA; yet, the shrew is not currently found here (Table 24). The ensemble consensus shows no suitable conditions predicted to be within any of the 14 NPS units in either 2050 or 2080 (Table 24).

The predicted area of suitable habitat currently within the CUPN (based on a threshold of 0.080 habitat probability) decreases substantially between the present and 2080 (Table 25). Part of this decrease is due to MaxEnt's over-prediction of the shrew's current range; however, the range still decreases slightly from 2050 to 2080. The ensemble consensus projects a marked decrease in suitable areas found in the CUPN from 2050 to 2080 (Table 25).

Table 24. Results of MaxEnt and ensemble model output (consensus of all 5 models) for each park within the CUPN. An "X" means that suitable Southeastern shrew habitat was predicted to be within that park. This does not reflect the amount of suitable habitat within each park. (Key to Park abbreviations can be found in Table 2).

		MaxEnt			Ensemble Consensus	
National Park	**NPS Records**	**Current**	**2050**	**2080**	**2050**	**2080**
ABLI						
CARL						
CHCH	X	X				
COWP		X				
CUGA		X	X	X		
FODO		X				
GUCO						
KIMO		X				
LIRI		X				
MACA		X				
NISI		X				
RUCA		X				
SHIL	X	X				
STRI	X	X				

Table 25. Predicted area of suitable habitat within the CUPN for the southeastern shrew (*Sorex longirostis*).

	Suitable Habitat Area (km^2)	
Projection	**MaxEnt**	**Ensemble Consensus**
Current	150,418	n/a
2050	33,055	7,072
2080	20,293	0

4.2.4 *Plantago cordata* (Heartleaf Plantain)

MaxEnt

The heartleaf plantain model has a training area under the curve (AUC) of 0.990 and a test data AUC of 0.653. This model had a true positive rate of 1.00 for the training data, but had only a true positive rate of 0.444 for the test data. This reveals that the model has a very low sensitivity (only correctly predicting 44% of the test data) and, thus, may not be a reliable predictor of habitat (perhaps because the model may be over-fitted to the training data).

In this model, soil type has the largest relative contribution of all the variables (Table 26). Results of the jack-knifing indicate soil is a much more important variable than the others, and had the highest gain when a model was constructed using only this variable (Appendix D: Figure 7).Conversely, precipitation in the driest month and precipitation in the driest quarter had no predictive capacity (Table 26).

The range of the heartleaf plantain is predicted to move westward with climate change. Suitable conditions are currently predicted around the southern Appalachians and by 2080 there is no suitable habitat left east of the mountains (Figures 12 and 13). The suitable habitat in the northwest of the study area also increases in the future. Even in areas that may be habitat (based on a threshold of 0.042) (Figure 21), the probability of those areas being suitable are very low (almost indistinguishable from zero habitat probability on the probability surface) (Figure 20). Very little clamping occurred in the projection of this model; therefore, we do not expect novel combinations of climatic variables to highly influence our habitat probability projections. (Appendix D: Figure 8).

Table 26. Estimates of relative contribution of each variable in the training model for heartleaf plantain (*Plantago cordata*).

Environmental Variables Used in Modeling	Percent Contribution
Soils	91.1
Mean Temperature Wettest Quarter (BIO8)	6.1
Temperature Annual Range (BIO7)	1.4
Precipitation Warmest Quarter (BIO18)	1.3
TRMI	0.1
Precipitation Driest Quarter (BIO17)	0
Precipitation Driest Month (BIO14)	0

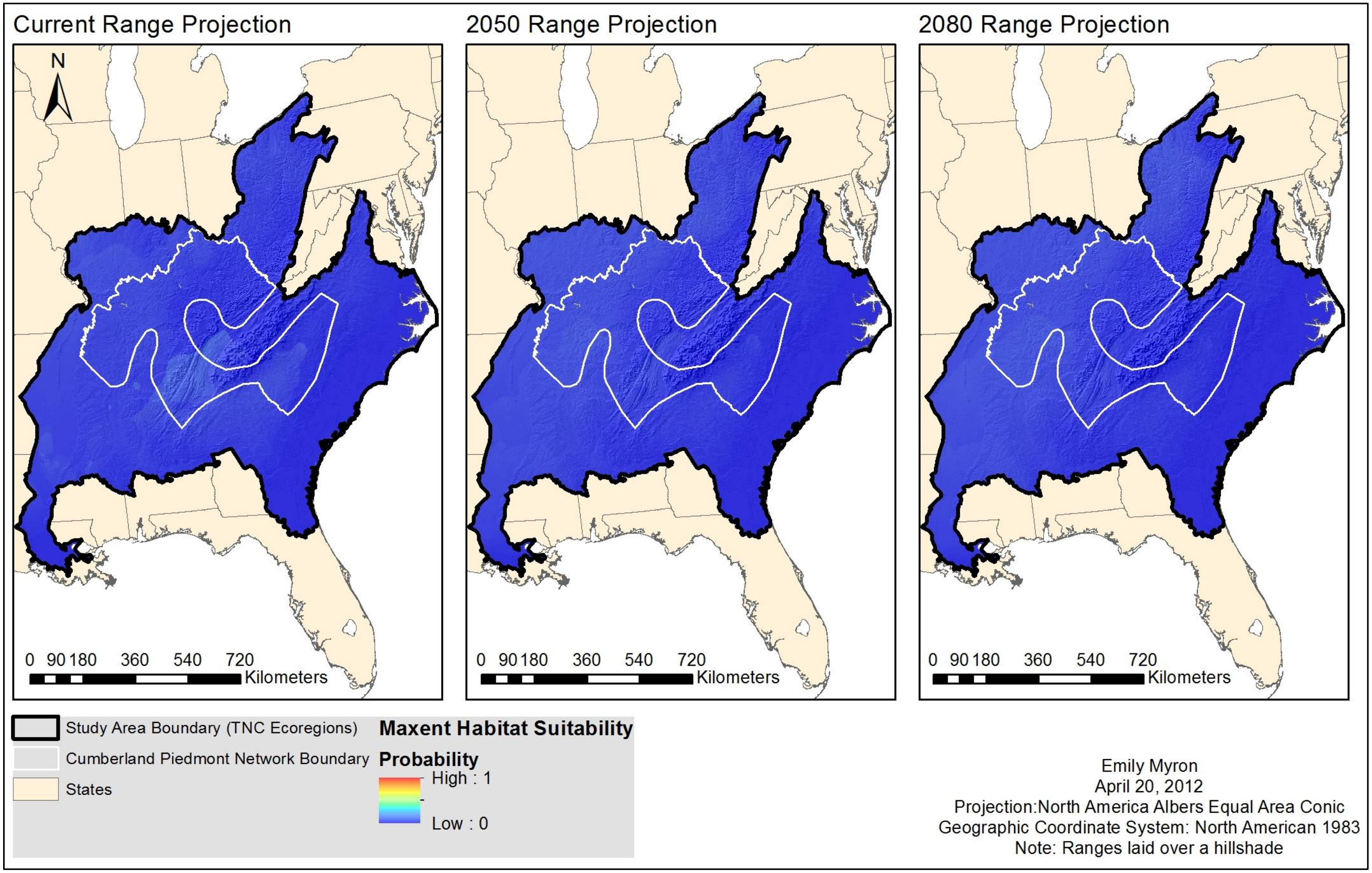


Figure 20. MaxEnt habitat suitability surface for heartleaf plantain (*Plantago cordata*). Red indicates high probability of climatically suitable habitat.

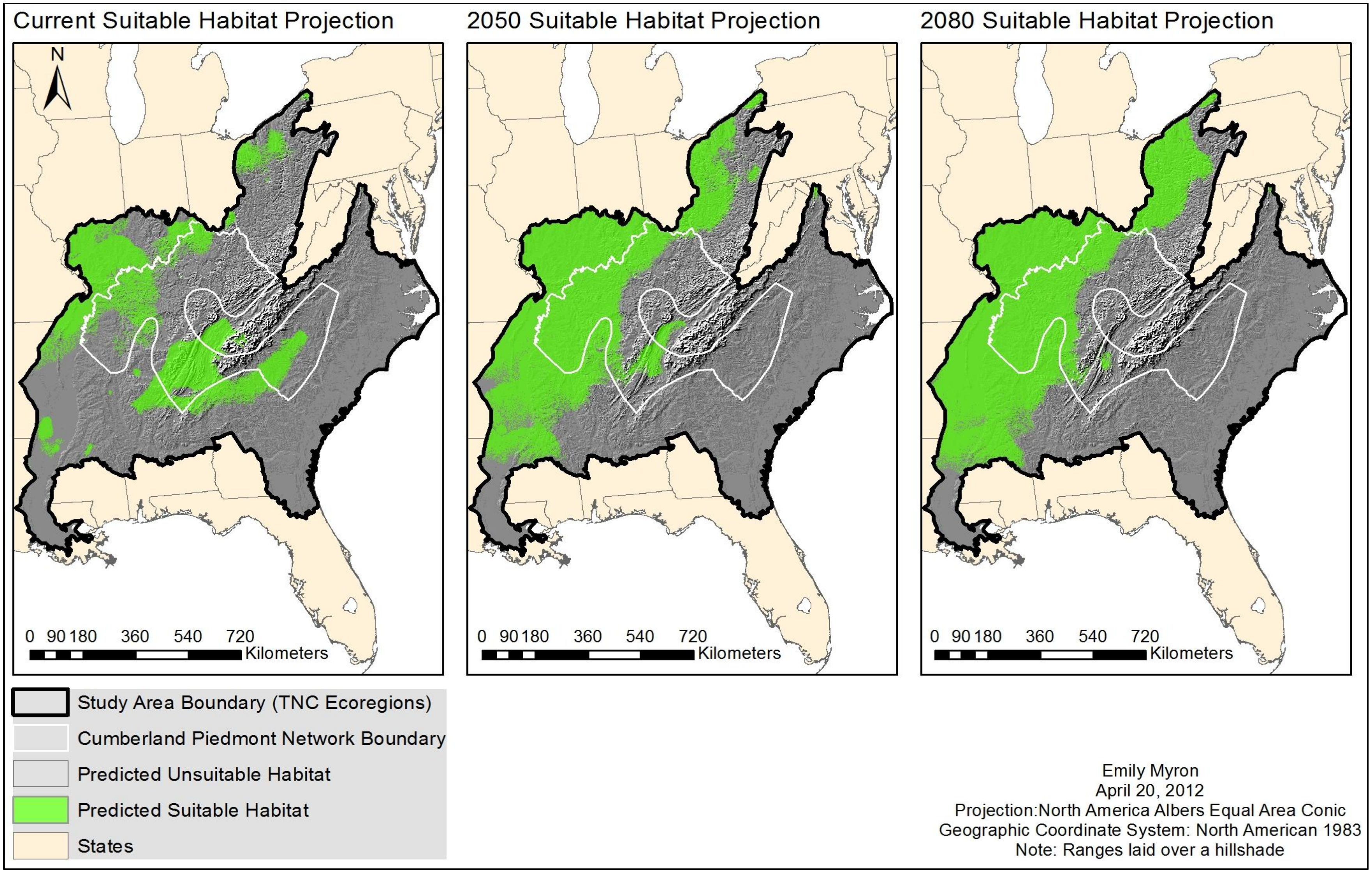


Figure 21. MaxEnt habitat suitability projections for heartleaf plantain (*Plantago cordata*). Binary predictions based on a threshold of 0.042 to balance training omission, predicted area and threshold value.

Biomod Ensemble

The GBM and MaxEnt model selected soils as the most important predictor variable, while the GLM selected precipitation in the warmest quarter, and the GAM selected annual range of temperature as the most important predictor variables (Table 26 and Appendix E: Figure 7). The GLM eliminated annual range of temperature, precipitation in the driest quarter, precipitation in the driest month, and TRMI from consideration. The GAM eliminated soils, precipitation in the driest month, and precipitation in the driest quarter from consideration (Appendix E: Figure 6). Exploratory data analysis revealed significant correlations (p-value < 0.05) between precipitation in the driest quarter, mean temperature in the wettest quarter and species presence (Appendix C: Figure 5). The CTA failed to perform.

The sensitivity scores range among the models, thus, confidence across model performance varies (Table 27). MaxEnt performed the worst, with a sensitivity score of 44.4, while the gradient boosting model performed the best with a sensitivity score of 96.774 (Table 27).

Both of the ensemble approaches show significant range contraction within our study area (Figures 22 and 23). The mean across all four models resulted in no areas predicted suitable (Figure 22). The model agreement approach shows areas where all four of the models within our ensemble agree (again, CTA failed to perform and was omitted from this species' analysis) (Figure 23).

Table 27: Sensitivity scores for each of the 5 models used in the ensemble for heartleaf plantain (*Plantago cordata*). (Test data)

Model	Sensitivity Score
CTA	n/a
GAM	77.419
GBM	96.774
GLM	61.29
MaxEnt	44.4

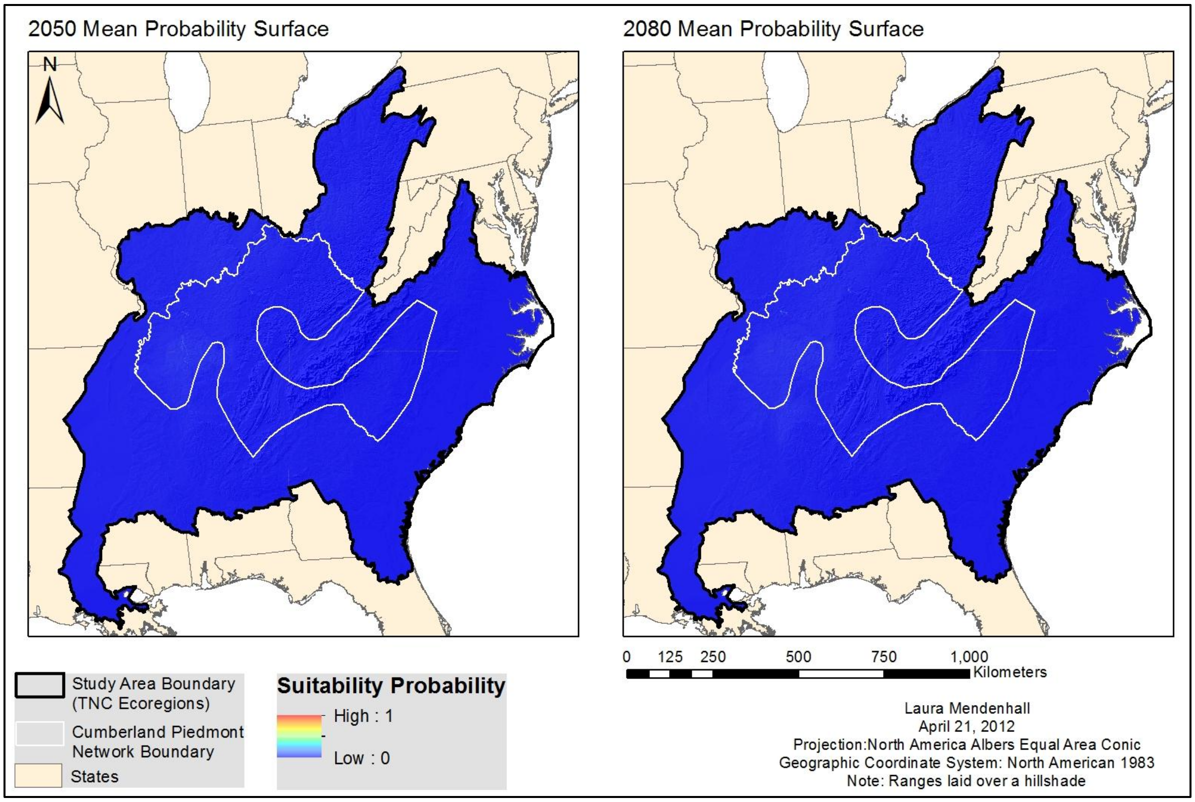


Figure 22. Mean taken across the probability surfaces of all five models. Red areas indicates high climatic suitability for the heartleaf plantain (*Plantago cordata*).

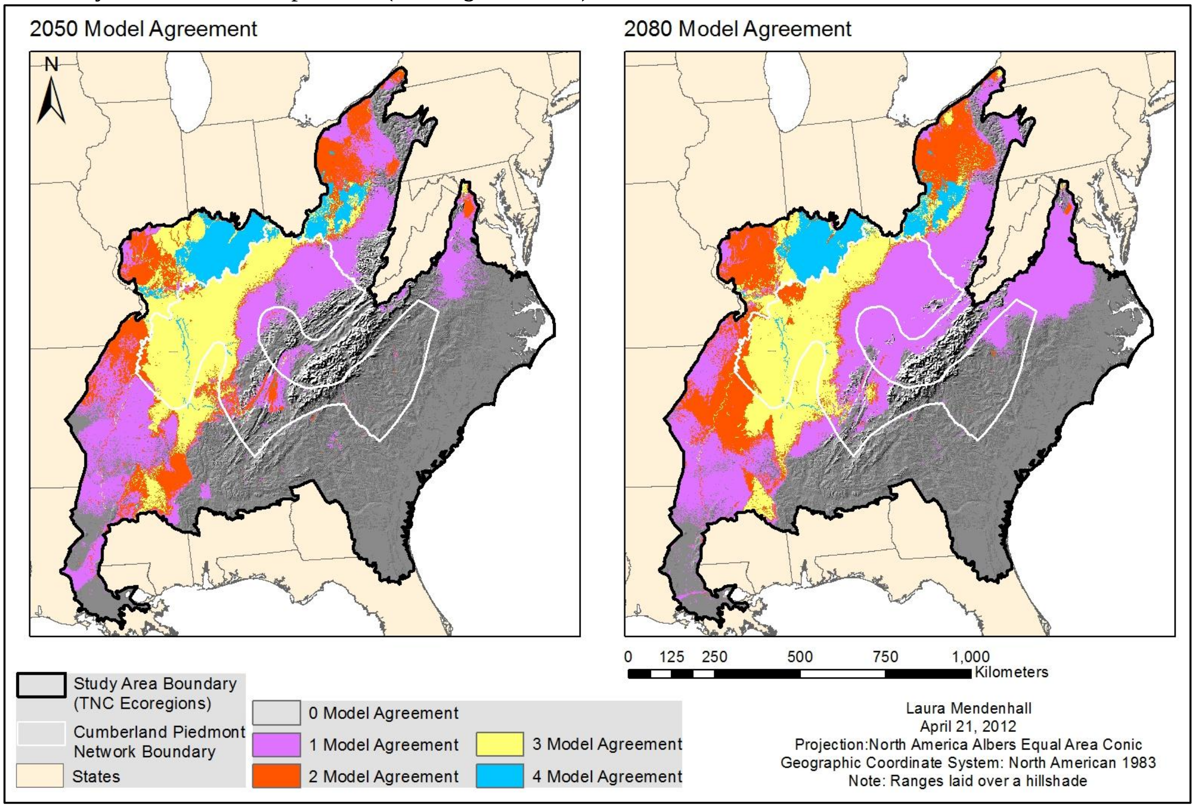


Figure 23. Ensemble of MaxEnt, GLM, GAM, GBM models for the heartleaf plantain (*Plantago cordata*).

Summary

NPS records indicate the heartleaf plantain is presumed present in one CUPN unit, CHCH, which is confirmed by our MaxEnt projection (Table 28). Much like the southeastern shrew, MaxEnt over-predicts suitable habitat for the plantain, showing that suitable habitat occurs in NPS units in which this species is not found. MaxEnt predicts suitable habitat for the plantain to remain in CHCH through 2050 and 2080, despite the CCVI predicting this species to be "Highly Vulnerable" to climate change. Interestingly, MaxEnt predicts suitable habitat for this species to be in many parks in 2050 and 2080, in addition to in CHCH. In fact, this is the only species we modeled that shows an increase in net suitable area within the CUPN with climate change (based on threshold of 0.042) (Table 29).

In contrast, the ensemble consensus (using agreement across all four models) suggests a shift of suitable bioclimatic conditions into FODO but a net a contraction for the entire CUPN with significantly less suitable bioclimatic conditions when compared to MaxEnt results (Tables 28 and 29). Wide-ranging sensitivity scores and lack of available presence data suggest a cautious interpretation of these results.

Table 28. Results of MaxEnt and ensemble model output (consensus of all 4 models) for each park within the CUPN. An "X" means that suitable heartleaf plantain habitat was predicted to be within that park. This does not reflect the amount of suitable habitat within each park. (Key to Park abbreviations can be found in Table 2).

		MaxEnt			Ensemble Consensus	
National Park	**NPS Records**	**Current**	**2050**	**2080**	**2050**	**2080**
ABLI				X		
CARL						
CHCH	X	X	X	X		
COWP		X				
CUGA						
FODO		X	X	X	X	X
GUCO						
KIMO		X				
LIRI		X				
MACA			X	X		
NISI		X				
RUCA		X				
SHIL			X	X		
STRI			X	X		

Table 29. Predicted area of suitable habitat within the CUPN for heartleaf plantain (*Plantago cordata*).

	Suitable Habitat Area (km^2)	
Projection	**MaxEnt**	**Ensemble Consensus**
Current	82,624	n/a
2050	103,791	3,237
2080	100,458	2,059

5.0 Discussion

5.1 Climate Change Vulnerability Index

5.1.1 The Influence of Taxonomic Group on Vulnerability

The taxonomic group with the highest number of vulnerable index rankings (MV, HV, or EV) in this assessment was mollusks. In fact, all species assessed in this taxonomic group produced at least a "Moderately Vulnerable" index ranking. These species are not only sessile, but also exist in a narrow physiological hydrological niche and are dependent on high water quality (Smith 1971). With high sensitivity to changes in water temperature and quality, this taxonomic group will require intensive future consideration and study to research the effects of climate change in the field.

On the opposite end of the vulnerability spectrum, avian species showed an overall low vulnerability to the effects of climate change. In fact, forty-four of the avian species yielded "Presumed Increase" vulnerability scores. Supporting models from the Atlas of Change (Matthews et al. 2011) provided further evidence of range increases for species such as Bachman's sparrow, the blue-winged teal, the little blue heron, and the great egret (Matthews et al. 2011). Because increases in range size require sufficient resource pools, future interspecific interactions in these ranges will determine whether these areas have the capacity to support new species. With birds, therefore, it is particularly important to integrate conservation status ranks into CCVI scores. Habitat degradation, disease, and other conservation threats are factored into conservation status rankings, but not the CCVI, to avoid double counting. Future monitoring programs of both the species and resources for particular species will be important in determining population viability.

The mammals that displayed consistent vulnerability were bat species. While not all of the bat species we evaluated depend solely on caves for habitat, some species, such as the gray myotis, roost almost exclusively in caves year-round (Tuttle 1976). The use of caves by the southeastern myotis differs regionally. In the CUPN, this species has been shown to winter in caves but is rarely found in caves during the summer months (Gardner et al. 1992). However, one large maternity colony has been reported in the region in the early 1990s. Rafineque's big-eared bat appears to utilize caves in southern states to a lesser degree, though rare nursery colonies have been found in Kentucky and Tennessee (Barbour & Davis 1969). While the reliance on caves as roosting or nursery sites varies among the above species, cave use increases environmental specificity and reduces the odds of finding suitable habitat elsewhere. Many caves are susceptible to both natural and human disturbance events, further increasing vulnerability for species reliant on those caves (Clark 1994). Because of these factors, bats assessed in this study appear to be poorly adapted to manage the effects of climate change. One point of interest in the future will be the degree of temperature changes within caves as well as the ability of individuals to disperse to new habitat, if necessary (Tuttle 1976). While long-distance migratory bats are few in number, individual gray myotis bats have the ability to move hundreds of kilometers from their home range (Barbour & David 1969). Migratory success to new winter roosts is, therefore, more likely for such species. Future monitoring and research programs with cave preservation efforts should be integrated into information gleaned on climate change effects to influence future management.

Amphibians represent one of the groups vulnerable to the effects to climate change (Byers & Norris 2011), but the CUPN provides habitat for only a handful of amphibian species of conservation concern. Thus, amphibians are not well represented in this study. With specific hydrologic requirements like high water quality and generally poor dispersal capabilities, these species may exhibit low adaptive abilities to the effects of climate change. Many reptiles are similarly incapable of long-distance migration and may possess vulnerabilities that are not represented in this study by the lone pine snake.

As a whole, the at-risk plants assessed in this study scored equally as vulnerable and "Presumed Stable." Unfortunately, many of the candidate species lacked adequate information for assessment. However, species that were assessed were more likely to be vulnerable if characterized by poor seed dispersal and a narrow hydrological niche. For some of the more rare plants on our original candidate list, more thorough study may yield dividends on both ecological importance and the susceptibility of these species to future climate change events.

Intuitively, species with greater environmental specificity will be more vulnerable to the effects of climate change. Species with more nuanced ecological requirements will likely have a more difficult time procuring necessary resources with changing temperature and moisture regimes. This is especially true for environmental specialists with strict hydrological requirements, as all areas assessed in the CUPN are predicted to experience net drying by 2050. Mollusks and amphibians provide prime examples of these species In contrast, more generalist species, with opportunistic diets and a wide variety of habitat requirements will likely be able to adapt to climate change effects. Long-distance migratory birds and those with general resource procurement traits, such as the eastern spotted skunk, will be most equipped to cope with changing resource landscapes in the face of climate change.

Species that fulfilled the selection criteria for multiple NPS units requires separate runs for each park due to differing degrees of exposure. It is therefore possible, though unlikely, for one species to produce disparate climate change vulnerability rankings. Any discrepancies in Index ranking would therefore be attributed to spatial heterogeneity of exposure, as the species' sensitivity would be identical. This occurred for Rafinesque's big-eared bat, where the species scored as "Highly Vulnerable" in Mammoth Cave but "Moderately Vulnerable" in Cumberland Gap and Shiloh National Military Park due to the greater predicted temperature and moisture changes in the park (Appendix B: Table 2). Butternut experienced a similar phenomenon, receiving "Highly Vulnerable" scores in Mammoth Cave and Stones River, but a "Moderately Vulnerable" score in Cumberland Gap. Again, the higher degree of predicted exposure was responsible for this increase in vulnerability. These results have implications for prioritizing management in the CUPN, which will be discussed in later sections.

5.1.2 Vulnerability by Park

Out of the 11 parks that contained moderately to extremely vulnerable species, Mammoth Cave easily contained the highest number, at twenty-two. Thirteen of these twenty-two species were sessile invertebrates, while the remaining eleven varied taxonomically. This park also included the highest number of CCVI candidates with 54 of the 153 species individuals in this study. This number is inflated somewhat due to the inclusion of migratory species that may not affect park management to the same degree as permanent park residents. Cumberland Gap followed, containing only six vulnerable species, while Chickamauga & Chattanooga produced five. Many of the parks contained only a few vulnerable species but also had much smaller species candidate pools. These results will be pertinent in defining management strategies for specific parks within the CUPN.

5.1.3 Conservation Status Ranks and Climate Change Vulnerability

The results from this study illustrate that NatureServe's Conservation Status Ranks alone cannot predict a species' vulnerability to climate change. Based on specific attributes evaluated in the CCVI, species that are rare or imperiled may not be vulnerable to climate change, while common species may not be resilient to climate change. For example, the Tennessee cave salamander is globally "imperiled" (G2) but "Presumed Stable," while the Canada warbler and the dark-eyed junco have G5 ranks, yet are considered "Moderately Vulnerable" to climate change. Byers and Norris (2011) further support this result by asserting that each species will behave and respond to climate change according to its unique life history characteristics, habitat requirements, and distribution. Conservation managers should use these Conservation Status Ranks in conjunction with the CCVI to develop comprehensive management plans and strategies to better account for the various factors threatening species within their assessment area.

When assessing the comparability of state and global Conservation Status Ranks to climate change vulnerability, the percentage results suggest that global ranks do better at predicting climate change vulnerability of specific species. Looking more closely at the results shows us that only 49 species individuals with ranks from G1 – G3 were evaluated in this study; whereas 151 species individuals within the S1 – S3 ranks were run through the CCVI. Because the analysis occurs within the states, conservation threats at the state scale are represented more in this study than global scale threats. State ranks probably do not predict climate change vulnerability very well because they often include species that are common in the middle of their range, but rare in the state due to the state's location at the edge of the species' range; therefore, they do not reflect the big pictures of a species' needs and range. NatureServe's definition of Conservation Status Ranks clarifies this idea by stating that all sub-national (i.e. state) species rankings must be equal to or lower than global rankings (NatureServe Online 2011). Thus, our species selection method worked well for the ecoregional scale of this project, but future studies that incorporate the CCVI should consider the tradeoffs of different species selection methods for their study areas.

5.2 Habitat Suitability Modeling

5.2.1 Assumptions and Uncertainties

A number of assumptions and uncertainties need to be taken into consideration prior to interpreting our habitat suitability model projections. The scale and resolution upon which our models are projected, the data chosen to represent predictor and response variables, and the limited capacity for validating future projections all lend uncertainty to our results. We are compelled to disambiguate each of these assumptions and uncertainties so resource managers may qualitatively assign confidence to our projections.

First, we assume the factors at work influencing species' habitat preferences are acting at a scale that is hierarchical in nature, with climate nearing the top of the hierarchy and biotic interactions nearing the bottom (Levin 1992). We use a resolution of one square kilometer under the assumption that this is fine enough to capture the nuances of climatic features across the study area, but coarse enough to exclude those factors that determine habitat suitability at the bottom of the hierarchy (e.g. competition or resource selection) (Hijmans & Graham 2006). In reality, biotic interactions may outweigh climatic features in determining patterns of habitat selection, even at this relatively coarse resolution. However, our aim is to establish only the bioclimatic niche for a species. The projections onto current and future climatic space show only expansion and/or contraction of the range of this bioclimatic niche and do not attempt to show areas of microhabitat or land cover preferences. For this reason, we limited variable selection to climatic variables (for which we have access to forecasted data) and variables that are assumed to remain static over the time range of the study (e.g. soils and TRMI). As an example, the model for the green salamander includes several climate variables and TRMI. Projections show bioclimatically-suitable regions in Louisiana and coastal North Carolina in 2050 and 2080. The green salamander relies on specific habitat requirements such as moist rocky outcrops and woody debris (Wilson 2003) and would not, in fact, thrive in coastal Louisiana and North Carolina. This result is by design; however, we recommend these projections and others are interpreted with knowledge of ecological constraints.

We attempted to capture the entire bioclimatic range of each species using species presence data across our study area. If the range of available data does not sufficiently represent the true range of a species (or an area in which natural disturbance resulted in historical extirpation), the model may not accurately estimate the environmental parameters and is limited when attempting to project into future climate space (Appendix F) (Phillips et al. 2006; Elith et al. 2011).

Additional data limitations lend uncertainty to our future projections. Future climate data is the product of downscaled GCM forecasting and may introduce additional uncertainties into our projections. We used species occurrence data collected at a temporal and geographic precision assumed to be adequate for use in our analyses (i.e. data needs to have been collected after 1975 and recorded as such, and geographic coordinates need to have been recorded at a location within one square kilometer of the actual observation). Additionally, National Heritage Program data and Natural History Museum species presence data can be prone to sampling biases (Phillips et al. 2004; Phillips et al. 2006; Elith at el. 2011). However, because our focus is on the bioclimatic niche, we did not attempt to account for sampling biases under the assumption data are not biased *bioclimatically*. Species absence points were not available for inclusion in our models so we created background data in the form of random points to contrast with observed presence points. This means we can only draw real conclusions on where suitable climatic habitat is, not where it is not.

Finally, we can assess how well models project onto current climate space because we have empirical data to use for validation. However, because we do not have species presence points from future climate space, we are unable to assess how well models project onto future climate conditions (Thuiller 2003). The ensemble approach somewhat accounts for this limitation by constraining prediction space to the mean across all models or where all, or some, of the projections are in agreement.

Despite these uncertainties and assumptions, our projections onto future climate surfaces are useful and cost-effective tools for managers, especially given the increasing urgency to inform management decisions under pressure from climate change. While we do strongly suggest further research into how more direct predictor variables, such as land use and land cover, can be included into future projections, careful consideration of these assumptions and limitations will allow NPS to use our results as broad guidance for collecting more species-environment data, increasing population monitoring in parks shown to be near the thresholds for bioclimatic suitability, and allocating resources to developing climate change adaptation plans.

5.2.1 Lapse Rates

It is important to note that the future climate surfaces generated from the HadCM3 GCM were downscaled from one degree by one degree resolution to one square kilometer resolution without taking into account the changes in temperature and moisture attributable to changes in elevation (Ramirez-Villegas and Jarvis 2010). When viewing our projections onto 2050 and 2080 climate surfaces, the reader should be aware that, while lateral shifts and contractions are true to the climate surfaces used to build the models, shifts upward in elevation (or lack thereof) must be calculated using known lapse rates for the southern Appalachian Mountains. A lapse rate is the change in temperature and moisture per 1000 meter gain in elevation (see: Bolstad et al. 1998). The CUPN is not largely affected by shifts attributable to elevation owing to its exclusion of the southern Appalachian Mountains (Appendix A: Figure 1). Interpretation of the results should reflect this caveat with the possibility of ranges shifting both laterally and upward in elevation.

5.3 Management Implications and Recommendations

5.3.1 Park Management Implications

5.3.1.1. Consolidating current management with climate change adaptation planning

The Vital Signs Monitoring Plan (Leibfreid et al. 2005), conducted by the NPS, documents important monitoring questions and management issues for each of the 14 NPS units of the CUPN. Many of management objectives already detailed by NPS coincide with goals that promote adaptation to climate change. Consolidating climate change adaptation planning with existing conservation plans can potentially streamline costs, increase efficiency, and effectiveness of programs. Mitigating other conservation threats, such as invasive species, pollution, and habitat degradation will not only benefit currently threatened species but also promote the future resilience of species affected by climate change (Heller & Zavaleta 2009). Table 30 summarizes prominent management objectives from the CUPN Vital Signs Plant that apply to current threats within the CUPN that can also facilitate species' resiliency in the face of climate change.

Table 30: CUPN management issues in the context of climate change.

Management Issue	Impact on Climate Change Vulnerability	Potential Management Action
Adjacent land use developments	Restricts species' ability to migrate to new suitable habitat and can degrade existing habitat in close proximity to developments	Participate actively in local zoning and developmental threats. Collaborate with local land trusts to establish conservation easements. Educate farmers on best management practices, habitat conservation initiatives, and forest stewardship programs
Exotic plant management	May compromise native species habitat; spread	Invasive species control and eradication program. Conduct

	potential	education and outreach programs, working with landowners, local governments, and landscapers to inform responsible action.
Water resources management	Drying conditions may reduce availability of ecologically important water resources (i.e. intermittent streams).	Enact water quality and quantity monitoring programs. Establish groundwater protection zones. Educate farmers and developers on best management practices to protect water resources.
Native aquatic species management and monitoring	Changes in water temperature/abundance may negatively affect species habitat suitability. Phenological changes may be	Integrate monitoring of relevant species with water resources management. Maintain riparian buffers, particularly in areas adjacent to developments.
Native terrestrial species management and monitoring	Long-term temperature and moisture changes may make current habitat unsuitable for some species.	Monitor species ranked as "vulnerable" in each park as well as environmental requirements for those species.
Disturbed area rehabilitation	Disturbed roost and nursing sites for bat species reduce available habitat and limit dispersal/movement to new sites.	Particularly relevant for vulnerable bat species in MACA, erect artificial roosts and protect/promote cavity-forming trees.
Geological resources management	Cave entrances are susceptible to natural and human disturbance but provide important habitat for cave-dwelling species with limited environmental specificity.	May include restricting visitor access to sites that host or can potentially host vulnerable species. Monitor sites deemed fragile.
Fire management	With increased drying events, fire risk may increase. In areas of previous fire suppression and increased fuel loads, these risks may compound.	Prescribed burns, silvicultural site prescriptions, and fuel reduction programs for areas of concern. Aim to reduce fire intensity.

Notable issues that relate to species' climate change vulnerability in this study include adjacent land use developments, geological resource management, exotic plant management, disturbed area rehabilitation, and water resource management. Therefore, prioritizing management actions associated with these issues may facilitate climate change adaptation planning. For example, collaborating with local land trusts to establish conservation easements can mitigate current developmental threats and also create opportunities for species to move into more suitable habitat in light of changes in climate.

By prioritizing species that are important to ecosystems, the CUPN can optimize the allocation of resources for species management during climate change. Marsh et al. (2007) explains that this optimization framework considers three criteria for the species: threat category, consequences of extinction, and the potential for successful recovery. This framework provides scientists, policy-makers and other stakeholders with the opportunity to discuss species conservation while separating the technical scientific data from the societal values in the decision-making process (Marsh et al. 2007). Climate change vulnerability scores can be integrated into the above criteria to gauge how future climate scenarios may affect trends in species' abundance and range. This idea conforms nicely when planning within the eco-regional networks that the NPS has designated for the Inventory and Monitoring Program. Furthermore, with the Inventory and Monitoring Program already established, the CUPN already has the ability to evaluate their data to adapt management plans to the needs of species and ecosystems within the region.

As mentioned in the above table, managers can also address habitat loss and fragmentation outside the units of the CUPN by employing partnership parks. Root and Schneider (2006) state that habitat fragmentation poses potentially one of the most serious conservation problems in the face of climate change. Although the NPS protects species within their own lands, they cannot legally manage species that move or migrate out of the National Parks system. Partnership parks will allow species to be connected to suitable habitat that may be outside the boundaries of the National Parks. This connectivity could increase a species' chances for survival (Williams et al. 2008). Thus, partnership parks provide a framework in which the NPS can collaborate with state and local governments, conservation organizations, and individual landowners to protect the natural, historical and cultural aspects of a specific area outside of the National Park System (Hamin 2001).

Coordination between the previously-mentioned stakeholders is especially important for managers of the CUPN since the whole ecoregion, and even several of NPS units, span multiple states. Neighboring state or local governments may have different conservation goals; therefore, the partnership parks concept builds a platform through which representatives of the NPS, government officials, conservation organizations and other stakeholders can come together to discuss priorities and objectives for current and future management plans. Local communities retain a voice in these plans by sitting on the commissions that assist in directing management decisions (Hamin 2001), and the NPS secures more protected lands that will help them fulfill their mission to conserve park resources and values without impairment for future generations. By involving and benefitting so many stakeholders, partnership parks encourage the horizontal, vertical and sectoral integration of management and policy strategies to address species vulnerability to climate change. This integration could create strong bonds among government entities and other organizations to take a proactive stance to reducing the impacts of climate change on species of importance.

5.3.1.2 Specific Modeled Species Concerns

One of the outcomes of this study is a coarse idea of which parks may lose species with climate change. As mentioned above, Mammoth Cave, Chickamauga & Chattanooga, and Cumberland Gap have the largest number of species vulnerable to climate change based on our assessment. This makes the incorporation of climate change into management plans for these parks imperative. This study began the process of modeling vulnerable species within the CUPN, but this work must be continued in order to understand how habitat suitability will change between now and 2080. Based on our modeling, we can make some management suggestions for the green salamander, large-flower skullcap, southeastern shrew, and heartleaf plantain. For each of these species, an adaptive management strategy, in which parks consider not only species vulnerability to climate change (Nicholls et al. 2008), but also species vulnerability to factors such as development or pollution adjacent to NPS units, should be used. This adaptive management approach allows decision-makers to be proactive about specific conservation issues, rather than taking the traditional reactive stance to problems (Williams et al. 2008). In taking a proactive approach, park managers of the CUPN have the ability to minimize habitat loss and fragmentation within their parks so as to improve species resilience to climate change.

Green Salamander

The green salamander is likely to disappear from Little River Canyon National Park (LIRI) and may disappear from Carl Sandburg Home National Historic Site (CARL) (Table 16). LIRI and CARL have already been identified by NPS as being highly susceptible to adjacent land use impacts (Vital Signs Workshop). The salamander's dispersal can be highly impacted by barriers, and they rarely are able to cross busy roads or bodies of water (NatureServe 2011). As the range of the green salamander shifts north-eastward, it could be crucial for these NPS units to partner with land trusts and other organizations to conserve land (perhaps through conservation easements), and corridors to land, that may become climatically suitable. Of utmost importance to conserving green salamander habitat is the maintenance of its habitat in and around moist rocky outcrops. For example, a 100-meter forest buffer surrounding the amphibians' habitat may help prevent disturbance to the salamander's habitat and preserve moisture conditions under the forest canopy (NatureServe Explorer 2011).

Fortunately, none of NPS units containing the salamander are in particular danger of disturbed geological structures (Vital Signs Workshop), which may ensure that the green salamander's microhabitat requirements persist in these units in limited refugia. As stated previously, this species is particularly reliant on microhabitat conditions (moist rocky outcrops and woody debris; Wilson 2003), but there is not available research to suggest whether these may persist even in the face of larger-scale climactic changes. If they do, habitat may remain in areas that our analysis was unable to identify because we did not built our models to include microhabitat requirements.

Large-flowered Skullcap

The large-flowered skullcap may face dispersal issues similar to the green salamander. Both MaxEnt and the ensemble of models predict that Chickamauga & Chattanooga (CHCH) will not contain climatically suitable skullcap habitat by 2050 (Table 20). Currently, this is the only NPS unit in which the skullcap currently can be found. However, the MaxEnt analysis suggests that Kings Mountain (KIMO) may contain suitable habitat in the future. KIMO and CHCH are not adjacent, and the skullcap has very limited dispersal capabilities (less than 5 meters) (NatureServe 2011). Additionally, skullcap has fairly specific soil requirements (shallow, rocky, and on the drier side) and may have elevation and slope requirements not included in our models (NatureServe 2011). Skullcap dispersal and habitat requirements raise concern as to whether this species would be able to naturally disperse to new areas of suitable habitat in the future, especially distances as far as from CHCH to KIMO. For species such as skullcap, assisted translocation may become a necessary management action if this plant is to reach future climatically suitable habitat. However, presence of pollinators (in this case, bees) and closely associated plant species (to help understand if an area has similar microhabitat conditions) must be confirmed in new locations.

In order to maintain suitable habitat for skullcap, managers will also have to pay attention to exotic plant species, as this species is susceptible to competition (NatureServe 2011). Both CHCH and KIMO have been identified as high concern for exotic plant species impacts (Vital Signs Workshop); therefore, work should be done to determine if these species are competing with the skullcap and if their ranges are expanding with climate change into areas with skullcap. Exotic species management may become a necessary part of skullcap management. Additionally, climate change may affect fire regimes which, if fires burn forest canopies, may have negative implications for the skullcap (NatureServe 2011). Conversely, small scale fires may actually benefit this species by reducing competing vegetation. Therefore, an understanding of local changes in fire regimes should be considered when managing for this species. Currently, KIMO has a buildup of fuelwood, making fire management a high priority in this park (Vital Signs Workshop) – the outcome of which will likely affect its suitability as skullcap habitat.

Finally, the MaxEnt analysis identified mean temperature in the wettest quarter as being the most important predictor variable for suitable skullcap habitat (Table 18). This analysis showed that temperatures around 5 degrees Celsius in this quarter correspond to suitable habitat; whereas higher temperatures severely decrease the probability of suitable habitat. Therefore, this variable will likely be in important determining factor for habitat in the future.

Southeastern Shrew

Despite being identified “Presumed Stable” through the CCVI, our habitat suitability projections show the southeastern shrew undergoing a range shift and loss from the park units in which it is currently found (CHCH, SHIL, and STRI). Currently, this is very widespread species throughout the CUPN (NatureServe 2011); however, in the future, its range is predicted to move northward, and the only unit that is predicted to contain suitable habitat into 2080 is CUGA. Much like the skullcap, this species has limited dispersal capabilities (thought to be no more than 5 km; NatureServe 2011), meaning it may be unable to reach new suitable habitat areas. Habitat for this species is driven both by temperature and precipitation (NatureServe 2011; our analyses), which may explain why models predict a northward shift in habitat when tracking climate change. It is possible, based on our models, that this species will move out of the CUPN entirely, or will only be found in the north-easternmost corner.

Heartleaf Plantain

Plantain is considered critically imperiled in 3 states in the CUPN (NC, TN, and AL) and is considered extirpated in another (KY) (NatureServe 2011). Even in the states in which the species is found, populations are very localized. Therefore, there were very few occurrence points within the study area available to use to build a model for this species (especially after withholding 30% of the points to test the model). This means that this model is not as robust as it would be with more points. Projections should be interpreted with less confidence as a result.

In consistency with Conservation Status Ranks, this species was identified as being "Highly Vulnerable" to climate change. Currently, the heartleaf plantain is found in states to the west of the CUPN, which is positive, given that the models predict its suitable habitat to move westward and encompass the western third of the CUPN. The plantain relies on semi-aquatic habitats, such a stream beds (NatureServe 2011). It is particularly sensitive to water quality and requires clear water; therefore, maintaining water quality is crucial to maintaining habitat. However, water quality is a high priority concern in all of the parks that are predicted to contain future suitable habitat for the plantain (Vital Signs Workshop).

This is the only species we modeled in which suitable habitat is predicted to increase. MaxEnt predicts there to be suitable habitat in many parks in which it is not currently found. Similarly to the aforementioned species, this begs the question of whether plantain would be able to disperse to other regions, whether suitable microhabitat requirements are available, and whether there will be adverse biotic interactions in novel areas. Transplanting has been tried with the heartleaf plantain with a survival rate of 25-100%, though long term survival of these transplants was not monitored (NatureServe 2011). Regardless, this reveals that transplanting may be a possibility for this species once potential suitable habitats have been analyzed for true suitability. However, again, the models for this species were built on very few occurrence points and exhibited very low sensitivity scores; therefore, all assertions regarding this species should be interpreted cautiously.

5.3.2 This Project as a Framework for Future Studies

This project provides a potential framework for the NPS, specifically park managers of the CUPN, to use in future climate change vulnerability studies of its parks. By prioritizing the conservation of species that are vulnerable or important to ecosystems, the CUPN can optimize the allocation of resources for species management during climate change. Park managers can assess species vulnerability through the CCVI and habitat suitability modeling to understand the problem from a both non-spatial and spatial perspective. This framework could provide decision-makers with a foundation of sound science from which to create new management strategies or park policies relating to climate change. Another theme behind this strategy is to provide scientists, policy-makers, and other stakeholders with the opportunity to discuss species conservation in a decision-making process that separates the technical scientific data from the societal values (Marsh et al. 2007; Hansen & Hoffman 2011). Park managers and facilitators of this process can then understand both sides of the issue so that they may later integrate them into a final comprehensive and informed decision.

Our decision to make this project an ecoregional study may also be useful in future ecological studies on climate change vulnerability. The NPS Inventory and Monitoring program makes a case for ecoregional research because it can link geographic similarities, common natural resources, and resource protection challenges in one study area (NPS Online). Although various government agencies and NGO's have different ecoregion schemes, based on their management objectives, our study has shown that combining the ecoregions and networks of NatureServe and the NPS, respectively, can be useful for understanding the climatology of a study area. Hansen and Hoffman (2011) support this idea by suggesting that people should view climate change within the context of regional climatology, hydrology, and ecology. Managers should seek to collaborate across political boundaries, as ecoregions will be an important management unit for future conservation purposes. Additionally, NPS networks such as the CUPN have the ability to facilitate and enhance collaboration, information communication, and research on an economically viable scale (NPS Online). Thus, we recommend that NatureServe and NPS continue to collaborate and employ the CCVI and bioclimatic habitat suitability modeling in order to effectively manage species conservation in the face of climate change.

To effectively employ these conservation methods, experts should perform the CCVI. While we are confident in our thorough CCVI evaluations, experts may have personal experience or knowledge that could allow them to tailor the CCVI to their specific geographic region or study area. For example, experts and managers of a certain park may have species-specific information that was not published or available for research in our study. Furthermore, knowledgeable experts may be able to better understand how a species might react to climate change, allowing them to efficiently communicate results to inform management strategies in the area of interest. This information could also be included in habitat suitability predictions for finer modeling scales and smaller study areas.

When modeling habitat suitability, we recommend that managers consider combining an ensemble of statistical models with MaxEnt to predict where species might reside as a result of changing climate. Each model has strengths and weaknesses that can be difficult to interpret, and an ensemble approach allows researchers to observe the variability within the different model projections. By seeing the variability in predicted suitable habitat, managers can be conservative with habitat estimates that inform species-specific management plans. They can also see the level of incongruence between models and, thus, prioritize areas that exhibit higher confidence through greater model agreement. After modeling habitat, managers should conduct field studies to ground-truth areas projected to be suitable habitat. Ground-truthing these areas provides information on whether or not a species is present in those locations. These studies may lead to further research and information that can support conservation initiatives in the region.

6.0 Conclusions

This paper outlines a transparent, integrative framework that NatureServe and NPS can employ to inform decision-making for climate change management strategies and policies within the CUPN. Although we do not currently know the exact future effects of climate change on species, predictive tools such as the CCVI and habitat suitability modeling provide useful information to understand how species may react to various climate scenarios. When considering species vulnerability in these scenarios, managers must remember to account for both Conservation Status Ranks and CCVI results. Being imperiled under conservation ranks does not necessarily imply that a species is vulnerable to climate change, as seen in this study and in others (Byers & Norris 2011; Schlesinger et al. 2011). Thus, species that are both imperiled under conservation ranks and vulnerable to climate change should be prioritized for conservation efforts.

After prioritization, park managers can then use habitat suitability modeling to observe the areas of potential future habitat for these species. We recommend that researchers use an ensemble modeling approach so that managers can see the variability in suitable habitat predictions when making management decisions. Results from our modeling show all four case study species to be disappearing from at least one National Park unit in the CUPN. These predictions demand the need for further research into the effects of climate change on species in the CUPN. Interestingly, our results also show NPS units that may contain suitable habitat in the future. Knowledge of this information now gives managers time to evaluate whether these new areas may be truly suitable and can enact new management plans to deal with this situation as they see fit.

Our project is a first step in addressing climate change vulnerability in management plans. We hope that our research and analysis will act as a springboard for future climate change vulnerability studies and management initiatives in conservation.

References

Anderson, R.P., Mart´ınez-Meyer, E., 2004. Modeling species' geographic distributions for preliminary conservation assessments: an implementation with the spiny pocket mice (Heteromys) of Ecuador. Biological Conservation **116**, 167–179.

American Ornithologists' Union (AOU). 1998. Check-list of North American birds. Seventh edition. American Ornithologists' Union, Washington, DC. 829 pp.

Araujo, M. B., R. G. Pearson, et al. 2005. Validation if species-climate impact models under climate change. Global Change Biology **11**: 1-10.

Austin, M. P. 2002. Spatial preciction of species distribution: an interface between ecological theory and statistical modelling. Ecological Modelling **157**: 101-118.

Barbour, R. W., and W. H. Davis. 1969. Bats of America. The University of Kentucky Press, Lexington, Kentucky.

Berry, P. M., M. D. A. Rounsevell, P. A. Harrison, and E. Audsley. 2006. Assessing the vulnerability of agricultural land use and species to climate change and the role of policy in facilitating adaptation. Environmental Science and Policy **9**: 189-204.

Bolstad, P.V. Swift, L. Collins, F. Régniére, J. 1998. Measured and predicted air temperatures at basin to regional scales in the southern Appalachian mountains. Agricultural and Forest Meteorology **91**: 161-176.

Boschung, H. T., and R. L. Mayden. 2004. Fishes of Alabama. Smithsonian Institution Press, Washington, D.C
Burger, J. 1990. Response of hatchling pine snakes (*Pituophis melanoleucus*) to cues of sympatric snakes. Copeia 1990:1160-3.

Buisson, L., W. Thuiller, et al. 2010. Uncertainty in ensemble forecasting of species distribution. Global Change Biology **16**: 1145-1157.

Byers, E. and S. Norris. 2011. Climate Change Vulnerability Assessment of Species of Concern in West Virginia. West Virginia Division of Natural Resources, Elkins, WV.

Caire, W., J. D. Tyler, B. P. Glass, and M. A. Mares. 1989. Mammals of Oklahoma. University of Oklahoma Press, Norman. Oklahoma. 567 pp.

Clark, M.K. 1994. Eastern big-eared bat survey of four holes swamp, S.C. Final report submitted to the South Carolina chapter of the Nature Conservancy.

Clark, J. S., D. M. Bell, et al. 2011. Climate change vulnerability of forest biodiversity: climate and competition tracking of demographic rates. Global Change Biology **17**(5): 1834-1849.

Collins, J.L. 1976. A revision of the annulate Scutellaria (*Labiatae*). Ph.D dissertation submitted to the Faculty of the Graduate School of Vanderbilt Univ., Nasheville, Tennessee. 294 pp.

ConserveOnline. 2009. Terrestrial Ecoregional Boundary Shapefile (TNC). Avaliable at: <http://conserveonline.org/workspaces/ecoregional.shapefile>.

Culver, D. C., M. C. Christman, W. R. Elliott, H. H. Hobbs, III, and J. R. Reddell. 2003. The North American obligate cave fauna: regional patterns. Biodiversity and Conservation **12**: 441-468.

Cushman, S. A., K. S. McKelvey, et al. 2008. "Use of empirically derived source-destination models to map regional conservation corridors." Conservation Biology **23**(2): 368-376.

Dawson, T. P., Jackson, S. T., House, J. I., Prentice, I. C., and G. M. Mace. 2011. Beyond predictions: biodiversity conservation in a changing climate. Science **332**: 53-58.

Dorman, C. F. 2011. Modelling species' distributions. Modelling Complex Ecological Dynamics. Verlag Berlin. Heidelberg, Springer.

Elith, J., S. J. Phillips, T. Hastie, M. Dudik, Y. E. Chee, C. J. Yates, 2011. A statistical explanation of MaxEnt for ecologists. Diversity and Distributions **17**: 43-57.

Franklin J. 2009. Mapping Species Distribution: Spatial Inference and Prediction. Cambridge University Press, New York, New York, USA.

French, T.W. 1980. Natural history of the southeastern shrew, SOREX LONGIROSTRIS (Bachman). Am. Midl. Nat. 104:13-31.

Gardner, J.E., et al. 1992. Distribution and status of MYOTIS AUSTRORIPARIUS (southeastern bat) in Illinoise, Unpubl report, III. Nat. Hist. Surv., Urbana, IL. 38pp.

Global Biodiversity Information Facility. 2011. Available at <http://data.gbif.org/welcome.htm>.

Goslee, S.C. and Urban, D.L. 2007. The ecodist package for dissimilarity-based analysis of ecological data. Journal of Statistical Software **22** (7):1-19.

Guisan, A. and N. E. Zimmermann. 2000. Predictive habitat distribution models in ecology. Ecological Modelling **135**: 147-186.

Halpin, P. N. 1997. Global climate change and natural-area protection: management responses and research directions. Ecological Applications **7**: 828-843.

Hamilton-Smith, E., and B. Finlayson. 2003. Beneath the surface: a natural history of Australian caves. University of New South Wales Press Ltd, Sydney, Australia.

Hamin, E. M. 2001. The US National Park Service's partnership parks: collaborative responses to middle landscapes. Land Use Policy **18**: 123-135.

Hansen, L. J., and J. R. Hoffman. 2011. Climate savvy: adapting conservation and resource management to a changing world. Island Press, Washington, DC, USA.

Harmon, David, ed. 2006. People, Places, and Parks: Proceedings of the 2005 George Wright Society Conference on Parks, Protected Areas, and Cultural Sites. Hancock, Michigan: The George Wright Society.

Harvey, M.J. 1991. Report to Environmental Sciences Division, Oak Ridge National Laboratory, Survey for Threatened and Endangered Mammals on the Right-of-Way of Proposed Segment 8D of the Foothills Parkway. 26pp.

Hernandez, P. A., C. H. Graham, et al. 2006. The effect of sample size and species characteristics on performance of different species distribution modeling methods. Ecography **29**: 773-785.

Heller, N.E., Zavaleta, E.S. 2009. Biodiversity management in the face of climate change: A review of 22 years of recommendations. Biological Conservation **142:** 14-32.

Hijmans, R. J., S. E. Cameron, et al. 2005. Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology **25**(15): 1965-1978.

Hijmans, R. J. and C. H. Graham 2006. The ability of climate envelope models to predict the effect of climate change on species distributions. Global Change Biology **12**: 2272-2281.

Intergovernmental Panel of Climate Change (IPCC) 2007 – Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson, eds. Cambridge University Press, Cambridge, UK, 976 pp. Available at: <http://www.ipcc.ch/publications_and_data/ar4/syr/en/spms1.html>

Intergovernmental Panel of Climate Change (IPCC) 2007 – Climate Change 2007: Synthesis Report. Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Pachauri, R. K., and A. Reisinger, eds. IPCC, Geneva, Switzerland, 104pp. Available at: <http://www.ipcc.ch/publications_and_data/ar4/syr/en/spms1.html>

Iverson, L. R., A. M. Prasad, et al. 2008. Estimating potential habitat for 134 eastern US tree species under six climate scenarios. Forest Ecology and Management **254**: 390-406.

Jeschke, J. M. and D. L. Strayer 2008. Usefulness of bioclimatic models for studying climate change and invasive species. Annals of the New York Academy of Sciences **1134**: 1-24.

Johns, T. C., J. M. Gregory, et al. 2003. Anthropogenic climate change for 1860 to 2100 simulated with the HadCM3 model under updated emissions scenarios. Climate Dynamics **20**(6): 583-612.

Lamoreux, J. 2004. Stygobites are more wide-ranging than troglobites. Journal of Cave and Karst Studies **66**: 18-19.

Leibfreid, T.R., R.L. Woodman, and S.C. Thomas. 2005. Vital Signs Monitoring Plan for the Cumberland Piedmont Network and Mammoth Cave National Park Prototype Monitoring Program: July 2005. National Park Service, Mammoth Cave, Kentucky, USA. 125 pp. plus appendices.

Levin, S. A. 1992. The Problem of Pattern and Scale in Ecology: The Robert H. MacArthur Award Lecture. Ecological Society of America **73**(6): 1943-1967.

Ligon, J. D., et al. 1986. Report of the American Ornithologists' Union Committee for the Conservation of the Red-cockaded Woodpecker. Auk 103:848-855.

Lookingbill, T. R. and D. L. Urban. 2005. Gradient analysis, the next generation: towards more plant-relevant explanatory variables. Canadian Journal of Forest Research **35**(7): 1744-1753.

Marsh, H., A. Dennis, H. Hines, A. Kutt, K. McDonald, E. Weber, S. Williams, and J. Winter. 2007. Optimizing allocation of management resources for wildlife. Conservation Biology **21**: 387-399.

Matthews, S. N., L. R. Iverson, et al. 2011. Modifying climate change habitat models using tree species-specific assessments of model uncertainty and life history-factors. Forest Ecology and Management **262**: 1460-1472.

Miller, N.A. 1999. Landscape and habitat predictors of Canada Warbler (*Wilsonia Canadensis*) and Northern Waterbrush (*Seiurus noveboracensis*) occurrence in Rhode Island swamps. Masters thesis. University of Rhode Island, Kingston, RI.

Moore, Bill. Ecologist, National Park Service. Personal Communication. 2012.

NatureServe Online. 2011. NatureServe Conservation Status: Global, National, and Subnational Assessments. Available at: <http://www.natureserve.org/explorer/ranking.htm#global>.

NatureServe. 2011. NatureServe Explorer: An online encyclopedia of life [web application]. Version 7.1. NatureServe, Arlington, Virginia. Available http://www.natureserve.org/explorer. (Accessed: March 2, 2012).

National Park Service. 2011. The list of state listed species came from NPSpecies database query, May 19, 2011.

National Park Service Inventory and Monitoring Program Cumberland Piedmont Network Online. Accessed on March 25, 2012. Available at: <http://science.nature.nps.gov/im/units/cupn/index.cfm>. (In text as: NPS Online)

Nicholls, R .J., P. P. Wong, V. Burkett, C. D. Woodroffe, and J. Hay. 2008. Climate change and coastal vulnerability assessment: scenarios for integrated assessment. Sustainability Science **3**: 89-102.

Parker, A. J. 1982. The topographic relative moisture index: An approach to soil-moisture assessment in mountain terrain. Physical Geography **3**: 160-168.

Pearson, R. G. 2007. Species' distribution modeling for conservation educators and practitioners. Synthesis, American Museum of Natural History.

Pearson, R. G. and T. P. Dawson. 2003. Predicting the impacts of climate change on the distribution of species: are bioclimate envelope models useful? Global Ecology & Biogeography **12**: 361-371.

Pearson, R. G., W. Thuiller. 2006. Model-based uncertainty in species range prediction. Journal of Biogeography **33**: 1704-1711.

Phillips, S.J., M. Dudik, and R.E. Schapire. 2004. A maximum entropy approach to species distribution modeling. ICML '04 Proceedings of the twenty-first international conference on Machine learning

Phillips, S.J., R.P. Anderson, and R.E. Schapire. 2006. Maximum entropy modeling of species geographic distributions. Ecological Modelling 190: 231-259.

Phillips, S. J., M. Dudik. 2009. Sample selection bias and presence-only distribution models: implications for background and pseudo-absence data. Ecological Applications **19**(1): 181-197.

R version 2.14.1 2011. Copyright © 2011 The R Foundation for Statistical Computing ISBN 3-900051-07-0 Platform: i386-pc-mingw32/i386 (32-bit).

Ramirez-Villegas and A. Jarvis. 2010. Downscaling Global Circulation Model Outputs: The Delta Method Decision and Policy Analsysi Working Paper No. 1. Agricultura Eco-Eficiente para Reducir la Pobreza.

Root, T. L., and S. H. Schneider. 2006. Conservation and climate change: the challenges ahead. Conservation Biology **20**: 706-708.

Schlesinger, M.D., J.D. Corser, K.A. Perkins, and E.L. White. 2011. Vulnerability of at-risk species to climate change in New York. New York Natural Heritage Program, Albany, NY.

Segurado, P. and M. Araujo. 2004. An evaluation of methods for modelling species distributions. Journal of Biogeography **31**: 1555-1568.

Skilling, D.D. 1992. Butternut canker study progress report. No. 2.

Smart, Lindsey. NatureServe. Personal Communication. 2012

Smith, P.W. 1971. Illinois streams: A classification based on their fishes and an analysis of factors responsible for disappearance of native species. Illinois Natural History Survey Biological Notes, 76: 1-14.

Thuiller, W. 2003. BIOMOD - optimizing predictions of species distributions and projecting potential future shifts under global change. Global Change Biology **9**: 1353-1362.

Turner II, B. L., R. E. Kasperson, P. A. Matson, J. J. McCarthy, R. W. Corell, L. Christensen, N. Eckley, J. X. Kasperson, A. Leurs, M. L. Martello, C. Polsky, A. Pulsipher, and A. Schiller. 2003. A framework for vulnerability analysis in sustainability science. Proceedings of the National Academy of Sciences **100**: 8,074-8,079.

Tuttle, M. D. 1976. Population ecology of the gray bat (*Myotis grisescens*): philopatry, timing, and patterns of movement, weight loss during migration, and seasonal adaptive strategies. University of Kansas Museum of Natural History Occasional Papers **54**:1-38.

U.S. Department of the Interior | U.S. Geological Survey 2006. Accessed 1/15/2012.
URL: http://www.npwrc.usgs.gov/resource/mammals/housebat/appendb.htm
Menlo Park, CA

USGS. Future Land Use and Land Cover Scenarios. 2011. Accessed 4/22/2012.
URL: http://www.usgs.gov/climate_landuse/land_carbon/Scenarios.asp.

Walters, J. R. 1990. The red-cockaded woodpecker: a "primitive cooperative breeder." In P. B. Stacey and W. D. Koenig, eds. Cooperative breeding in birds: long-term studies of ecology and behavior. Cambridge University Press.

Williams, S. E., L. P. Shoo, J. L. Isaac, A. A. Hoffman, and G. Langham. 2008. Towards an integrated framework for assessing the vulnerability of species to climate change. PLoS Biology **6**: e325.

Wilson, C. R. 2003. Woody and arboreal habitats of the green salamander (*Aneides aeneus*) in the Blue Ridge Mountains. Contemporary Herpetology 2003(2).

Young, B., Byers, E., Gravuer, K., Hall, K., Hammerson, G., and A. Redder. 2010. Guidelines for Using the NatureServe Climate Change Vulnerability Index. Available at: <http://www.natureserve.org/prodServices/climatechange/pdfs/Guidelines_NatureServeClimateChangeVulnerabilityIndex_r2.0_Apr10.pdf>

Young, B., Byers, E., Gravuer, K., Hall, K., Hammerson, G., Redder, A., Szabo, K., and J.E. Newmark. 2009. Using the NatureServe Climate Change Vulnerability Index: A Nevada Case Study. Available at: <http://www.natureserve.org/prodServices/climatechange/NVCaseStudy.jsp>

Appendices

Appendix A: Study Area

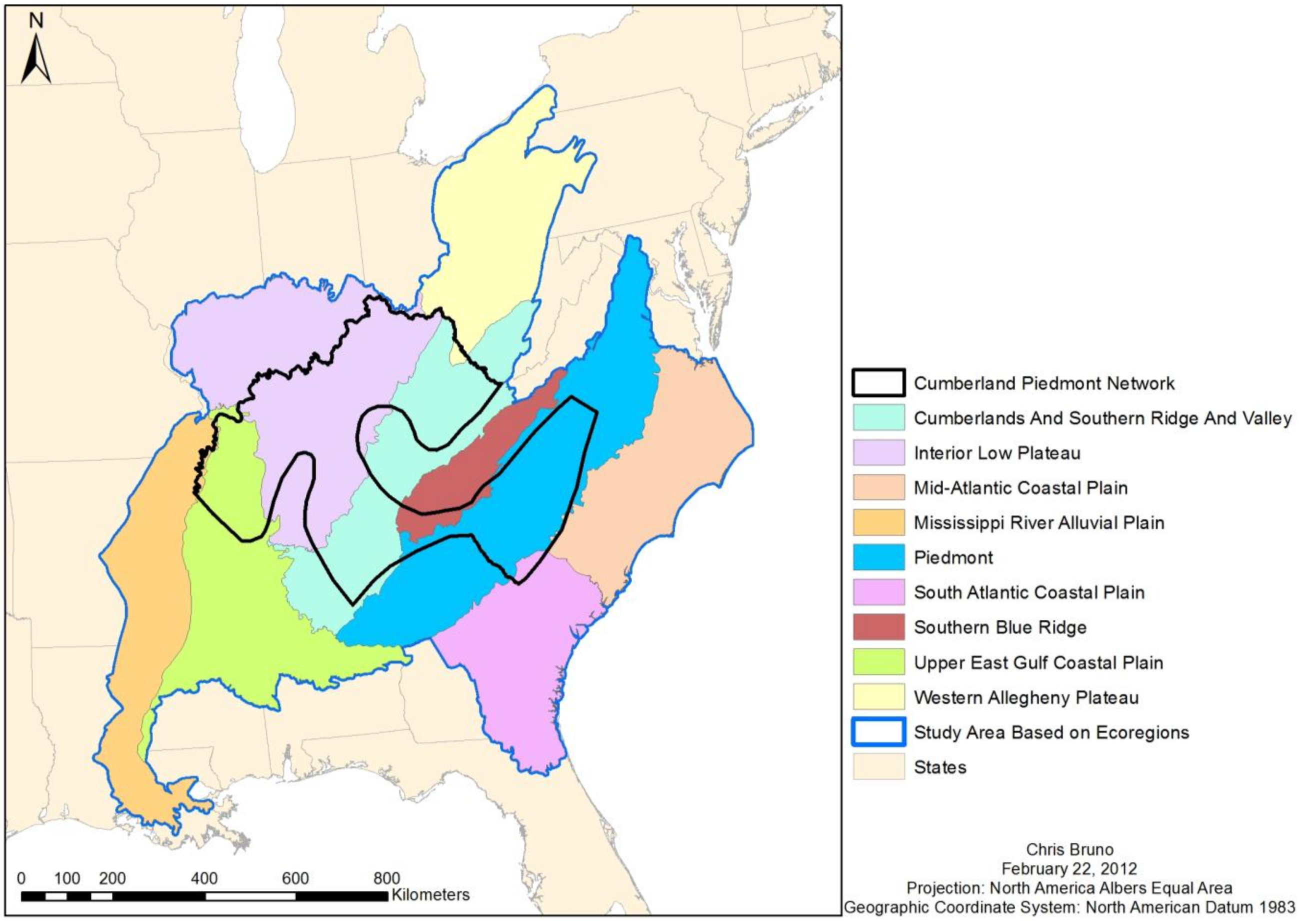


Figure 1. The Nature Conservancy's nine Ecoregions that overlap with the CUPN. This is the area we used for modeling (obtained from ConserveOnline 2009).

Appendix B: CCVI

Table 1: CCVI factors by component

Initial information
Taxonomic group
Relation of species' range to assessment area
Obligation to cave or groundwater aquatic systems
State conservation status rank (S-rank)
Global conservation status rank (G-rank)

Direct exposure to climate change
Percentage of species' range in 5 categories of temperature change:

>5.5° F (3.1° C) warmer
5.1-5.5° F (2.8-3.1° C) warmer
>5.5° F (3.1° C) warmer
3.9-4.4° F (2.2-2.4° C) warmer
< 3.9° F (2.2° C) warmer

Percentage of species' range in 6 categories of moisture change (Hamon AET:PET Moisture Metric):

< -0.119
-0.097 0.119
-0.074 - -0.096
-0.051 - -0.073
-0.028 - -0.050
>-0.028

Indirect exposure to climate change
Exposure to sea level rise
Distribution relative to natural barriers
Distribution relative to anthropogenic barriers
Predicted impact of land use changes resulting from human response to climate change

Sensitivity
Dispersal and movements
Predicted sensitivity to changes in temperature
Predicted sensitivity to changes in precipitation, hydrology, or moisture regime
Dependence on a specific disturbance regime likely to be impacted by climate change
Dependence on ice, ice-edge, or snow-cover habitats
Restriction to uncommon geological features or derivatives
Dependence on other species to generate habitat
Dietary versatility (animals only)
Pollinator versatility (plants only)
Dependence on other species for propagule dispersal
Other interspecific interactions
Measured genetic variation
Occurrence of bottlenecks in recent evolutionary history
Phenological response to changing seasonal temperature and precipitation dynamics

<u>Documented or modeled response to climate change</u>
Documented response to recent climate change
Modeled future (2050) change in abundance or range size
Overlap of modeled future (2050) range with current range
Occurrence of protected areas in modeled future (2050) distribution

Table 2. Temperature and Hamon moisture metric category breakdown by park .

National Park	Temperature Change (°F)	Park Temperature Percentage (%)	Moisture (AET:PET)	Park AET:PET Percentage
ABLI	5.1-5.5	100	-0.074 - -0.096	100
CARL	4.5-5.0	100	-0.028 - -0.050	100
CHCH	4.5-5.0	100	-0.051 - -0.073	100
COWP	4.5-5.0	100	-0.051 - -0.073	100
CUGA	4.5-5.0	100	-0.051 - -0.073	100
FODO	4.5 - 5	65	-0.074 - -0.096	100
	5.1 - 5.5	35		
GUCO	4.5-5.0	100	-0.051 - -0.073	100
KIMO	4.5-5.0	100	-0.051 - -0.073	100
LIRI	4.5-5.0	100	-0.074 - -0.096	98
			-0.051 - -0.073	2
MACA	5.1 - 5.5	100	-0.074 - -0.096	100
NISI	4.0 - 4.5	100	-0.051 - -0.073	100
RUCA	4.5-5.0	100	-0.051 - -0.073	100
SHIL	4.5-5.0	100	-0.074 - -0.096	100
STRI	4.5-5.0	100	-0.074 - -0.096	100

Table 3. CCVI scores for each species individual in the National Parks of the CUPN. All notes, citations, and sources are documented in a separate word document. Much of the species information to determine these CCVI scores came from NatureServe Explorer.

Scientific Name	Common Name	GRank	SRank	Index	Confidence	Park
Amphibians						
Aneides aeneus	Green Salamander	G3G4	S3	MV	VH	CARL
Aneides aeneus	Green Salamander	G3G4	S3	MV	VH	LIRI
Aneides aeneus	Green Salamander	G3G4	S3	MV	VH	RUCA
Gyrinophilus palleucus	Tennessee Cave Salamander	G2	S2	PS	VH	CUGA
Birds						
Accipiter cooperii	Cooper's Hawk	G5	S3B, S4N	IL	VH	LIRI
Accipiter cooperii	Cooper's Hawk	G5	S3B, S4N	IL	VH	RUCA
Accipiter striatus	Sharp-shinned Hawk	G5	S3B	IL	Mod	CHCH
Accipiter striatus	Sharp-shinned Hawk	G5	S3B	IL	High	CUGA
Accipiter striatus	Sharp-shinned Hawk	G5	S3B	IL	High	FODO
Accipiter striatus	Sharp-shinned Hawk	G5	S3B	IL	High	SHIL
Accipiter striatus	Sharp-shinned Hawk	G5	S3B	IL	Mod	STRI
Accipiter striatus	Sharp-shinned Hawk	G5	S3B, S4N	IL	Mod	ABLI
Accipiter striatus	Sharp-shinned Hawk	G5	S3B, S4N	IL	Mod	MACA
Aegolius acadicus	Northern Saw-whet Owl	G5	S1	PS	VH	CUGA
Aegolius acadicus	Northern Saw-whet Owl	G5	S1B, S2N	PS	VH	CUGA
Aimophilia astivalis	Bachman's Sparrow	G3	S1/S2b	PS	VH	CUGA
Aimophilia astivalis	Bachman's Sparrow	G3	S1b	PS	VH	MACA
Aimophilia astivalis	Bachman's Sparrow	G3	S2	PS	VH	CHCH
Ammodramus hanslowii	Henslow's Sparrow	G4	S3B	PS	Low	MACA
Anas discors	Blue-winged Teal	G5	S1,S2B	PS	VH	MACA
Aquila chrysaetos	Golden Eagle	G5	S1	PS	VH	CUGA
Ardea alba	Great Egret	G5	S2B,S3N	IL	VH	CHCH
Ardea alba	Great Egret	G5	S2B,S3N	IL	VH	FODO
Ardea alba	Great Egret	G5	S2B,S3N	IL	VH	SHIL
Certhia americana	Brown Creeper	G5	S1S2B,S4S5N	PS	VH	ABLI

Certhia americana	Brown Creeper	G5	S1S2B,S4S5N	PS	VH	CUGA
Certhia americana	Brown Creeper	G5	S1S2B,S4S5N	PS	VH	MACA
Chondestes grammacus	Lark Sparrow	G5	S2S3B	IL	VH	ABLI
Circus cyaneus	Northern Harrier	G5	S1S2B,S3N	PS	VH	ABLI
Circus cyaneus	Northern Harrier	G5	S1S2B,S3N	PS	VH	CUGA
Circus cyaneus	Northern Harrier	G5	S1S2B,S3N	PS	VH	MACA
Cistorthorus platensis	Sedge Wren	G5	S3B	PS	VH	MACA
Contopus cooperi	Olive-sided Flycatcher	G4	S1	IL	VH	CHCH
Contopus cooperi	Olive-sided Flycatcher	G4	S1	IL	VH	CUGA
Corvus corax	Common Raven	G5	S1,S2	PS	VH	CUGA
Dendroica cerulea	Cerulean Warbler	G4	S1	PS	VH	CHCH
Dendroica cerulea	Cerulean Warbler	G4	S3B	PS	VH	CHCH
Dendroica cerulea	Cerulean Warbler	G4	S3B	PS	VH	CUGA
Dendroica cerulea	Cerulean Warbler	G4	S3B	PS	VH	FODO
Dendroica cerulea	Cerulean Warbler	G4	S3B	PS	VH	SHIL
Dendroica cerulea	Cerulean Warbler	G4	S3B	PS	VH	STRI
Dendroica fusca	Blackburnian Warbler	G5	S1S2B	PS	VH	ABLI
Dendroica fusca	Blackburnian Warbler	G5	S1S2B	PS	VH	CUGA
Dendroica fusca	Blackburnian Warbler	G5	S1S2B	PS	VH	MACA
Dendroica magnolia	Magnolia Warbler	G5	S1S2B	PS	VH	CUGA
Egretta caerulea	Little Blue Heron	G5	S1B	IL	VH	MACA
Egretta caerulea	Little Blue Heron	G5	S2B,S3N	IL	VH	FODO
Egretta caerulea	Little Blue Heron	G5	S2B,S3N	IL	VH	SHIL
Egretta thula	Snowy Egret	G5	S2B,S3N	IL	VH	SHIL
Epidonax minimus	Least Flycatcher	G5	S1B	IL	VH	ABLI
Epidonax minimus	Least Flycatcher	G5	S1B	IL	VH	CUGA
Epidonax minimus	Least Flycatcher	G5	S1B	IL	VH	MACA
Falco peregrinus	Peregrine Falcon	G4	S1b,S1n,S2n	PS	VH	CUGA
Falco peregrinus	Peregrine Falcon	G4	S1n	PS	VH	FODO

Fulica americana	American Coot	G5	S1B	IL	VH	MACA
Gallinula chloropus	Common Moorhen	G5	S1S2B	PS	VH	MACA
Gallinula chloropus	Common Moorhen	G5	S1S2B	PS	VH	MACA
Haliaeetus leucocephalus	Bald Eagle	G5	S2B,S2S3N	PS	VH	MACA
Haliaeetus leucocephalus	Bald Eagle	G5	S2S3B,S3N	PS	VH	CUGA
Haliaeetus leucocephalus	Bald Eagle	G5	S3B	PS	VH	LIRI
Haliaeetus leucocephalus	Bald Eagle	G5	S3B	PS	VH	RUCA
Ictinia mississippiensis	Mississippi Kite	G5	S2S3	IL	VH	FODO
Junco hyemalis	Dark Eyed Junco	G5	S2S3B,S5N	MV	VH	ABLI
Junco hyemalis	Dark Eyed Junco	G5	S2S3B,S5N	MV	VH	CUGA
Junco hyemalis	Dark Eyed Junco	G5	S2S3B,S5N	MV	VH	MACA
Limnothlypis swainsonii	Swainson's Warbler	G4	S2B	PS	Low	CUGA
Lophodytes cucullatus	Hooded Merganser	G5	S1S2B,S3S4N	PS	VH	MACA
Nycticorax nycticorax	Black-crowned Night-heron	G5	S1S2B	PS	VH	MACA
Pandion haliaetus	Osprey	G5	S2S3B	IL	VH	ABLI
Pandion haliaetus	Osprey	G5	S2S3B	IL	VH	CUGA
Pandion haliaetus	Osprey	G5	S2S3B	IL	VH	MACA
Passerculus sandwichensis	Savannah Sparrow	G5	S2S3B,S2S3N	PS	Low	MACA
Pheucticus ludovicianus	Rose-breasted Grosbeak	G4	S2S4B	PS	VH	ABLI
Pheucticus ludovicianus	Rose-breasted Grosbeak	G4	S2S4B	PS	VH	CUGA
Pheucticus ludovicianus	Rose-breasted Grosbeak	G4	S2S4B	PS	VH	MACA
Picoides borealis	Red-Cockaded Woodpecker	G3	S1	HV	VH	CUGA
Picoides borealis	Red-Cockaded Woodpecker	G3	S2	HV	VH	CHCH
Podilymbus podiceps	Pied-billed Grebe	G4	S1b, S4N	PS	VH	MACA
Pooecetes gramineus	Vesper Sparrow	G5	S1B	PS	VH	MACA
Pooecetes gramineus	Vesper Sparrow	G5	S1B, S4N	PS	VH	CHCH
Rallus elegans	King Rail	G4	S1B	IL	VH	MACA
Regulus satrapa	Golden-crowned Kinglet	G5	S2B,S5N	PS	Low	CUGA
Riparia riparia	Bank Swallow	G5	S3B	PS	VH	MACA

Sitta canadensis	Red-Breasted Nuthatch	G5	S1B	IL	VH	ABLI
Sitta canadensis	Red-Breasted Nuthatch	G5	S1B	IL	VH	CUGA
Sitta canadensis	Red-Breasted Nuthatch	G5	S1B	IL	VH	MACA
Sphyrapicus varius	Yellow-bellied Sapsucker	G5	S1B, S4N	IL	VH	CHCH
Sphyrapicus varius	Yellow-bellied Sapsucker	G5	S1B, S4N	IL	VH	CUGA
Sphyrapicus varius	Yellow-bellied Sapsucker	G5	S1B, S4N	IL	VH	FODO
Sphyrapicus varius	Yellow-bellied Sapsucker	G5	S1B, S4N	IL	VH	SHIL
Sphyrapicus varius	Yellow-bellied Sapsucker	G5	S1B, S4N	IL	VH	STRI
Thryomanes bewickii	Bewick's Wren	G5	S1	IL	VH	CHCH
Thryomanes bewickii	Bewick's Wren	G5	S1	IL	VH	STRI
Thryomanes bewickii	Bewick's Wren	G5	S3B	IL	VH	MACA
Troglodytes troglodytes	Winter Wren	G5	S2B,S4N	IL	VH	CUGA
Vermivora chrysoptera	Golden-winged Warbler	G4	S1	IL	VH	CHCH
Vermivora chrysoptera	Golden-winged Warbler	G5	S2B	IL	VH	ABLI
Vermivora chrysoptera	Golden-winged Warbler	G5	S2B	IL	VH	CUGA
Vermivora chrysoptera	Golden-winged Warbler	G5	S2B	IL	VH	MACA
Wilsonia canadensi	Canada Warbler	G5	S3B	MV	VH	ABLI
Wilsonia canadensi	Canada Warbler	G5	S3B	MV	VH	CUGA
Wilsonia canadensi	Canada Warbler	G5	S3B	MV	VH	MACA
Fish						
Ammocrypta clara	Western Sand Darter	G3	S1	PS	VH	CUGA
Cyprinella caerulea	Blue Shiner	G2	S1	PS	VH	LIRI
Etheostoma collis	Carolina Darter	G3	SNR	MV	VH	KIMO
Etheostoma maculatum	Spotted Darter	G2	S2	PS	VH	MACA
Phoxinus cumberlandensis	Mountain Blackside Dace	G2	S1S2	PS	VH	CUGA
Typhlichthys subterraneus	Southern Cavefish	G4	S2S3	HV	VH	MACA
Invertebrates - Mollusks						
Cumberlandia monodonta	Spectaclecase	G3	S1	EV	High	MACA
Cyprogenia stegaria	Fanshell	G1	S1	HV	VH	MACA

Epioblasma torulosa rangiana	Northern Riffleshell	G2T2	S1	EV	VH	MACA
Epioblasma triquetra	Snuffbox	G3	S1	EV	Mod	MACA
Fusconaia subrotunda	Longsolid	G3	S3S4	HV	Mod	MACA
Lampsilis abrupta	Pink Mucket	G2	S1	HV	Mod	MACA
Lampsilis ovata	Pocketbook	G5	S1	MV	Low	MACA
Obovaria restusa	Ring Pink	G1	S1	EV	VH	MACA
Plethobasus cyphyus	Sheepnose	G3	S1	HV	VH	MACA
Pleurobema clava	Clubshell	G1G2	S1	EV	VH	MACA
Pleurobema plenum	Rough Pigtoe	G1	S1	EV	Mod	MACA
Pleurobema rubrum	Pyramid Pigtoe	G2G3	S1	HV	Mod	MACA
Villosa ortmanni	Kentucky Creekshell	G2	S2	EV	VH	MACA
Mammals						
Corynorhinus rafinesquii	Rafinesque's Big-eared Bat	G3G4	S3	HV	VH	MACA
Corynorhinus rafinesquii	Rafinesque's Big-eared Bat	G3G4	S3	MV	VH	CUGA
Corynorhinus rafinesquii	Rafinesque's Big-eared Bat	G3G4	S3	MV	VH	SHIL
Myotis austroriparius	Southeastern myotis	G3G4	S1S2	MV	VH	MACA
Myotis grisescens	Gray Myotis	G3	S1S2	MV	VH	CHCH
Myotis grisescens	Gray Myotis	G3	S1S2	MV	VH	CUGA
Myotis grisescens	Gray Myotis	G3	S1S2	MV	VH	FODO
Myotis grisescens	Gray Myotis	G3	S2	MV	VH	LIRI
Myotis grisescens	Gray Myotis	G3	S2	MV	VH	MACA
Myotis grisescens	Gray Myotis	G3	S2	MV	VH	SHIL
Myotis leibii	Eastern Small-footed Myotis	G3	S2	PS	VH	CUGA
Myotis leibii	Eastern Small-footed Myotis	G3	S2	PS	VH	MACA
Myotis sodalis	Indiana Bat	G2	S1S2	PS	VH	CUGA
Myotis sodalis	Indiana Bat	G2	S1S2	PS	VH	MACA
Neotoma magister	Allegheny Woodrat	G3G4	S3	PS	VH	CUGA
Sorex longirostris	Southeastern Shrew	G5	S4	MV	VH	SHIL
Sorex longirostris	Southeastern Shrew	G5	S4	MV	VH	STRI

Sorex longirostris	Southeastern Shrew	G5	S4	PS	VH	CHCH
Spilogale putorius	Eastern Spotted Skunk	G5	S2S3	IL	VH	CUGA
Reptiles						
Pituophis melanoleucus	Pine Snake	G4	S3S4	PS	VH	NISI
Vascular Plants						
Apios priceana	Traveler's Delight	G2	S2	PS	VH	FODO
Carex decomposita	Cypress-Knee Sedge	G3G4	S2	MV	VH	MACA
Dodecatheon frenchii	French's Shootingstar	G3	S3	PS	VH	MACA
Gymnopogon ambiguus	Bearded Skeletongrass	G4	S2S3	PS	VH	MACA
Juglans cinerea	Butternut	G4	S2S3	HV	VH	MACA
Juglans cinerea	Butternut	G4	S2S3	HV	VH	STRI
Juglans cinerea	Butternut	G4	S2S3	MV	VH	CUGA
Plantago cordata	Heartleaf Plantain	G4	S1	HV	Low	CHCH
Quercus oglethorpensis	Oglethorpe's Oak	G3	S3	PS	VH	NISI
Scutellaria montana	Large-flower Skullcap	G3	S2	MV	VH	CHCH
Thaspium pinnatifidum	Cutleaf Meadow-Parsnip	G2G3	S1	MV	VH	CHCH
Trillium rugelii	Ill-scented Wakerobin	G3	S2	PS	VH	FODO

Table 4. Intrinsic and modeled risk factor scores from the CCVI. All notes, citations, and sources are documented in a separate word document. Much of the species information to determine these CCVI scores came from NatureServe Explorer.

Scientific Name	Common Name	Dispersal/Movement	historical thermal niche	physiological thermal niche	historical hydrological niche	physiological hydrological niche	Disturbance	Ice/snow	Phys habitat	Other spp for hab	Diet	Pollinators	Other spp disp	Other spp interaction	Genetic var	Gen bottleneck	Phenol response	Doc response	Modeled change	Modeled overlap	Protected Areas	Park
Amphibians																						
Aneides aeneus	Green Salamander	SI	N	N	SI	SI	N	N	Inc	N	N	N/A	N	N	U	U	U	U	U	U	U	RUCA
Aneides aeneus	Green Salamander	SI	N	N	N	SI	N	N	Inc	N	N	N/A	N	N	U	U	U	U	U	U	U	CARL
Aneides aeneus	Green Salamander	SI	N	N	SI	SI	N	N	Inc	N	N	N/A	N	N	U	U	U	U	U	U	U	LIRI
Gyrinophilus palleucus	Tennessee Cave Salamander	Inc	N	N	N	N	N	N	Inc	N	N	N/A	N	N	U	N	U	U	U	U	U	CUGA
Birds																						
Accipiter cooperii	Cooper's Hawk	SD	N	N	SD	N	N	N	De c	N	N	N/A	N	N	U	N	U	U	U	U	U	LIRI
Accipiter cooperii	Cooper's Hawk	SD	N	N	SD	N	N	N	De c	N	N	N/A	N	N	U	N	U	U	U	U	U	RUCA
Accipiter striatus	Sharp-shinned Hawk	SD	N-SD	SI-N	SD	N	N	N	N	N	N	N/A	U	N	U	N	U	N	U	U	U	CHCH
Accipiter striatus	Sharp-shinned Hawk	SD	N-SD	SI-N	SD	N	N	N	N	N	N	N/A	U	N	U	N	U	N	U	U	U	CUGA
Accipiter striatus	Sharp-shinned Hawk	SD	N-SD	SI-N	SD	N	N	N	N	N	N	N/A	U	N	U	N	U	N	U	U	U	FODO
Accipiter striatus	Sharp-shinned Hawk	SD	N-SD	SI-N	SD	N	N	N	N	N	N	N/A	U	N	U	N	U	N	U	U	U	SHIL
Accipiter striatus	Sharp-shinned Hawk	SD	N-SD	SI-N	SD	N	N	N	N	N	N	N/A	U	N	U	N	U	N	U	U	U	STRI

Scientific Name	Common Name	Dispersal/Movement	historical thermal niche	physiological thermal niche	historical hydrological niche	physiological hydrological niche	Disturbance	Ice/snow	Phys habitat	Other spp for hab	Diet	Pollinators	Other spp disp	Other spp interaction	Genetic var	Gen bottleneck	Phenol response	Doc response	Modeled change	Modeled overlap	Protected Areas	Park
Accipiter striatus	Sharp-shinned Hawk	SD	N-SD	SI-N	SD	N	N	N	N	N	N	N/A	U	N	U	N	U	N	U	U	U	ABLI
Accipiter striatus	Sharp-shinned Hawk	SD	N-SD	SI-N	SD	N	N	N	N	N	N	N/A	U	N	U	N	U	N	U	U	U	MACA
Aegolius acadicus	Northern Saw-whet Owl	N	N	Inc	SD	N	SI	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	CUGA (TN)
Aegolius acadicus	Northern Saw-whet Owl	N	N	Inc	SD	N	SI	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	CUGA (VA)
Aimophilia astivalis	Bachman's Sparrow	SD	SI	N	SD	N	SD	N	N	SI	N	N/A	N	N	U	N	U	U	SD	N	SI	CUGA
Aimophilia astivalis	Bachman's Sparrow	SD	SI	N	SD	N	SD	N	N	SI	N	N/A	N	N	U	N	U	U	SD	N	SI	MACA
Aimophilia astivalis	Bachman's Sparrow	SD	SI	N	SD	N	SD	N	N	SI	N	N/A	N	N	U	N	U	U	SD	N	SI	CHCH
Ammodramus hanslowii	Henslow's Sparrow	SD	N	N	SI-N	SI	SI	N	N	N	N	N/A	U	N	U	N	U	U	U	U	U	MACA
Anas discors	Blue-winged Teal	SD	N	N	SD	Inc	N-SD	N	N	SI	N	N/A	U	N	U	N	U	U	SD	SI	SI	MACA
Aquila chrysaetos	Golden Eagle	N	N	N	SD	N	SI	N	SI	N	N	N/A	N	N	U	U	U	U	U	U	U	CUGA
Ardea alba	Great Egret	Dec	N	N-SD	N	Inc-SI	N	N	N	N	SI	N/A	N	N	U	U	U	U	Dec	U	U	CHCH
Ardea alba	Great Egret	Dec	N	N-SD	N	Inc-SI	N	N	N	N	SI	N/A	N	N	U	U	U	U	Dec	U	U	FODO
Ardea alba	Great Egret	Dec	N	N-SD	N	Inc-SI	N	N	N	N	SI	N/A	N	N	U	U	U	U	Dec	U	U	SHIL
Certhia americana	Brown Creeper	Dec	N	N	SD	SI	N	N	N	N	N	N/A	N	SI	U	U	U	U	SI	N	U	ABLI
Certhia	Brown	Dec	N	N	SD	SI	N	N	N	N	N	N/A	N	SI	U	U	U	U	SI	N	U	CUGA

Scientific Name	Common Name	Dispersal/Movement	historical thermal niche	physiological thermal niche	historical hydrological niche	physiological hydrological niche	Disturbance	Ice/snow	Phys habitat	Other spp for hab	Diet	Pollinators	Other spp disp	Other spp interaction	Genetic var	Gen bottleneck	Phenol response	Doc response	Modeled change	Modeled overlap	Protected Areas	Park
americana	Creeper																					
Certhia americana	Brown Creeper	Dec	N	N	SD	SI	N	N	N	N	N	N/A	N	SI	U	U	U	U	SI	N	U	MACA
Chondestes grammacus	Lark Sparrow	SD	N	N	SD	N	N	N	N	N	S D	N/A	N	N	U	U	U	U	U	U	U	ABLI
Circus cyaneus	Northern Harrier	Dec	N	N	SD	SI	N	N	N	N	N	N/A	N	N	U	U	U	U	SI	N	U	ABLI
Circus cyaneus	Northern Harrier	Dec	N	N	SD	SI	N	N	N	N	N	N/A	N	N	U	U	U	U	SI	N	U	CUGA
Circus cyaneus	Northern Harrier	Dec	N	N	SD	SI	N	N	N	N	N	N/A	N	N	U	U	U	U	SI	N	U	MACA
Cistorthorus platensis	Sedge Wren	Dec	N	N	N-SD	SI	SI	N	N	N	N	N/A	N	N	N	N/A	N	U	SD	N	U	MACA
Contopus cooperi	Olive-sided Flycatcher	SD	N	N	SD	N	SD	N	N	N	N	N/A	N	N	U	U	U	U	N	U	U	CHCH
Contopus cooperi	Olive-sided Flycatcher	SD	N	N	SD	N	SD	N	N	N	N	N/A	N	N	U	U	U	U	N	U	U	CUGA
Corvus corax	Common Raven	N	N	N	SD	N	N	N	SI-N	N	N	N/A	U	N	U	U	N	U	U	U	U	CUGA
Dendroica cerulea	Cerulean Warbler	Dec	N	SD	SI	SI	N	N	N	N	N	N/A	N	N	U	U	U	U	SI	N	U	CHCH
Dendroica cerulea	Cerulean Warbler	Dec	N	N	SI	SI	N	N	N	N	N	N/A	N	N	U	U	U	U	SI	N	U	CHCH
Dendroica cerulea	Cerulean Warbler	SD	N	N-SD	SI	SI	N	N	N	SI -N	N	N/A	U	N	U	U	U	U	SI	N	N	CUGA
Dendroica cerulea	Cerulean Warbler	Dec	N	N	SI	SI	N	N	N	N	N	N/A	N	N	U	U	U	U	SI	N	U	FODO
Dendroica cerulea	Cerulean Warbler	Dec	N	N	SI	SI	N	N	N	N	N	N/A	N	N	U	U	U	U	SI	N	U	SHIL
Dendroica cerulea	Cerulean Warbler	Dec	N	N	SI	SI	N	N	N	N	N	N/A	N	N	U	U	U	U	SI	N	U	STRI
Dendroica fusca	Blackburnian Warbler	Dec	N	N	SD	N	N	N	N	N	N	N/A	N	N	U	U	U	U	SI	SI	U	ABLI

Scientific Name	Common Name	Dispersal/Movement	historical thermal niche	physiological thermal niche	historical hydrological niche	physiological hydrological niche	Disturbance	Ice/snow	Phys habitat	Other spp for hab	Diet	Pollinators	Other spp disp	Other spp interaction	Genetic var	Gen bottleneck	Phenol response	Doc response	Modeled change	Modeled overlap	Protected Areas	Park
Dendroica fusca	Blackburnian Warbler	Dec	N	N	SD	N	N	N	N	N	N	N/A	N	N	U	U	U	U	SI	SI	U	CUGA
Dendroica fusca	Blackburnian Warbler	Dec	N	N	SD	N	N	N	N	N	N	N/A	N	N	U	U	U	U	SI	SI	U	MACA
Dendroica magnolia	Magnolia Warbler	Dec	N	N	SD	N	N	N	N	N	N	N/A	N	N	U	U	U	U	SI	SI	U	CUGA
Egretta caerulea	Little Blue Heron	N	N	N	N	SI	N	N	SD	N	S D	N/A	N	N	U	U	U	U	Dec	N	U	MACA
Egretta caerulea	Little Blue Heron	SD	N	N	N	SI	N	N	N	N	N	N/A	N	N	U	U	U	U	Dec	U	U	FODO
Egretta caerulea	Little Blue Heron	SD	N	N	N	SI	N	N	N	N	N	N/A	N	N	U	U	U	U	Dec	U	U	SHIL
Egretta thula	Snowy Egret	Dec	N	N-SD	N	Inc -SI	N	N	N	N	SI	N/A	N	N	U	U	U	U	Dec	U	U	SHIL
Epidonax minimus	Least Flycatcher	Dec	N	N	SD	N	N	N	N	N	N	N/A	N	N	U	U	U	U	N	U	U	ABLI
Epidonax minimus	Least Flycatcher	Dec	N	N	SD	N	N	N	N	N	N	N/A	N	N	U	U	U	U	N	U	U	CUGA
Epidonax minimus	Least Flycatcher	Dec	N	N	SD	N	N	N	N	N	N	N/A	N	N	U	U	U	U	N	U	U	MACA
Falco peregrinus	Peregrine Falcon	N	N	N	N	SI	N	N	N	N	N	N/A	N	N	U	N	U	U	U	U	U	CUGA
Falco peregrinus	Peregrine Falcon	N	N	N	N	SI	N	N	N	N	N	N/A	N	N	U	N	U	U	U	U	U	FODO
Fulica americana	American Coot	SD	N	N	SD	SI	N	N	SD	N	N	N/A	N	N	N	N/A	U	U	N	N	U	MACA
Gallinula chloropus	Common Moorhen	SD	N	N	SD	SI	N	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	MACA
Gallinula chloropus	Common Moorhen	Dec	N	N	SD	Inc	N	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	MACA
Haliaeetus leucocephalus	Bald Eagle	SD	SI-N	N	N	SI	N	N	N	N	SI	N/A	N	N	U	N	U	U	U	U	U	MACA
Haliaeetus	Bald Eagle	SD	SI-	N	N	SI	N	N	N	N	SI	N/A	N	N	U	N	U	U	U	U	U	CUGA

Scientific Name	Common Name	Dispersal/Movement	historical thermal niche	physiological thermal niche	historical hydrological niche	physiological hydrological niche	Disturbance	Ice/snow	Phys habitat	Other spp for hab	Diet	Pollinators	Other spp disp	Other spp interaction	Genetic var	Gen bottleneck	Phenol response	Doc response	Modeled change	Modeled overlap	Protected Areas	Park
leucocephalus			N																			
Haliaeetus leucocephalus	Bald Eagle	SD	SI-N	N	N	SI	N	N	N	N	SI	N/A	U	N	U	N	U	U	U	U	U	LIRI
Haliaeetus leucocephalus	Bald Eagle	SD	SI-N	N	N	SI	N	N	N	N	SI	N/A	U	N	U	N	U	U	U	U	U	RUCA
Ictinia mississippiensis	Mississippi Kite	Dec	N	N	N	N	N	N	N	N	N	N/A	N	N	U	U	U	U	Dec	U	U	FODO
Junco hyemalis	Dark Eyed Junco	N	N	N	N	N	N	N	N	N	SI	N/A	U	N	U	N	U	U	Inc	N	SI	ABLI
Junco hyemalis	Dark Eyed Junco	N	N	N	N	N	N	N	N	N	SI	N/A	U	N	U	N	U	U	Inc	N	SI	CUGA
Junco hyemalis	Dark Eyed Junco	N	N	N	N	N	N	N	N	N	SI	N/A	U	N	U	N	U	U	Inc	N	SI	MACA
Limnothlypis swainsonii	Swainson's Warbler	SD	N	N-SD	SD	N	SI	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	CUGA
Lophodytes cucullatus	Hooded Merganser	Dec	N	N	SD	Inc	N	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	MACA
Nycticorax nycticorax	Black-crowned Night-heron	Dec	N	N	SD	Inc	N	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	MACA
Pandion haliaetus	Osprey	SD	N	N	SD	N	N	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	ABLI
Pandion haliaetus	Osprey	SD	N	N	SD	N	N	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	CUGA
Pandion haliaetus	Osprey	SD	N	N	SD	N	N	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	MACA
Passerculus sandwichensis	Savannah Sparrow	SD	N-SD	N	SD	N	SI	N	N	N	SD	N/A	U	N	U	U	SI	SI-N	Inc-SI	N	N	MACA
Pheucticus ludovicianus	Rose-breasted Grosbeak	Dec	N	N	Inc	N	N	N	U	N	N	N/A	N	N	U	U	U	U	SI	N	U	ABLI
Pheucticus ludovicianus	Rose-breasted	Dec	N	N	Inc	N	N	N	U	N	N	N/A	N	N	U	U	U	U	SI	N	U	CUGA

Scientific Name	Common Name	Dispersal/Movement	historical thermal niche	physiological thermal niche	historical hydrological niche	physiological hydrological niche	Disturbance	Ice/snow	Phys habitat	Other spp for hab	Diet	Pollinators	Other spp disp	Other spp interaction	Genetic var	Gen bottleneck	Phenol response	Doc response	Modeled change	Modeled overlap	Protected Areas	Park
	Grosbeak																					
Pheucticus ludovicianus	Rose-breasted Grosbeak	Dec	N	N	GI	N	N	N	U	N	N	N/A	N	N	U	U	U	U	SI	N	U	MACA
Picoides borealis	Red-Cockaded Woodpecker	N	N	N	SD	N	Inc	N	N	SI	N	N/A	SI	N	U	U	U	U	U	U	U	CUGA
Picoides borealis	Red-Cockaded Woodpecker	N	N	N	SD	N	Inc	N	N	SI	N	N/A	SI	N	U	U	U	U	U	U	U	CHCH
Podilymbus podiceps	Pied-billed Grebe	N	SD	SD	SD	SI	N	N	SI	N	N	N/A	N	N	U	U	U	U	U	U	U	MACA
Pooecetes gramineus	Vesper Sparrow	SD	N	N	SD	N	SD	N	N	N	N	N/A	N	N	U	U	U	U	N	U	U	MACA
Pooecetes gramineus	Vesper Sparrow	SD	N	N	SD	N	SD	N	N	N	N	N/A	N	N	U	U	U	U	N	U	U	CHCH
Rallus elegans	King Rail	SD	N	N	N	SI	N	N	SD	N	N	N/A	N	N	U	U	U	U	U	U	U	MACA
Regulus satrapa	Golden-crowned Kinglet	Dec	N	SI-N	SD	N	SI	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	CUGA
Riparia riparia	Bank Swallow	Dec	N	N	N	SI	N	N	N	N	N	N/A	N	N	U	U	U	U	N	N	U	MACA
Sitta canadensis	Red-Breasted Nuthatch	Dec	N	N	SD	N	N	N	N	N	N	N/A	N	N	U	U	U	U	N	U	U	ABLI
Sitta canadensis	Red-Breasted Nuthatch	Dec	N	N	SD	N	N	N	N	N	N	N/A	N	N	U	U	U	U	N	U	U	CUGA
Sitta canadensis	Red-Breasted Nuthatch	Dec	N	N	SD	N	N	N	N	N	N	N/A	N	N	U	U	U	U	N	U	U	MACA
Sphyrapicus varius	Yellow-bellied Sapsucker	SD	N	N	SD	N	SD	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	CHCH
Sphyrapicus varius	Yellow-bellied	SD	N	N	SD	N	SD	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	CUGA

Scientific Name	Common Name	Dispersal/Movement	historical thermal niche	physiological thermal niche	historical hydrological niche	physiological hydrological niche	Disturbance	Ice/snow	Phys habitat	Other spp for hab	Diet	Pollinators	Other spp disp	Other spp interaction	Genetic var	Gen bottleneck	Phenol response	Doc response	Modeled change	Modeled overlap	Protected Areas	Park
	Sapsucker																					
Sphyrapicus varius	Yellow-bellied Sapsucker	SD	N	N	SD	N	SD	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	FODO
Sphyrapicus varius	Yellow-bellied Sapsucker	SD	N	N	SD	N	SD	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	SHIL
Sphyrapicus varius	Yellow-bellied Sapsucker	SD	N	N	SD	N	SD	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	STRI
Thryomanes bewickii	Bewick's Wren	SD	N	N	SD	N	SD	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	CHCH
Thryomanes bewickii	Bewick's Wren	SD	N	N	SD	N	SD	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	STRI
Thryomanes bewickii	Bewick's Wren	SD	N	N	SD	N	SD	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	MACA
Troglodytes troglodytes	Winter Wren	Dec	N	N	SD	N	N	N	N	N	N	N/A	N	N	U	U	U	U	SD	U	U	CUGA
Vermivora chrysoptera	Golden-winged Warbler	SD	N	N	SD	N	SD	N	N	N	N	N/A	N	N	U	U	U	U	N	N	U	CHCH
Vermivora chrysoptera	Golden-winged Warbler	SD	N	N	SD	N	SD	N	N	N	N	N/A	N	N	U	U	U	U	N	N	U	CUGA
Vermivora chrysoptera	Golden-winged Warbler	SD	N	N	SD	N	SD	N	N	N	N	N/A	N	N	U	U	U	U	N	N	U	MACA
Vermivora chrysoptera	Golden-winged Warbler	SD	N	N	SD	N	SD	N	N	N	N	N/A	N	N	U	U	U	U	N	N	U	ABLI
Wilsonia canadensi	Canada Warbler	Dec	N	N	SD	SI	N	N	N	SI	N	N/A	N	N	U	U	U	U	SI	SI	U	CUGA
Wilsonia	Canada	Dec	N	N	SD	SI	N	N	N	SI	N	N/A	N	N	U	U	U	U	SI	SI	U	MACA

Scientific Name	Common Name	Dispersal/Movement	historical thermal niche	physiological thermal niche	historical hydrological niche	physiological hydrological niche	Disturbance	Ice/snow	Phys habitat	Other spp for hab	Diet	Pollinators	Other spp disp	Other spp interaction	Genetic var	Gen bottleneck	Phenol response	Doc response	Modeled change	Modeled overlap	Protected Areas	Park
canadensi	Warbler																					
Wilsonia canadensi	Canada Warbler	Dec	N	N	SD	SI	N	N	N	SI	N	N/A	N	N	U	U	U	U	SI	SI	U	ABLI
Fish																						
Ammocrypta clara	Western Sand Darter	SI	N	N	N	N	N	N	N	N	N	N/A	N	N	U	N	U	U	U	U	U	CUGA
Cyprinella caerulea	Blue Shiner	N	N	N	Inc	N	N	N	SI	N	N	N/A	N	N	U	N	U	U	U	U	U	LIRI
Etheostoma collis	Carolina Darter	N	N	N	N	Inc	N	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	KIMO
Etheostoma maculatum	Spotted Darter	U	N	N	N	SI	N	N	SI	N	N	N/A	N	N	U	U	U	U	U	U	U	MACA
Phoxinus cumberlandensis	Mountain Blackside Dace	N	N	SI	SI	SI	N	N	SI	SI	N	N/A	N	N	U	U	U	U	U	U	U	CUGA
Typhlichthys subterraneus	Southern Cavefish	Inc	Inc	Inc	N	Inc	SI	N	Inc	N	N	N/A	N	N	U	U	U	U	U	U	U	MACA
Invertebrates - Mollusks																						
Cumberlandia monodonta	Spectaclecase	GI-Inc	N	SI	N	N	SI	N	SI	N	N	N/A	SI-N	SI-N	N	N/A	U	U	U	U	U	MACA
Cyprogenia stegaria	Fanshell	Inc	N	SI	N	N	SI	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	MACA
Epioblasma torulosa rangiana	Northern Riffleshell	Inc	N	SI	SI	SI	SI	N	SI	N	N	N/A	SI	SI-N	U	N	U	U	U	U	U	MACA
Epioblasma triquetra	Snuffbox	Inc	N	SI	N	N	SI	N	SI	N	N	N/A	SI-N	SI-N	U	N	U	U	U	U	U	MACA
Fusconaia subrotunda	Longsolid	Inc	N	SI	N	N	SI	N	N	N	N	N/A	SI-N	SI-N	U	N	U	U	U	U	U	MACA
Lampsilis abrupta	Pink Mucket	Inc	N	SI	N	N	SI	N	N	N	N	N/A	SI-N	SI-N	U	N	U	U	U	U	U	MACA

Scientific Name	Common Name	Dispersal/Movement	historical thermal niche	physiological thermal niche	historical hydrological niche	physiological hydrological niche	Disturbance	Ice/snow	Phys habitat	Other spp for hab	Diet	Pollinators	Other spp disp	Other spp interaction	Genetic var	Gen bottleneck	Phenol response	Doc response	Modeled change	Modeled overlap	Protected Areas	Park
Lampsilis ovata	Pocketbook	Inc	N	SI-N	N	N	SI	N	SD	N	N	N/A	SI-N	SI-N	U	N	U	U	U	U	U	MACA
Obovaria restusa	Ring Pink	GI	N	SI	N	N	SI	N	SI	N	N	N/A	SI-N	SI-N	U	SI-N	U	U	U	U	U	MACA
Plethobasus cyphyus	Sheepnose	Inc	N	SI	N	N	SI	N	N	N	N	N/A	N	N	U	N	U	U	U	U	U	MACA
Pleurobema clava	Clubshell	Inc	N	SI	SI	SI	SI	N	SI	N	N	N/A	SI	SI	U	U	U	U	U	U	U	MACA
Pleurobema plenum	Rough Pigtoe	GI	N	SI	N	N	SI	N	N	N	N	N/A	SI-N	SI-N	U	N	U	U	U	U	U	MACA
Pleurobema rubrum	Pyramid Pigtoe	Inc	N	SI	N	N	SI	N	N	N	N	N/A	SI-N	SI-N	U	N	U	U	U	U	U	MACA
Villosa ortmanni	Kentucky Creekshell	Inc	N	SI	SI	N	SI	N	SI	N	N	N/A	SI-N	U	U	U	U	U	U	U	U	MACA
Mammals																						
Corynorhinus rafinesquii	Rafinesque's Big-eared Bat	N	N	N	SD	SI	SI	N	Inc	SI	N	N/A	N	N	U	U	U	U	U	U	U	CUGA
Corynorhinus rafinesquii	Rafinesque's Big-eared Bat	N	N	N	SD	N	SI	N	Inc	SI	N	N/A	N	N	U	U	U	U	U	U	U	MACA
Corynorhinus rafinesquii	Rafinesque's Big-eared Bat	N	N	N	SD	N	SI	N	Inc	SI	N	N/A	N	N	U	U	U	U	U	U	U	SHIL
Myotis austroriparius	Southeastern myotis	N	N	N	SD	SI	SI	N	Inc	N	N	N/A	N	N	U	U	U	U	U	U	U	MACA
Myotis grisescens	Gray Myotis	SD	N	N	SD	SI	SI	N	Inc	N	SI	N/A	N	N	U	U	U	U	U	U	U	CUGA
Myotis grisescens	Gray Myotis	SD	N	N	SD	SI	SI	N	Inc	N	SI	N/A	N	N	U	U	U	U	U	U	U	CHCH
Myotis grisescens	Gray Myotis	SD	N	N	SD	SI	SI	N	Inc	N	SI	N/A	N	N	U	U	U	U	U	U	U	FODO
Myotis	Gray Myotis	SD	N	N	SD	SI	SI	N	Inc	N	SI	N/A	N	N	U	U	U	U	U	U	U	LIRI

Scientific Name	Common Name	Dispersal/Movement	historical thermal niche	physiological thermal niche	historical hydrological niche	physiological hydrological niche	Disturbance	Ice/snow	Phys habitat	Other spp for hab	Diet	Pollinators	Other spp disp	Other spp interaction	Genetic var	Gen bottleneck	Phenol response	Doc response	Modeled change	Modeled overlap	Protected Areas	Park
grisescens																						
Myotis grisescens	Gray Myotis	SD	N	N	SD	SI	SI	N	Inc	N	SI	N/A	N	N	U	U	U	U	U	U	U	MACA
Myotis grisescens	Gray Myotis	SD	N	N	SD	SI	SI	N	Inc	N	SI	N/A	N	N	U	U	U	U	U	U	U	SHIL
Myotis leibii	Eastern Small-footed Myotis	SD	N	N	SD	N	SI	N	SI	N	SI	N/A	N	N	U	U	U	U	U	U	U	CUGA
Myotis leibii	Eastern Small-footed Myotis	SD	N	N	SD	N	SI	N	SI	N	SI	N/A	N	N	U	U	U	U	U	U	U	MACA
Myotis sodalis	Indiana Bat	N	N	SI	SD	SI	N	N	SI	N	N	N/A	N	N	U	N	U	U	U	U	U	MACA
Myotis sodalis	Indiana Bat	N	N	SI	SD	SI	N	N	SI	N	N	N/A	N	N	U	N	U	U	U	U	U	CUGA
Neotoma magister	Allegheny Woodrat	N	N	N	SD	N	N	N	Inc	N	N	N/A	N	SI	N	N/A	U	U	U	U	U	CUGA
Sorex longirostris	Southeastern Shrew	N	N	N	SI	SI	N	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	CHCH
Sorex longirostris	Southeastern Shrew	N	N	N	SI	SI	N	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	SHIL
Sorex longirostris	Southeastern Shrew	N	N	N	Inc	SI	N	N	N	N	N	N/A	N	N	U	U	U	U	U	U	U	STRI
Spilogale putorius	Eastern Spotted Skunk	N	N	N	SD	N	N	N	N	N	SD	N/A	N	N	U	U	U	U	U	U	U	CUGA
Reptiles																						
Pituophis melanoleucus	Pine Snake	N	N	N	N	N	SD	N	N	N	N	N/A	N	N	U	N	U	U	U	U	U	NISI
Vascular Plants																						
Apios priceana	Traveler's Delight	Inc	N	N	SD	N	SI	N	N	N	N/A	N	N	N	U	U	U	U	U	U	U	FODO
Carex decomposita	Cypress-Knee Sedge	Dec	N	N	N	SI	SI	N	N	Inc	N/A	N	N	N	U	U	U	U	U	U	U	MACA

Scientific Name	Common Name	Dispersal/Movement	historical thermal niche	physiological thermal niche	historical hydrological niche	physiological hydrological niche	Disturbance	Ice/snow	Phys habitat	Other spp for hab	Diet	Pollinators	Other spp disp	Other spp interaction	Genetic var	Gen bottleneck	Phenol response	Doc response	Modeled change	Modeled overlap	Protected Areas	Park
Dodecatheon frenchii	French's Shootingstar	SI	N	N	SD	N	N	N	Inc	N	N/A	N	N	N	U	U	U	U	U	U	U	MACA
Gymnopogon ambiguus	Bearded Skeletongrass	N	N	N	N	SD	SI	N	SI	N	N/A	N	N	N	U	U	U	U	U	U	U	MACA
Juglans cinerea	Butternut	SI	N	N	SD	SI	SI	N	SI	N	N/A	U	SI	N	SI	N/A	U	U	GI	U	U	MACA
Juglans cinerea	Butternut	SI	N	N	SD	SI	SI	N	SI	N	N/A	U	SI	N	SI	N/A	U	U	GI	U	U	STRI
Juglans cinerea	Butternut	SI	N	N	SD	SI	SI	N	SI	N	N/A	U	SI	N	SI	N/A	U	U	GI	U	U	CUGA
Plantago cordata	Heartleaf Plantain	Inc-SI	N	N	N	Inc	SI	N	N	N	N/A	N	N	SI	U	U	U	U	U	U	U	CHCH
Quercus oglethorpensis	Oglethorpe's Oak	SI	N	N	SD	N	N	N	N	N	N/A	U	N	SI	U	SI	U	U	U	U	U	NISI
Scutellaria montana	Large-flower Skullcap	Inc	N	N	N	N	N	N	N	N	N/A	N	N	N	N	N/A	U	U	U	U	U	CHCH
Thaspium pinnatifidum	Cutleaf Meadow-Parsnip	N	N	N	SD	SI	N	N	Inc	N	N/A	U	N	N	U	U	U	U	U	U	U	CHCH
Trillium rugelii	Ill-scented Wakerobin	Inc	N	N	SD	N	N	N	N	N	N/A	N	N	N	U	U	U	U	U	U	U	FODO

Table 5. Exposure and geography risk factor scores from the CCVI. All notes, citations, and sources are documented in a separate word document. Much of the species information to determine these CCVI scores came from NatureServe Explorer.

Scientific Name	Common Name	>5.5° F warmer	5.1-5.5 ° F warmer	4.5-5.0 ° F warmer	3.9-4.4 ° F warmer	<3.9 ° F warmer	Hamon AET:PET Moisture Metric Scope (< -0.119)	Hamon AET:PET Moisture Metric Scope (-0.097 - -0.119)	Hamon AET:PET Moisture Metric Scope (-0.074 - -0.096)	Hamon AET:PET Moisture Metric Scope (-0.051 - -0.073)	Hamon AET:PET Moisture Metric Scope (-0.028 - -0.050)	Hamon AET:PET Moisture Metric Scope (>-0.028)	Sea level	Natural barriers	Anthropogenic barriers	CC mitigation	Park
Amphibians																	
Aneides aeneus	Green Salamander	0	100	0	0	0	0	0	0	100	0	0	N	N	SI	N	CARL
Aneides aeneus	Green Salamander	0	0	100	0	0	0	0	0	100	0	0	N	N	N	N	LIRI
Aneides aeneus	Green Salamander	0	100	0	0	0	0	0	98	2	0	0	N	N	N	N	RUCA
Gyrinophilus palleucus	Tennessee Cave Salamander	0	100	0	0	0	0	0	0	100	0	0	N	SI	SI	N	CUGA
Birds																	
Accipiter cooperii	Cooper's Hawk	0	100	0	0	0	0	0	98	2	0	0	N	N	N	U	LIRI
Accipiter cooperii	Cooper's Hawk	0	100	0	0	0	0	0	0	100	0	0	N	N	N	U	RUCA
Accipiter striatus	Sharp-shinned Hawk	0	0	100	0	0	0	0	0	100	0	0	N	N	SI-N	N-SD	CHCH
Accipiter striatus	Sharp-shinned Hawk	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N-SD	CUGA

Scientific Name	Common Name	>5.5° F warmer	5.1-5.5 ° F warmer	4.5-5.0 ° F warmer	3.9-4.4 ° F warmer	<3.9 ° F warmer	Hamon AET:PET Moisture Metric Scope (< -0.119)	Hamon AET:PET Moisture Metric Scope (-0.097 - -0.119)	Hamon AET:PET Moisture Metric Scope (-0.074 - -0.096)	Hamon AET:PET Moisture Metric Scope (-0.051 - -0.073)	Hamon AET:PET Moisture Metric Scope (-0.028 - -0.050)	Hamon AET:PET Moisture Metric Scope (>-0.028)	Sea level	Natural barriers	Anthropogenic barriers	CC mitigation	Park
Accipiter striatus	Sharp-shinned Hawk	0	35	65	0	0	0	0	100	0	0	0	N	N	N	N-SD	FODO
Accipiter striatus	Sharp-shinned Hawk	0	100	0	0	0	0	0	100	0	0	0	N	N	N	N-SD	SHIL
Accipiter striatus	Sharp-shinned Hawk	0	0	100	0	0	0	0	100	0	0	0	N	N	SI-N	N-SD	STRI
Accipiter striatus	Sharp-shinned Hawk	0	100	0	0	0	0	0	0	100	0	0	N	N	SI-N	N-SD	ABLI
Accipiter striatus	Sharp-shinned Hawk	0	100	0	0	0	0	0	100	0	0	0	N	N	SI-N	N-SD	MACA
Aegolius acadicus	Northern Saw-whet Owl	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	CUGA (TN)
Aegolius acadicus	Northern Saw-whet Owl	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	CUGA (VA)
Aimophilia astivalis	Bachman's Sparrow	0	100	0	0	0	0	0	0	100	0	0	N	N	N	SI	CUGA
Aimophilia astivalis	Bachman's Sparrow	0	100	0	0	0	0	0	100	0	0	0	N	N	N	SI	MACA

Scientific Name	Common Name	>5.5° F warmer	5.1-5.5 ° F warmer	4.5-5.0 ° F warmer	3.9-4.4 ° F warmer	<3.9 ° F warmer	Hamon AET:PET Moisture Metric Scope (< -0.119)	Hamon AET:PET Moisture Metric Scope (-0.097 - -0.119)	Hamon AET:PET Moisture Metric Scope (-0.074 - -0.096)	Hamon AET:PET Moisture Metric Scope (-0.051 - -0.073)	Hamon AET:PET Moisture Metric Scope (-0.028 - -0.050)	Hamon AET:PET Moisture Metric Scope (>-0.028)	Sea level	Natural barriers	Anthropogenic barriers	CC mitigation	Park
Aimophilia astivalis	Bachman's Sparrow	0	0	100	0	0	0	0	0	100	0	0	N	N	SI	SI	CHCH
Ammodramus hanslowii	Henslow's Sparrow	0	100	0	0	0	0	0	100	0	0	0	N	N	N	SI	MACA
Anas discors	Blue-winged Teal	0	100	0	0	0	0	0	100	0	0	0	N	N	SI	N	MACA
Aquila chrysaetos	Golden Eagle	0	100	0	0	0	0	0	0	100	0	0	N	N	N	SI	CUGA
Ardea alba	Great Egret	0	0	100	0	0	0	0	0	100	0	0	N	N	N	U	CHCH
Ardea alba	Great Egret	0	35	65	0	0	0	0	100	0	0	0	N	N	N	U	FODO
Ardea alba	Great Egret	0	100	0	0	0	0	0	100	0	0	0	N	N	N	U	SHIL
Certhia americana	Brown Creeper	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	ABLI
Certhia americana	Brown Creeper	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	CUGA
Certhia americana	Brown Creeper	0	100	0	0	0	0	0	100	0	0	0	N	N	N	N	MACA
Chondestes grammacus	Lark Sparrow	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	ABLI
Circus cyaneus	Northern Harrier	0	100	0	0	0	0	0	0	100	0	0	N	N	SI	N	ABLI

Scientific Name	Common Name	>5.5° F warmer	5.1-5.5 ° F warmer	4.5-5.0 ° F warmer	3.9-4.4 ° F warmer	<3.9 ° F warmer	Hamon AET:PET Moisture Metric Scope (< -0.119)	Hamon AET:PET Moisture Metric Scope (-0.097 - -0.119)	Hamon AET:PET Moisture Metric Scope (-0.074 - -0.096)	Hamon AET:PET Moisture Metric Scope (-0.051 - -0.073)	Hamon AET:PET Moisture Metric Scope (-0.028 - -0.050)	Hamon AET:PET Moisture Metric Scope (>-0.028)	Sea level	Natural barriers	Anthropogenic barriers	CC mitigation	Park
Circus cyaneus	Northern Harrier	0	100	0	0	0	0	0	0	100	0	0	N	N	SI	N	CUGA
Circus cyaneus	Northern Harrier	0	100	0	0	0	0	0	100	0	0	0	N	N	SI	N	MACA
Cistorthorus platensis	Sedge Wren	0	100	0	0	0	0	0	100	0	0	0	N	N	N	SI	MACA
Contopus cooperi	Olive-sided Flycatcher	0	0	100	0	0	0	0	0	100	0	0	N	N	N	N	CHCH
Contopus cooperi	Olive-sided Flycatcher	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	CUGA
Corvus corax	Common Raven	0	100	0	0	0	0	0	0	100	0	0	N	SI	N	N	CUGA
Dendroica cerulea	Cerulean Warbler	0	0	100	0	0	0	0	0	100	0	0	N	N	N	N	CHCH
Dendroica cerulea	Cerulean Warbler	0	0	100	0	0	0	0	0	100	0	0	N	N	N	N	CHCH
Dendroica cerulea	Cerulean Warbler	0	100	0	0	0	0	0	0	100	0	0	N	N	SI	N	CUGA
Dendroica cerulea	Cerulean Warbler	0	35	65	0	0	0	0	100	0	0	0	N	N	N	N	FODO
Dendroica cerulea	Cerulean Warbler	0	100	0	0	0	0	0	100	0	0	0	N	N	N	N	SHIL
Dendroica cerulea	Cerulean Warbler	0	0	100	0	0	0	0	100	0	0	0	N	N	N	N	STRI

Scientific Name	Common Name	>5.5° F warmer	5.1-5.5 ° F warmer	4.5-5.0 ° F warmer	3.9-4.4 ° F warmer	<3.9 ° F warmer	Hamon AET:PET Moisture Metric Scope (< -0.119)	Hamon AET:PET Moisture Metric Scope (-0.097 - -0.119)	Hamon AET:PET Moisture Metric Scope (-0.074 - -0.096)	Hamon AET:PET Moisture Metric Scope (-0.051 - -0.073)	Hamon AET:PET Moisture Metric Scope (-0.028 - -0.050)	Hamon AET:PET Moisture Metric Scope (>-0.028)	Sea level	Natural barriers	Anthropogenic barriers	CC mitigation	Park
Dendroica fusca	Blackburnian Warbler	0	100	0	0	0	0	0	0	100	0	0	N	N	SI	N	ABLI
Dendroica fusca	Blackburnian Warbler	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	CUGA
Dendroica fusca	Blackburnian Warbler	0	100	0	0	0	0	0	100	0	0	0	N	N	N	N	MACA
Dendroica magnolia	Magnolia Warbler	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	CUGA
Egretta caerulea	Little Blue Heron	0	100	0	0	0	0	0	100	0	0	0	N	N	N	SD	MACA
Egretta caerulea	Little Blue Heron	0	35	65	0	0	0	0	100	0	0	0	N	N	N	SI	FODO
Egretta caerulea	Little Blue Heron	0	100	0	0	0	0	0	100	0	0	0	N	N	N	SI	SHIL
Egretta thula	Snowy Egret	0	100	0	0	0	0	0	100	0	0	0	N	N	N	U	SHIL
Epidonax minimus	Least Flycatcher	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	ABLI
Epidonax minimus	Least Flycatcher	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	CUGA
Epidonax minimus	Least Flycatcher	0	100	0	0	0	0	0	100	0	0	0	N	N	N	N	MACA
Falco peregrinus	Peregrine Falcon	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	CUGA

Scientific Name	Common Name	>5.5° F warmer	5.1-5.5 ° F warmer	4.5-5.0 ° F warmer	3.9-4.4 ° F warmer	<3.9 ° F warmer	Hamon AET:PET Moisture Metric Scope (< -0.119)	Hamon AET:PET Moisture Metric Scope (-0.097 - -0.119)	Hamon AET:PET Moisture Metric Scope (-0.074 - -0.096)	Hamon AET:PET Moisture Metric Scope (-0.051 - -0.073)	Hamon AET:PET Moisture Metric Scope (-0.028 - -0.050)	Hamon AET:PET Moisture Metric Scope (>-0.028)	Sea level	Natural barriers	Anthropogenic barriers	CC mitigation	Park
Falco peregrinus	Peregrine Falcon	0	35	65	0	0	0	0	100	0	0	0	N	N	N	N	FODO
Fulica americana	American Coot	0	100	0	0	0	0	0	100	0	0	0	N	N	N	SD	MACA
Gallinula chloropus	Common Moorhen	0	100	0	0	0	0	0	100	0	0	0	N	N	N	N	MACA
Gallinula chloropus	Common Moorhen	0	100	0	0	0	0	0	100	0	0	0	N	N	SI	N	MACA
Haliaeetus leucocephalus	Bald Eagle	0	100	0	0	0	0	0	100	0	0	0	N	N	N	U	MACA
Haliaeetus leucocephalus	Bald Eagle	0	100	0	0	0	0	0	0	100	0	0	N	N	N	U	CUGA
Haliaeetus leucocephalus	Bald Eagle	0	100	0	0	0	0	0	98	2	0	0	N	N	N	U	LIRI
Haliaeetus leucocephalus	Bald Eagle	0	100	0	0	0	0	0	0	100	0	0	N	N	N	U	RUCA
Ictinia mississippiensis	Mississippi Kite	0	35	65	0	0	0	0	100	0	0	0	N	N	N	N	FODO
Junco hyemalis	Dark Eyed Junco	0	100	0	0	0	0	0	0	100	0	0	N	N	SI-N	U	ABLI

Scientific Name	Common Name	>5.5° F warmer	5.1-5.5 ° F warmer	4.5-5.0 ° F warmer	3.9-4.4 ° F warmer	<3.9 ° F warmer	Hamon AET:PET Moisture Metric Scope (< -0.119)	Hamon AET:PET Moisture Metric Scope (-0.097 - -0.119)	Hamon AET:PET Moisture Metric Scope (-0.074 - -0.096)	Hamon AET:PET Moisture Metric Scope (-0.051 - -0.073)	Hamon AET:PET Moisture Metric Scope (-0.028 - -0.050)	Hamon AET:PET Moisture Metric Scope (>-0.028)	Sea level	Natural barriers	Anthropogenic barriers	CC mitigation	Park
Junco hyemalis	Dark Eyed Junco	0	100	0	0	0	0	0	0	100	0	0	N	N	N	U	CUGA
Junco hyemalis	Dark Eyed Junco	0	100	0	0	0	0	0	100	0	0	0	N	N	N	U	MACA
Limnothlypis swainsonii	Swainson's Warbler	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	CUGA
Lophodytes cucullatus	Hooded Merganser	0	100	0	0	0	0	0	100	0	0	0	N	N	SI	N	MACA
Nycticorax nycticorax	Black-crowned Night-heron	0	100	0	0	0	0	0	100	0	0	0	N	N	SI	N	MACA
Pandion haliaetus	Osprey	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	ABLI
Pandion haliaetus	Osprey	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	CUGA
Pandion haliaetus	Osprey	0	100	0	0	0	0	0	100	0	0	0	N	N	N	N	MACA
Passerculus sandwichensis	Savannah Sparrow	0	100	0	0	0	0	0	100	0	0	0	N	N	N	U	MACA
Pheucticus ludovicianus	Rose-breasted Grosbeak	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	ABLI

Scientific Name	Common Name	>5.5° F warmer	5.1-5.5 ° F warmer	4.5-5.0 ° F warmer	3.9-4.4 ° F warmer	<3.9 ° F warmer	Hamon AET:PET Moisture Metric Scope (< -0.119)	Hamon AET:PET Moisture Metric Scope (-0.097 - -0.119)	Hamon AET:PET Moisture Metric Scope (-0.074 - -0.096)	Hamon AET:PET Moisture Metric Scope (-0.051 - -0.073)	Hamon AET:PET Moisture Metric Scope (-0.028 - -0.050)	Hamon AET:PET Moisture Metric Scope (>-0.028)	Sea level	Natural barriers	Anthropogenic barriers	CC mitigation	Park
Pheucticus ludovicianus	Rose-breasted Grosbeak	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	CUGA
Pheucticus ludovicianus	Rose-breasted Grosbeak	0	100	0	0	0	0	0	100	0	0	0	N	N	N	N	MACA
Picoides borealis	Red-Cockaded Woodpecker	0	100	0	0	0	0	0	0	100	0	0	N	N	Inc	Inc	CUGA
Picoides borealis	Red-Cockaded Woodpecker	0	0	100	0	0	0	0	0	100	0	0	N	SI	Inc	Inc	CHCH
Podilymbus podiceps	Pied-billed Grebe	0	100	0	0	0	0	0	100	0	0	0	N	N	SI	N	MACA
Pooecetes gramineus	Vesper Sparrow	0	100	0	0	0	0	0	100	0	0	0	N	N	N	Inc	MACA
Pooecetes gramineus	Vesper Sparrow	0	0	100	0	0	0	0	0	100	0	0	N	N	N	Inc	CHCH
Rallus elegans	King Rail	0	100	0	0	0	0	0	100	0	0	0	N	N	N	SD	MACA
Regulus satrapa	Golden-crowned Kinglet	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	CUGA

Scientific Name	Common Name	>5.5° F warmer	5.1-5.5 ° F warmer	4.5-5.0 ° F warmer	3.9-4.4 ° F warmer	<3.9 ° F warmer	Hamon AET:PET Moisture Metric Scope (< -0.119)	Hamon AET:PET Moisture Metric Scope (-0.097 - -0.119)	Hamon AET:PET Moisture Metric Scope (-0.074 - -0.096)	Hamon AET:PET Moisture Metric Scope (-0.051 - -0.073)	Hamon AET:PET Moisture Metric Scope (-0.028 - -0.050)	Hamon AET:PET Moisture Metric Scope (>-0.028)	Sea level	Natural barriers	Anthropogenic barriers	CC mitigation	Park
Riparia riparia	Bank Swallow	0	100	0	0	0	0	0	100	0	0	0	N	N	N	N	MACA
Sitta canadensis	Red-Breasted Nuthatch	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	ABLI
Sitta canadensis	Red-Breasted Nuthatch	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	CUGA
Sitta canadensis	Red-Breasted Nuthatch	0	100	0	0	0	0	0	100	0	0	0	N	N	N	N	MACA
Sphyrapicus varius	Yellow-bellied Sapsucker	0	0	100	0	0	0	0	0	100	0	0	N	N	SI	N	CHCH
Sphyrapicus varius	Yellow-bellied Sapsucker	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	CUGA
Sphyrapicus varius	Yellow-bellied Sapsucker	0	35	65	0	0	0	0	100	0	0	0	N	N	N	N	FODO
Sphyrapicus varius	Yellow-bellied Sapsucker	0	100	0	0	0	0	0	100	0	0	0	N	N	N	N	SHIL
Sphyrapicus varius	Yellow-bellied Sapsucker	0	0	100	0	0	0	0	100	0	0	0	N	N	SI	N	STRI

Scientific Name	Common Name	>5.5° F warmer	5.1-5.5 ° F warmer	4.5-5.0 ° F warmer	3.9-4.4 ° F warmer	<3.9 ° F warmer	Hamon AET:PET Moisture Metric Scope (< -0.119)	Hamon AET:PET Moisture Metric Scope (-0.097 - -0.119)	Hamon AET:PET Moisture Metric Scope (-0.074 - -0.096)	Hamon AET:PET Moisture Metric Scope (-0.051 - -0.073)	Hamon AET:PET Moisture Metric Scope (-0.028 - -0.050)	Hamon AET:PET Moisture Metric Scope (>-0.028)	Sea level	Natural barriers	Anthropogenic barriers	CC mitigation	Park
Thryomanes bewickii	Bewick's Wren	0	0	100	0	0	0	0	0	100	0	0	N	N	N	N	CHCH
Thryomanes bewickii	Bewick's Wren	0	0	100	0	0	0	0	100	0	0	0	N	N	N	N	STRI
Thryomanes bewickii	Bewick's Wren	0	100	0	0	0	0	0	100	0	0	0	N	N	N	N	MACA
Troglodytes troglodytes	Winter Wren	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	CUGA
Vermivora chrysoptera	Golden-winged Warbler	0	100	0	0	0	0	0	100	0	0	0	N	N	N	SI	CHCH
Vermivora chrysoptera	Golden-winged Warbler	0	100	0	0	0	0	0	0	100	0	0	N	N	N	SI	CUGA
Vermivora chrysoptera	Golden-winged Warbler	0	100	0	0	0	0	0	100	0	0	0	N	N	N	SI	MACA
Vermivora chrysoptera	Golden-winged Warbler	0	100	0	0	0	0	0	0	100	0	0	N	N	N	SI	ABLI
Wilsonia canadensi	Canada Warbler	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	CUGA

Scientific Name	Common Name	>5.5° F warmer	5.1-5.5 ° F warmer	4.5-5.0 ° F warmer	3.9-4.4 ° F warmer	<3.9 ° F warmer	Hamon AET:PET Moisture Metric Scope (< -0.119)	Hamon AET:PET Moisture Metric Scope (-0.097 - -0.119)	Hamon AET:PET Moisture Metric Scope (-0.074 - -0.096)	Hamon AET:PET Moisture Metric Scope (-0.051 - -0.073)	Hamon AET:PET Moisture Metric Scope (-0.028 - -0.050)	Hamon AET:PET Moisture Metric Scope (>-0.028)	Sea level	Natural barriers	Anthropogenic barriers	CC mitigation	Park
Wilsonia canadensi	Canada Warbler	0	100	0	0	0	0	0	100	0	0	0	N	N	N	N	MACA
Wilsonia canadensi	Canada Warbler	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	ABLI
Fish																	
Ammocrypta clara	Western Sand Darter	0	100	0	0	0	0	0	0	100	0	0	N	GI	Inc	N	CUGA
Cyprinella caerulea	Blue Shiner	0	100	0	0	0	0	0	98	2	0	0	N	Inc	GI	SI	LIRI
Etheostoma collis	Carolina Darter	0	0	100	0	0	0	0	0	100	0	0	N	Inc	SI	N	KIMO
Etheostoma maculatum	Spotted Darter	0	100	0	0	0	0	0	100	0	0	0	N	Inc	SI	N	MACA
Phoxinus cumberlandensis	Mountain Blackside Dace	0	100	0	0	0	0	0	0	100	0	0	N	GI	SI	SI	CUGA
Typhlichthys subterraneus	Southern Cavefish	0	100	0	0	0	0	0	100	0	0	0	N	GI	Inc	SI	MACA
Invertebrates - Mollusks																	

Scientific Name	Common Name	>5.5° F warmer	5.1-5.5 ° F warmer	4.5-5.0 ° F warmer	3.9-4.4 ° F warmer	<3.9 ° F warmer	Hamon AET:PET Moisture Metric Scope (< -0.119)	Hamon AET:PET Moisture Metric Scope (-0.097 - -0.119)	Hamon AET:PET Moisture Metric Scope (-0.074 - -0.096)	Hamon AET:PET Moisture Metric Scope (-0.051 - -0.073)	Hamon AET:PET Moisture Metric Scope (-0.028 - -0.050)	Hamon AET:PET Moisture Metric Scope (>-0.028)	Sea level	Natural barriers	Anthropogenic barriers	CC mitigation	Park
Cumberlandia monodonta	Spectaclecase	0	100	0	0	0	0	0	100	0	0	0	N	Inc	SI	Dec	MACA
Cyprogenia stegaria	Fanshell	0	100	0	0	0	0	0	100	0	0	0	N	Inc	SI	Dec	MACA
Epioblasma torulosa rangiana	Northern Riffleshell	0	100	0	0	0	0	0	100	0	0	0	N	Inc	SI	Dec	MACA
Epioblasma triquetra	Snuffbox	0	100	0	0	0	0	0	100	0	0	0	N	Inc	SI	Dec	MACA
Fusconaia subrotunda	Longsolid	0	100	0	0	0	0	0	100	0	0	0	N	Inc	SI	Dec	MACA
Lampsilis abrupta	Pink Mucket	0	100	0	0	0	0	0	100	0	0	0	N	Inc	SI	Dec	MACA
Lampsilis ovata	Pocketbook	0	100	0	0	0	0	0	100	0	0	0	N	Inc	SI	Dec	MACA
Obovaria restusa	Ring Pink	0	100	0	0	0	0	0	100	0	0	0	N	Inc	SI	Dec	MACA
Plethobasus cyphyus	Sheepnose	0	100	0	0	0	0	0	100	0	0	0	N	Inc	SI	Dec	MACA
Pleurobema clava	Clubshell	0	100	0	0	0	0	0	100	0	0	0	N	Inc	SI	Dec	MACA
Pleurobema plenum	Rough Pigtoe	0	100	0	0	0	0	0	100	0	0	0	N	Inc	SI	Dec	MACA

Scientific Name	Common Name	>5.5° F warmer	5.1-5.5 ° F warmer	4.5-5.0 ° F warmer	3.9-4.4 ° F warmer	<3.9 ° F warmer	Hamon AET:PET Moisture Metric Scope (< -0.119)	Hamon AET:PET Moisture Metric Scope (-0.097 - -0.119)	Hamon AET:PET Moisture Metric Scope (-0.074 - -0.096)	Hamon AET:PET Moisture Metric Scope (-0.051 - -0.073)	Hamon AET:PET Moisture Metric Scope (-0.028 - -0.050)	Hamon AET:PET Moisture Metric Scope (>-0.028)	Sea level	Natural barriers	Anthropogenic barriers	CC mitigation	Park
Pleurobema rubrum	Pyramid Pigtoe	0	100	0	0	0	0	0	100	0	0	0	N	Inc	SI	Dec	MACA
Villosa ortmanni	Kentucky Creekshell	0	100	0	0	0	0	0	100	0	0	0	N	Inc	SI	Dec	MACA
Mammals																	
Corynorhinus rafinesquii	Rafinesque's Big-eared Bat	0	100	0	0	0	0	0	0	100	0	0	N	N	SI	SI	CUGA
Corynorhinus rafinesquii	Rafinesque's Big-eared Bat	0	100	0	0	0	0	0	100	0	0	0	N	N	SI	SI	MACA
Corynorhinus rafinesquii	Rafinesque's Big-eared Bat	0	100	0	0	0	0	0	100	0	0	0	N	N	SI	SI	SHIL
Myotis austroriparius	Southeastern myotis	0	100	0	0	0	0	0	100	0	0	0	N	N	SI	N	MACA
Myotis grisescens	Gray Myotis	0	100	0	0	0	0	0	0	100	0	0	N	N	SI	N	CUGA
Myotis grisescens	Gray Myotis	0	0	100	0	0	0	0	0	100	0	0	N	N	Inc	N	CHCH
Myotis grisescens	Gray Myotis	0	35	65	0	0	0	0	100	0	0	0	N	N	Inc	N	FODO

Scientific Name	Common Name	>5.5° F warmer	5.1-5.5 ° F warmer	4.5-5.0 ° F warmer	3.9-4.4 ° F warmer	<3.9 ° F warmer	Hamon AET:PET Moisture Metric Scope (< -0.119)	Hamon AET:PET Moisture Metric Scope (-0.097 - -0.119)	Hamon AET:PET Moisture Metric Scope (-0.074 - -0.096)	Hamon AET:PET Moisture Metric Scope (-0.051 - -0.073)	Hamon AET:PET Moisture Metric Scope (-0.028 - -0.050)	Hamon AET:PET Moisture Metric Scope (>-0.028)	Sea level	Natural barriers	Anthropogenic barriers	CC mitigation	Park
Myotis grisescens	Gray Myotis	0	100	0	0	0	0	0	98	2	0	0	N	N	Inc	N	LIRI
Myotis grisescens	Gray Myotis	0	100	0	0	0	0	0	100	0	0	0	N	N	SI	N	MACA
Myotis grisescens	Gray Myotis	0	100	0	0	0	0	0	100	0	0	0	N	N	Inc	N	SHIL
Myotis leibii	Eastern Small-footed Myotis	0	100	0	0	0	0	0	0	100	0	0	N	N	SI	N	CUGA
Myotis leibii	Eastern Small-footed Myotis	0	100	0	0	0	0	0	100	0	0	0	N	N	Inc	N	MACA
Myotis sodalis	Indiana Bat	0	100	0	0	0	0	0	100	0	0	0	N	N	N	N	MACA
Myotis sodalis	Indiana Bat	0	100	0	0	0	0	0	0	100	0	0	N	N	SI	N	CUGA
Neotoma magister	Allegheny Woodrat	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	CUGA
Sorex longirostris	Southeastern Shrew	0	0	100	0	0	0	0	0	100	0	0	N	N	SI	N	CHCH
Sorex longirostris	Southeastern Shrew	0	100	0	0	0	0	0	100	0	0	0	N	N	N	N	SHIL
Sorex longirostris	Southeastern Shrew	0	0	100	0	0	0	0	100	0	0	0	N	N	SI	N	STRI
Spilogale putorius	Eastern Spotted Skunk	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	CUGA

Scientific Name	Common Name	>5.5° F warmer	5.1-5.5 ° F warmer	4.5-5.0 ° F warmer	3.9-4.4 ° F warmer	<3.9 ° F warmer	Hamon AET:PET Moisture Metric Scope (< -0.119)	Hamon AET:PET Moisture Metric Scope (-0.097 - -0.119)	Hamon AET:PET Moisture Metric Scope (-0.074 - -0.096)	Hamon AET:PET Moisture Metric Scope (-0.051 - -0.073)	Hamon AET:PET Moisture Metric Scope (-0.028 - -0.050)	Hamon AET:PET Moisture Metric Scope (>-0.028)	Sea level	Natural barriers	Anthropogenic barriers	CC mitigation	Park
Reptiles																	
Pituophis melanoleucus	Pine Snake	0	0	0	100	0	0	0	0	100	0	0	N	N	SI-N	SI-N	NISI
Vascular Plants																	
Apios priceana	Traveler's Delight	0	35	65	0	0	0	0	100	0	0	0	N	N	N	N	FODO
Carex decomposita	Cypress-Knee Sedge	0	100	0	0	0	0	0	100	0	0	0	N	N	SI	N	MACA
Dodecatheon frenchii	French's Shootingstar	0	100	0	0	0	0	0	100	0	0	0	N	N	N	N	MACA
Gymnopogon ambiguus	Bearded Skeletongrass	0	100	0	0	0	0	0	100	0	0	0	N	N	SI	N	MACA
Juglans cinerea	Butternut	0	100	0	0	0	0	0	100	0	0	0	N	N	N	N	MACA
Juglans cinerea	Butternut	0	0	100	0	0	0	0	100	0	0	0	N	N	N	N	STRI
Juglans cinerea	Butternut	0	100	0	0	0	0	0	0	100	0	0	N	N	N	N	CUGA
Plantago cordata	Heartleaf Plantain	0	0	100	0	0	0	0	0	100	0	0	N	N	SI	N	CHCH
Quercus	Oglethorpe's Oak	0	0	0	100	0	0	0	0	100	0	0	N	N	N	N	NISI

Scientific Name	Common Name	>5.5° F warmer	5.1-5.5 ° F warmer	4.5-5.0 ° F warmer	3.9-4.4 ° F warmer	<3.9 ° F warmer	Hamon AET:PET Moisture Metric Scope (< -0.119)	Hamon AET:PET Moisture Metric Scope (-0.097 - -0.119)	Hamon AET:PET Moisture Metric Scope (-0.074 - -0.096)	Hamon AET:PET Moisture Metric Scope (-0.051 - -0.073)	Hamon AET:PET Moisture Metric Scope (-0.028 - -0.050)	Hamon AET:PET Moisture Metric Scope (>-0.028)	Sea level	Natural barriers	Anthropogenic barriers	CC mitigation	Park
oglethorpensis																	
Scutellaria montana	Large-flower Skullcap	0	0	100	0	0	0	0	0	100	0	0	N	N	Inc	N	CHCH
Thaspium pinnatifidum	Cutleaf Meadow-Parsnip	0	0	100	0	0	0	0	0	100	0	0	N	N	Inc	N	CHCH
Trillium rugelii	Ill-scented Wakerobin	0	35	65	0	0	0	0	100	0	0	0	N	N	N	N	FODO

Appendix C: Exploratory Data Analysis

Correlation Coefficients

	Bioclimatic Variables																				
	TRMI	DEM	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
TRMI	Inf	-0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
DEM	-0.1	Inf	-0.6	0.1	0.0	0.1	-0.8	-0.5	0.1	-0.3	-0.3	-0.8	-0.5	0.2	0.0	0.5	-0.6	-0.1	0.5	0.1	0.1
1	0.0	-0.6	Inf	0.2	0.6	-0.7	0.9	1.0	-0.7	0.1	0.7	0.9	1.0	0.4	0.6	-0.1	0.6	0.6	0.0	0.3	0.5
2	0.0	0.1	0.2	Inf	0.7	-0.4	0.2	0.2	-0.1	-0.2	0.2	0.1	0.3	0.2	0.2	0.2	-0.2	0.1	0.2	0.0	0.3
3	0.0	0.0	0.6	0.7	Inf	-0.9	0.4	0.7	-0.8	0.0	0.4	0.4	0.8	0.5	0.6	0.3	0.2	0.6	0.3	0.5	0.5
4	0.0	0.1	-0.7	-0.4	-0.9	Inf	-0.4	-0.9	1.0	-0.1	-0.4	-0.5	-0.9	-0.5	-0.7	-0.3	-0.4	-0.7	-0.3	-0.7	-0.5
5	0.0	-0.8	0.9	0.2	0.4	-0.4	Inf	0.8	-0.3	0.0	0.7	1.0	0.8	0.1	0.3	-0.2	0.5	0.3	-0.2	-0.1	0.3
6	0.0	-0.5	1.0	0.2	0.7	-0.9	0.8	Inf	-0.9	0.1	0.6	0.9	1.0	0.4	0.6	0.0	0.6	0.7	0.1	0.4	0.5
7	0.0	0.1	-0.7	-0.1	-0.8	1.0	-0.3	-0.9	Inf	-0.1	-0.4	-0.5	-0.8	-0.5	-0.7	-0.2	-0.4	-0.7	-0.3	-0.7	-0.5
8	0.0	-0.3	0.1	-0.2	0.0	-0.1	0.0	0.1	-0.1	Inf	-0.4	0.1	0.1	-0.5	-0.3	-0.4	0.3	-0.2	-0.5	0.3	-0.6
9	0.0	-0.3	0.7	0.2	0.4	-0.4	0.7	0.6	-0.4	-0.4	Inf	0.7	0.6	0.6	0.6	0.3	0.2	0.6	0.4	0.0	0.8
10	0.0	-0.8	0.9	0.1	0.4	-0.5	1.0	0.9	-0.5	0.1	0.7	Inf	0.9	0.2	0.4	-0.2	0.6	0.4	-0.1	0.1	0.4
11	0.0	-0.5	1.0	0.3	0.8	-0.9	0.8	1.0	-0.8	0.1	0.6	0.9	Inf	0.4	0.6	0.0	0.5	0.7	0.1	0.4	0.5
12	0.0	0.2	0.4	0.2	0.5	-0.5	0.1	0.4	-0.5	-0.5	0.6	0.2	0.4	Inf	0.9	0.8	0.0	0.9	0.9	0.4	0.9
13	0.0	0.0	0.6	0.2	0.6	-0.7	0.3	0.6	-0.7	-0.3	0.6	0.4	0.6	0.9	Inf	0.5	0.4	1.0	0.6	0.6	0.8
14	0.0	0.5	-0.1	0.2	0.3	-0.3	-0.2	0.0	-0.2	-0.4	0.3	-0.2	0.0	0.8	0.5	Inf	-0.5	0.5	1.0	0.2	0.7
15	0.0	-0.6	0.6	-0.2	0.2	-0.4	0.5	0.6	-0.4	0.3	0.2	0.6	0.5	0.0	0.4	-0.5	Inf	0.5	-0.5	0.4	0.0
16	0.0	-0.1	0.6	0.1	0.6	-0.7	0.3	0.7	-0.7	-0.2	0.6	0.4	0.7	0.9	1.0	0.5	0.5	Inf	0.5	0.6	0.7
17	0.0	0.5	0.0	0.2	0.3	-0.3	-0.2	0.1	-0.3	-0.5	0.4	-0.1	0.1	0.9	0.6	1.0	-0.5	0.5	Inf	0.3	0.7
18	0.0	0.1	0.3	0.0	0.5	-0.7	-0.1	0.4	-0.7	0.3	0.0	0.1	0.4	0.4	0.6	0.2	0.4	0.6	0.3	Inf	0.1
19	0.0	0.1	0.5	0.3	0.5	-0.5	0.3	0.5	-0.5	-0.6	0.8	0.4	0.5	0.9	0.8	0.7	0.0	0.7	0.7	0.1	Inf

Bioclimatic Variables

Figure 1: Table showing correlation coefficients between variables (Matthews 2011). Highly correlated variables are coefficients greater than the absolute value of 0.07.

Variable	Correlation Coefficient
TRMI	-0.02
DEM	0.37
Bioclim 1	-0.10
Bioclim 2	0.08
Bioclim 3	0.12
Bioclim 4	-0.11
Bioclim 5	-0.21
Bioclim 6	-0.05
Bioclim 7	-0.10
Bioclim 8	-0.24
Bioclim 9	0.06
Bioclim 10	-0.18
Bioclim 11	-0.04
Bioclim 12	0.43
Bioclim 13	0.29
Bioclim 14	0.50
Bioclim 15	-0.21
Bioclim 16	0.27
Bioclim 17	0.51
Bioclim 18	0.22
Bioclim 19	0.30

Figure 2: Pearson correlation coefficients between variables and green salamander presence (Goslee and Urban 2007). All variables significant at p-values less than 0.05 unless correlation coefficient is equal to zero.

Variable	Correlation Coefficient
soil	0.00
TRMI	0.05
Bioclim 1	-0.03
Bioclim 2	0.00
Bioclim 3	0.00
Bioclim 4	0.00
Bioclim 5	-0.05
Bioclim 6	0.00
Bioclim 7	-0.02
Bioclim 8	-0.22
Bioclim 9	0.09
Bioclim 10	-0.04
Bioclim 11	-0.02
Bioclim 12	0.17
Bioclim 13	0.14
Bioclim 14	0.16
Bioclim 15	-0.05
Bioclim 16	0.11
Bioclim 17	0.18
Bioclim 18	0.00
Bioclim 19	0.16

Figure 3. Pearson correlation coefficients between variables and large-flowered skullcap presence (Goslee and Urban 2007). All variables significant at p-values less than 0.05 unless correlation coefficient is equal to zero.

Variable	Correlation Coefficient
TRMI	0.00
soils	-0.03
Bioclim 1	-0.02
Bioclim 2	0.02
Bioclim 3	0.00
Bioclim 4	0.00
Bioclim 5	-0.02
Bioclim 6	-0.02
Bioclim 7	0.02
Bioclim 8	-0.10
Bioclim 9	0.07
Bioclim 10	-0.02
Bioclim 11	-0.02
Bioclim 12	0.08
Bioclim 13	0.04
Bioclim 14	0.07
Bioclim 15	-0.05
Bioclim 16	0.03
Bioclim 17	0.08
Bioclim 18	-0.02
Bioclim 19	0.08

Figure 4. Pearson correlation coefficients between variables and southeastern shrew (Goslee and Urban 2007). All variables significant at p-values less than 0.05 unless correlation coefficient is equal to zero.

Variable	Correlation Coefficient
TRMI	0.00
soils	-0.02
Bioclim 1	0.00
Bioclim 2	0.00
Bioclim 3	0.00
Bioclim 4	0.03
Bioclim 5	0.00
Bioclim 6	-0.02
Bioclim 7	0.03
Bioclim 8	-0.03
Bioclim 9	0.00
Bioclim 10	0.00
Bioclim 11	-0.02
Bioclim 12	0.00
Bioclim 13	0.00
Bioclim 14	0.00
Bioclim 15	0.00
Bioclim 16	0.00
Bioclim 17	0.00
Bioclim 18	-0.03
Bioclim 19	0.00

Figure 5. Pearson correlation coefficients between variables and heartleaf plantain presence (Goslee and Urban 2007). All variables significant at p-values less than 0.05 unless correlation coefficient is equal to zero.

Appendix D: MaxEnt

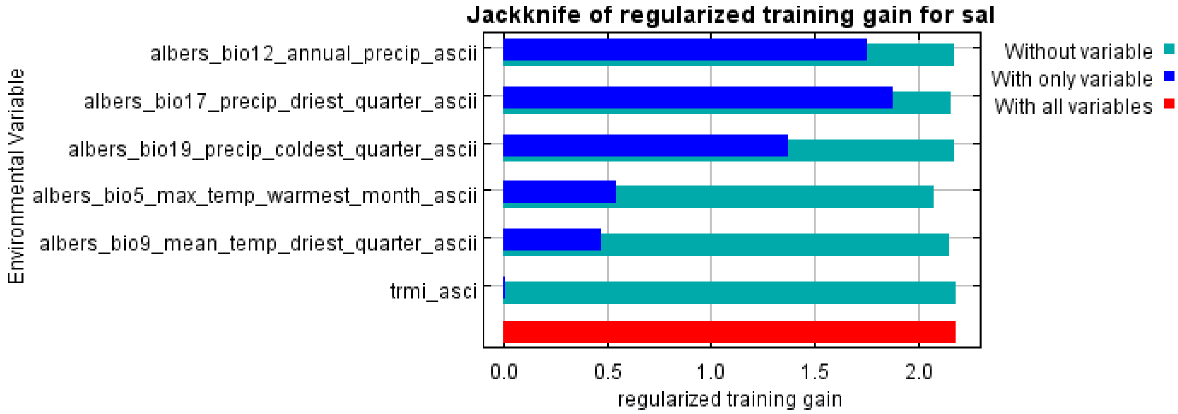


Figure 1. Jackknife results for the green salamander. Precipitation in the driest quarter and annual precipitation have the largest gain when used alone, revealing that they contain important, unique information. Conversely, alone, TRMI has little predictive capacity. Jackknife tests using test gain and AUC showed the same pattern.

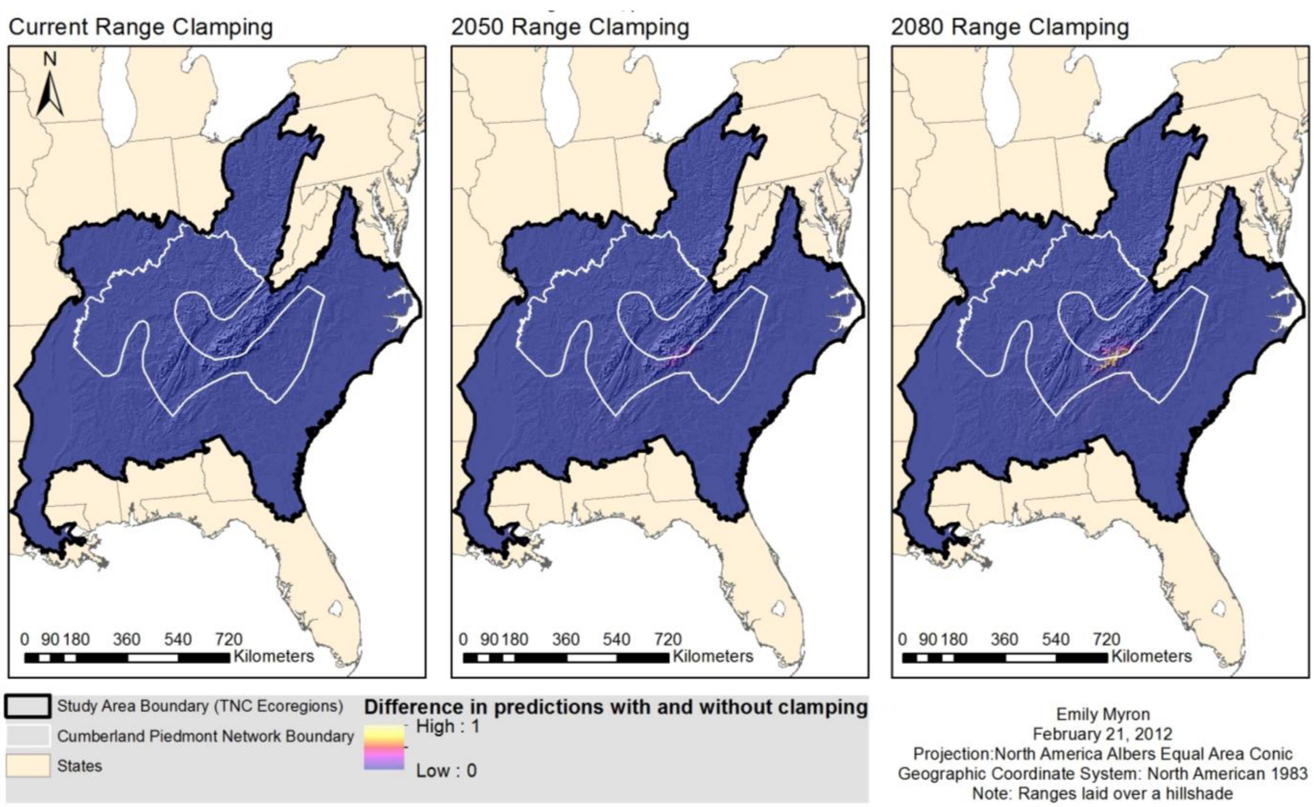


Figure 2. MaxEnt clamping for the green salamander; areas of high clamping correspond to areas where the variables were outside of the training range of the model. In these areas, we are less certain of habitat predictions because we have no way of knowing how the green salamander will respond to novel climatic conditions. In the 2080 scenario, areas of high clamping overlap with areas predicted to be suitable habitat (Figure 9).

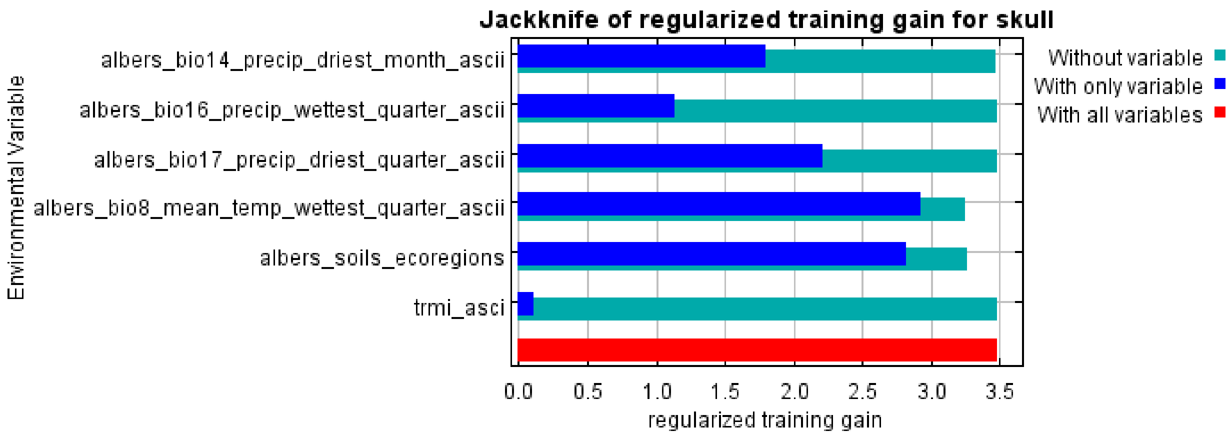


Figure 3. Jackknife results for the large-flowered skullcap. Mean temperature in the wettest quarter and soils have the largest gain when used alone, revealing that they contain important, unique information. Conversely, alone, TRMI has little predictive capacity. Jackknife tests using test gain and AUC showed the same pattern.

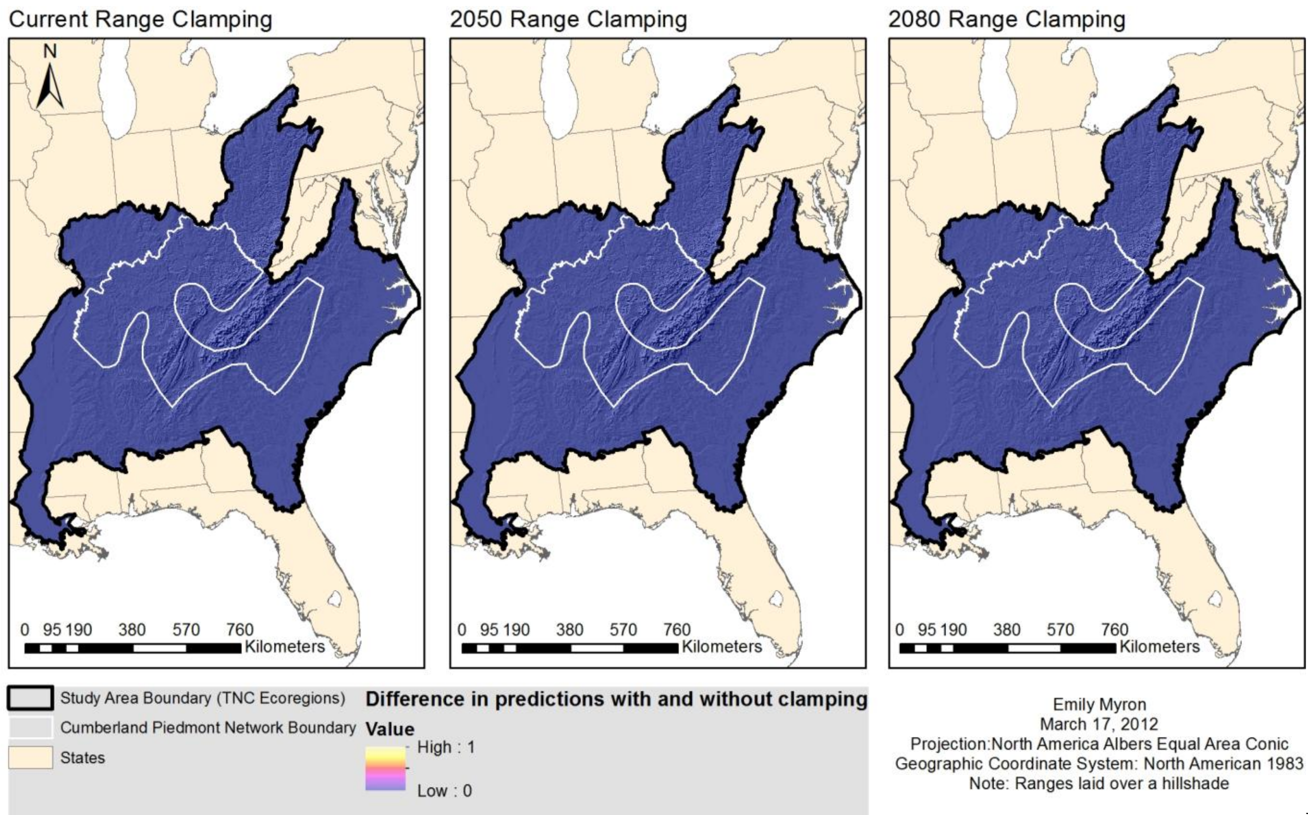


Figure 4.

MaxEnt clamping for the large-flowered skullcap; areas of high clamping correspond to areas where the variables were outside of the training range of the model. This model experienced very little clamping, which allows us to be more confident in habitat suitability predictions.

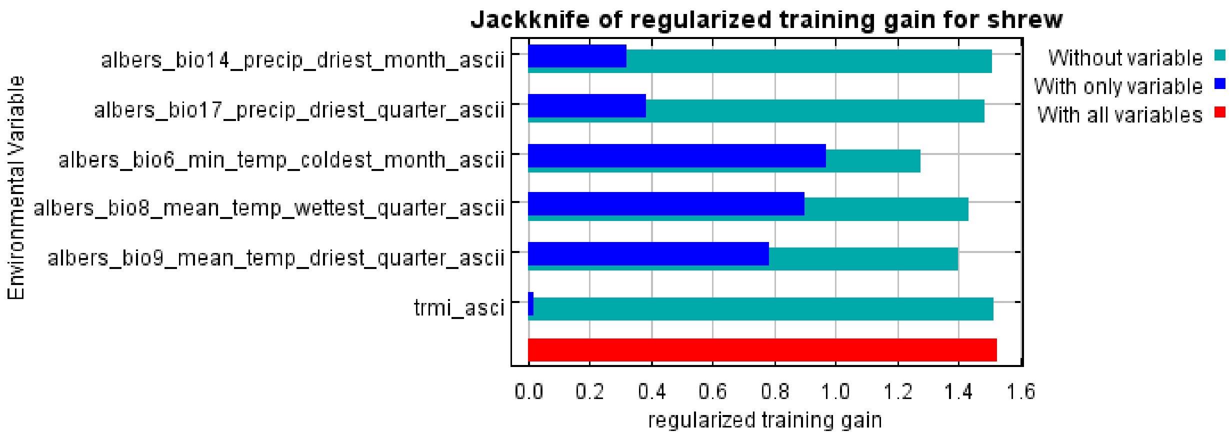


Figure 5. Jackknife results for the southeastern shrew. Min temperature in the coldest money and mean temp in the wettest quarter have the largest gain when used alone, revealing that they contain important, unique information. Conversely, alone, TRMI has little predictive capacity. Jackknife tests using test gain and AUC showed the same pattern.

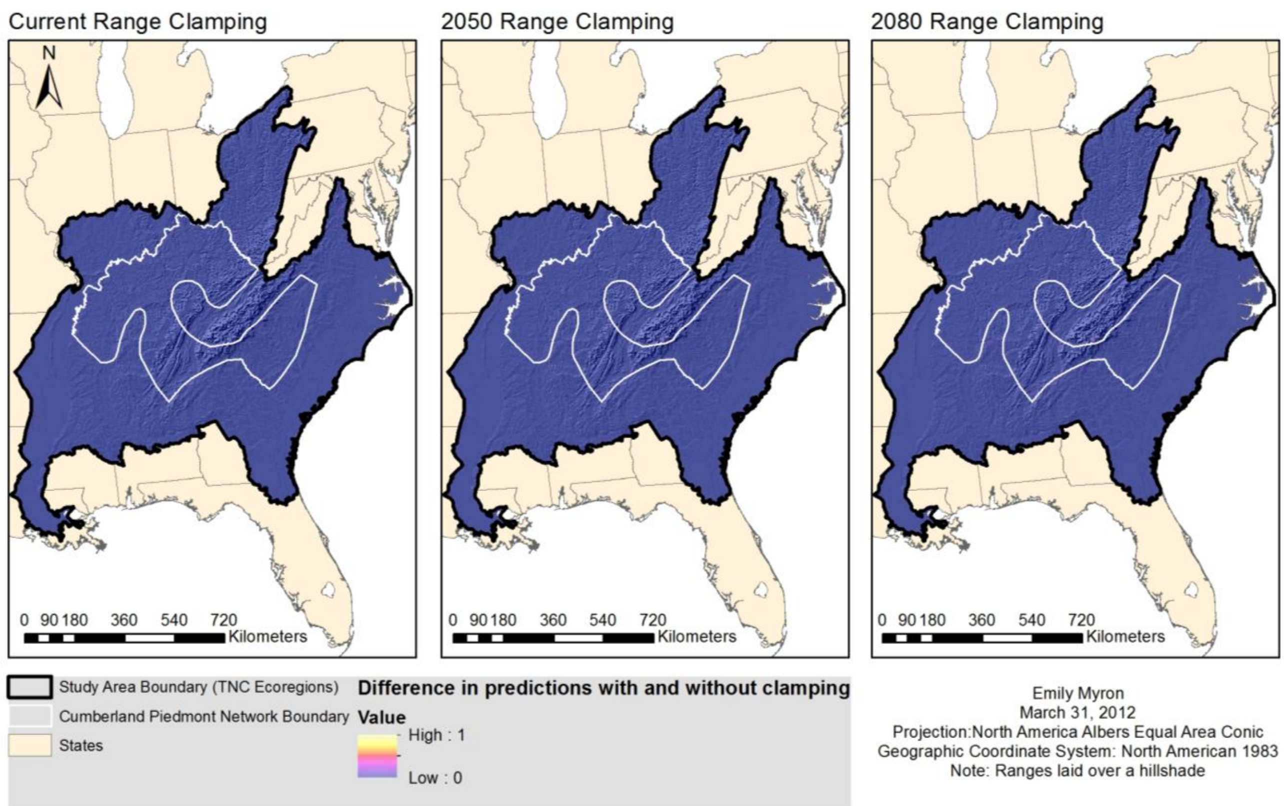


Figure 6. MaxEnt clamping for the southeastern shrew; areas of high clamping correspond to areas where the variables were outside of the training range of the model. This model experienced very little clamping, which allows us to be more confident in habitat suitability predictions.

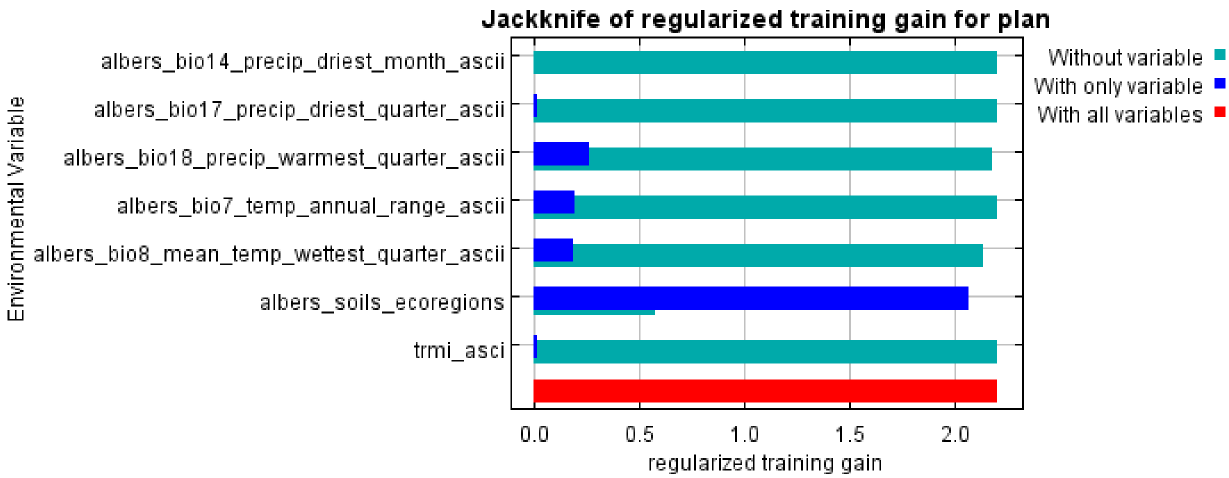


Figure 7. Jackknife results for the heartleaf plantain. Soil type has, by far, the largest gain when used alone, revealing that it contains important, unique information. Conversely, alone, precipitation in the driest month, in the driest quarter, and TRMI have little predictive capacity. Jackknife tests using test gain and AUC showed the same pattern.

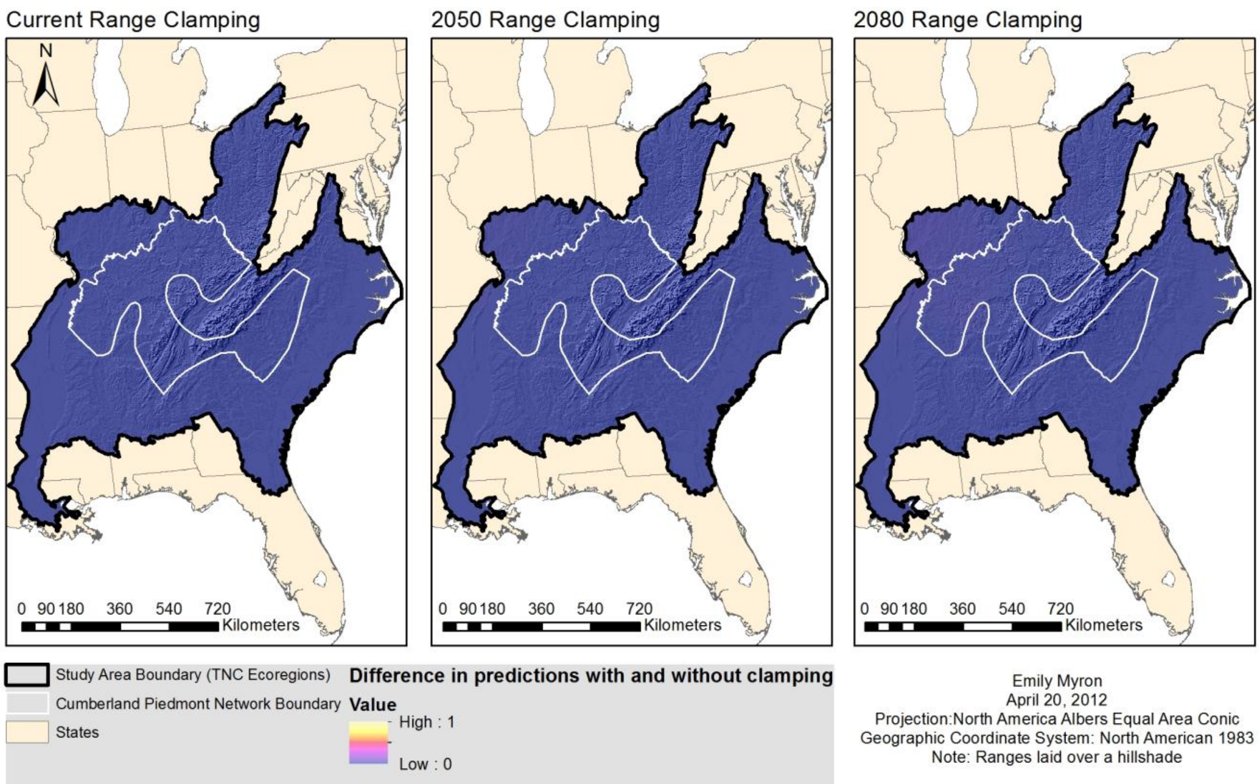


Figure 8. MaxEnt clamping for the heartleaf plantain; areas of high clamping correspond to areas where the variables were outside of the training range of the model. This model experienced very little clamping, which allows us to be more confident in habitat suitability predictions.

Appendix E: BIOMOD/Ensemble

Green salamander:

GLM

f(x) = sal ~ bioclim17 + bioclim19 + bioclim12

GAM

sal ~ s(bioclim5, 3) + s(bioclim9, 3) + s(bioclim12, 3) + s(bioclim17, 3) + s(bioclim19, 3)

CTA

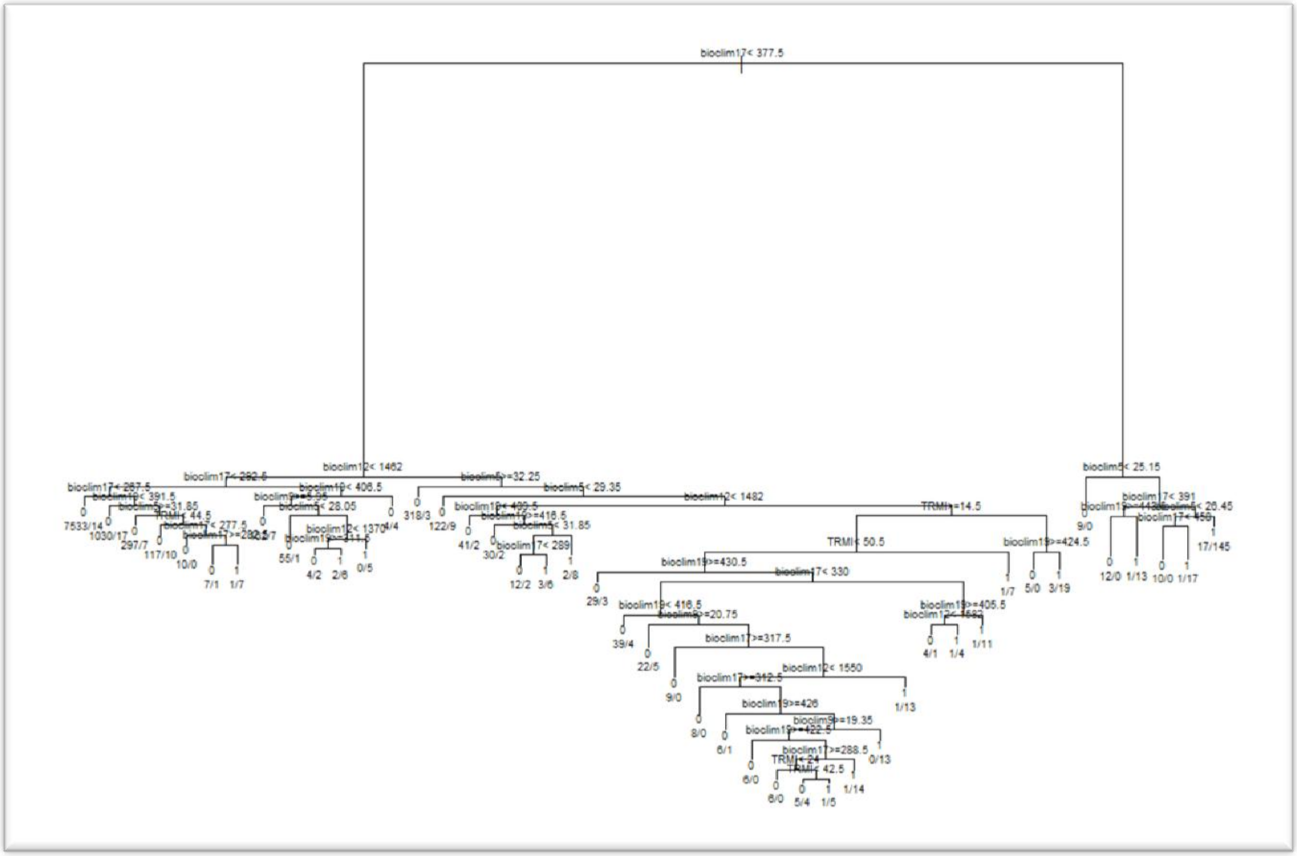


Figure 1: Classification tree for green salamander after 50 cross-validation. Bioclim variable 17 was the first variable upon which the division was made. Based on the length of leaves, bioclim variable 17 is by far the most important variable for dividing the data.

GBM

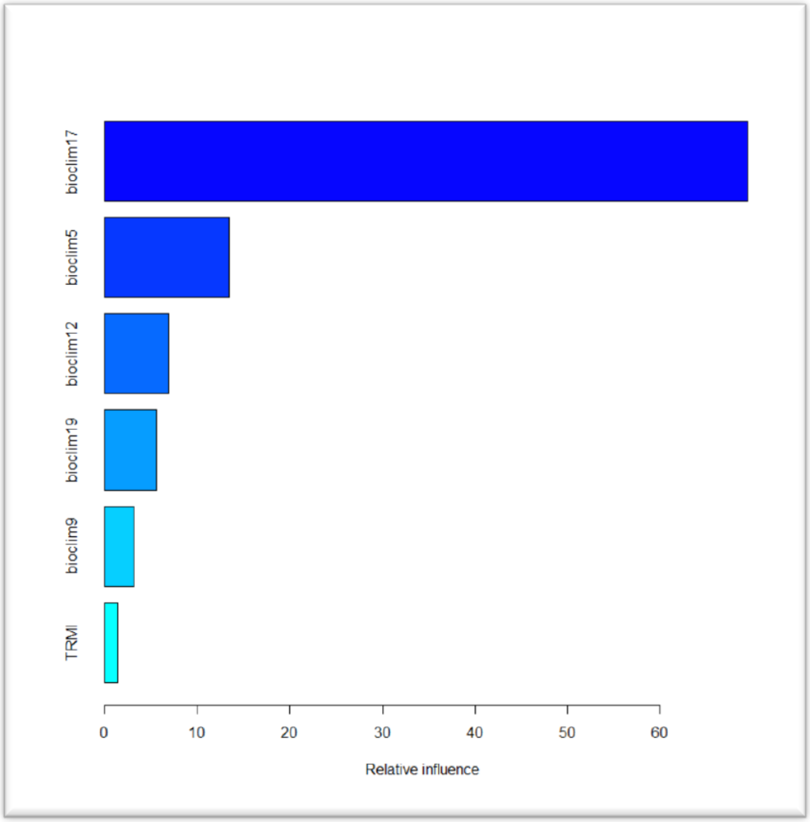


Figure 2: GBM results showing relative influence of each variable on the green salamander model.

Large-flowered Skullcap:

GLM

f(x) = skullcap ~ X8 + X17 + trmi + X16 + X14

GAM

skullcap ~ s(soil, 3) + s(trmi, 3) + s(X8, 3) + s(X17, 3) + s(X16, 3) + s(X14, 3)

CTA

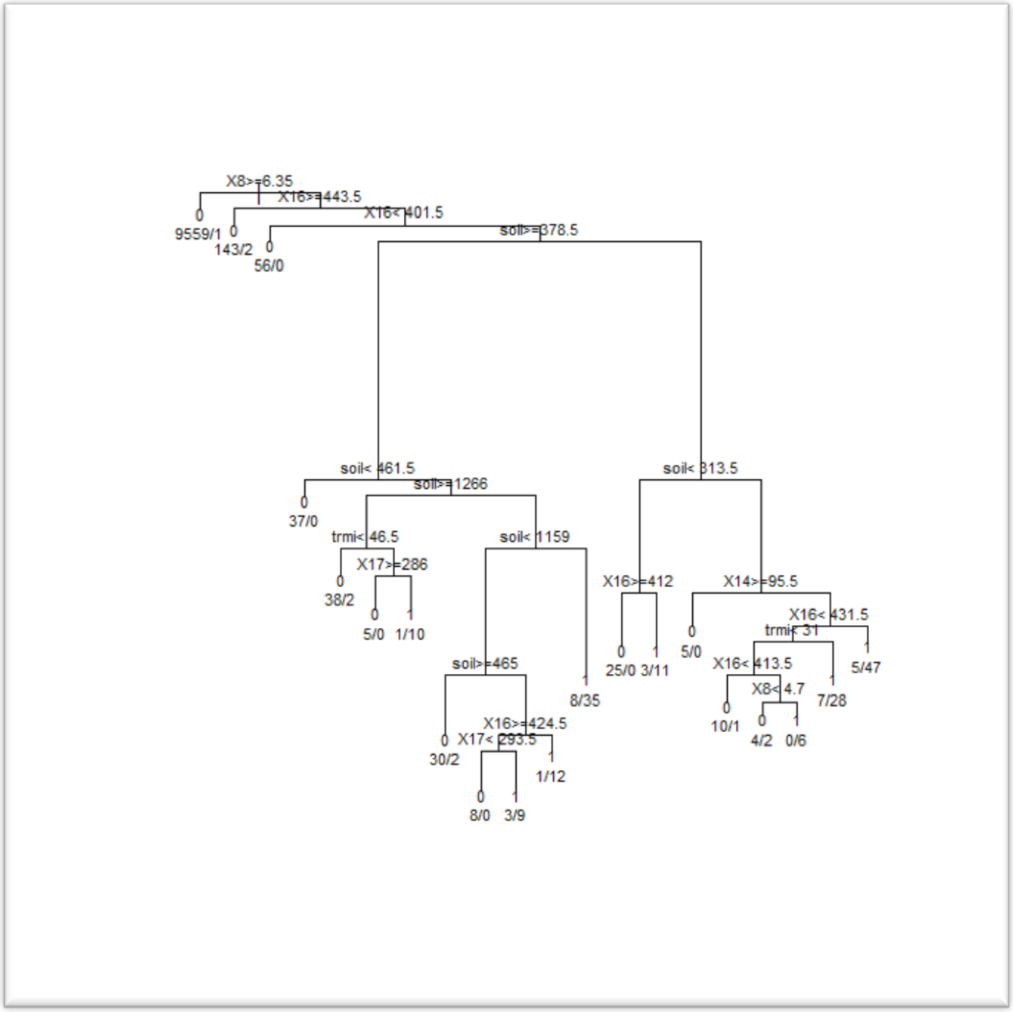


Figure 3: Classification tree for Large-flowered Skullcap after 50 cross-validation. Bioclim variable 8 was the first variable upon which the division was made. Soil made the most divisive cut (seen here in the central portion with longest leaves).

GBM

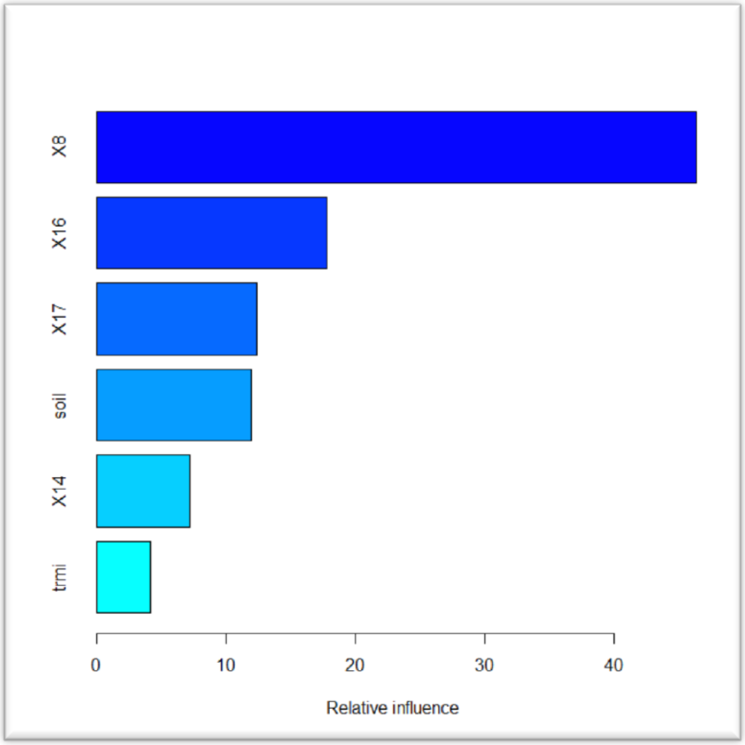


Figure 4: GBM results showing relative influence of each variable on the Large-flowered Skullcap model (X8 = bioclim8, X16 = bioclim16, X17 = bioclim17, X14 = bioclim14).

Southeastern shrew:

GLM

f(x) = shrew ~ bioclim8 + bioclim6+ bioclim9

GAM

shrew ~ s(bioclim6, 3) + s(bioclim8, 3) + s(bioclim9, 3) + s(bioclim14, 3) + s(bioclim17, 3)

CTA

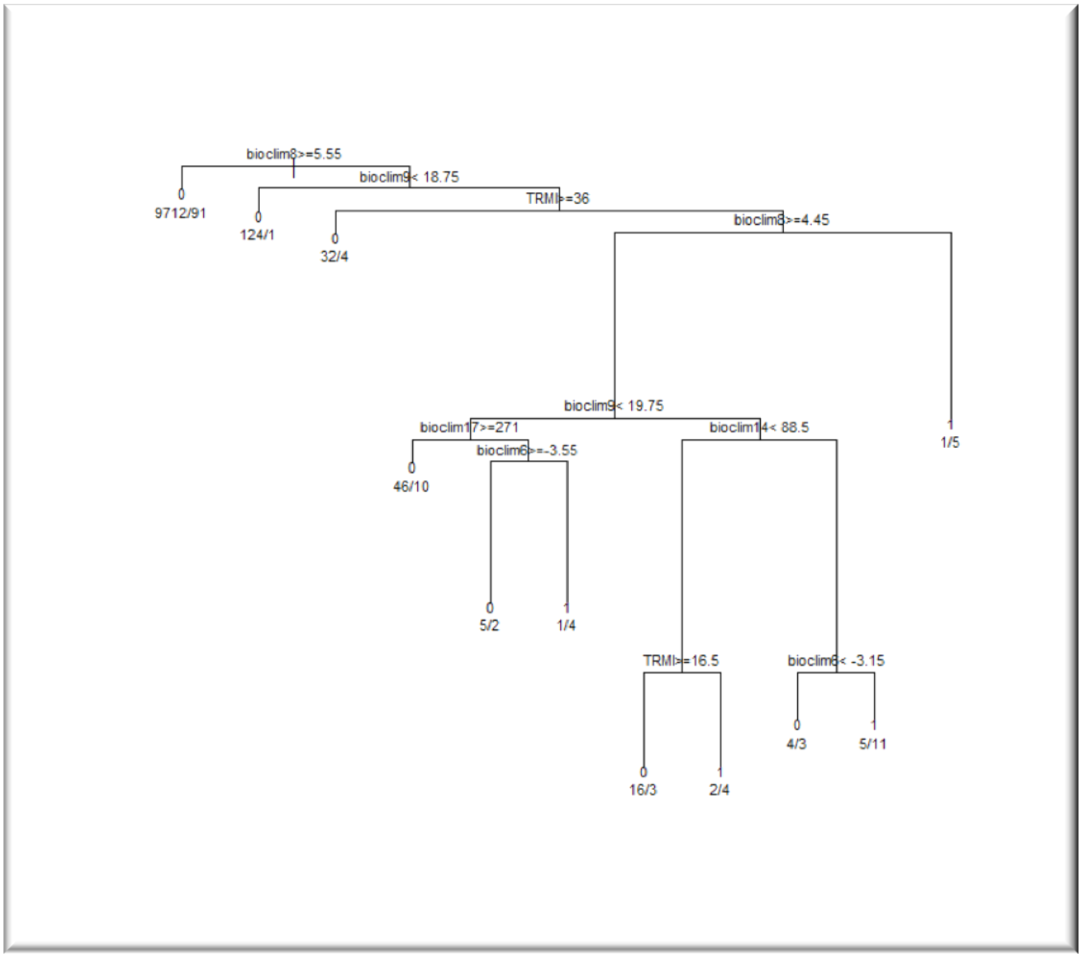


Figure 5: Classification tree for southeastern shrew after 50 cross-validation. The first division was made using bioclim variable 8. He most important division, seen near the bottom right with the longest leaves, was made using bioclim variable 14.

GBM

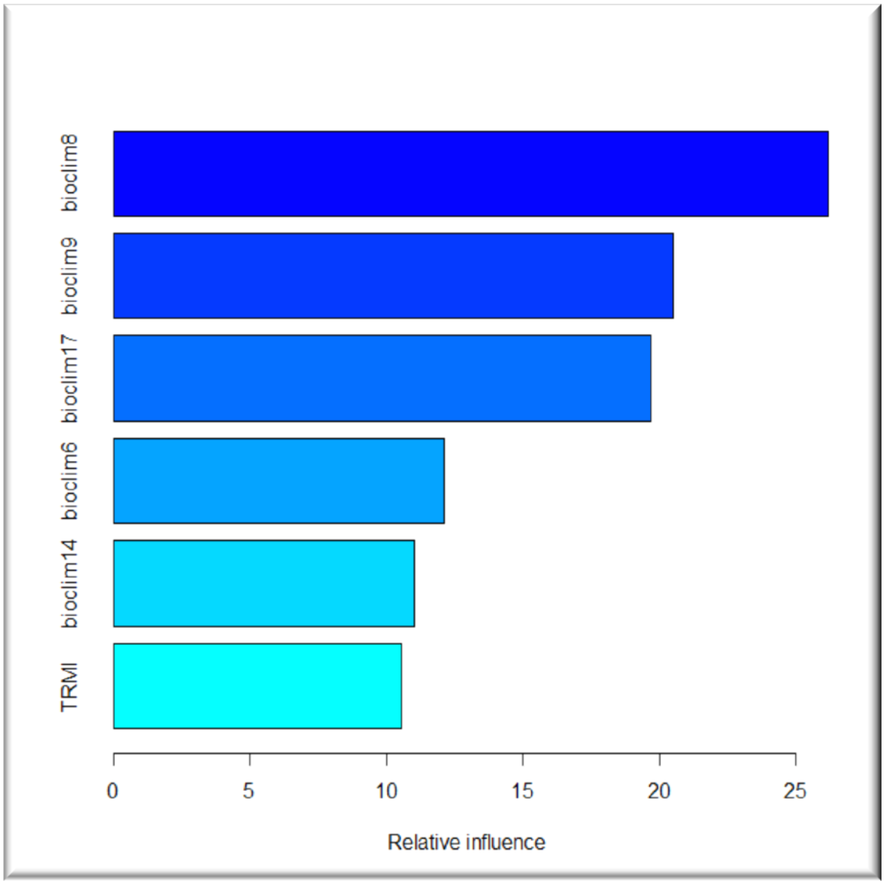


Figure 6: GBM results showing relative influence of each variable on the southeastern shrew model.

Heartleaf plantain:

GLM

f(x) = plantago ~ bioclim18 + bioclim8 + soil

GAM

plantago ~ s(bioclim7, 3) + s(bioclim8, 3) + s(bioclim18, 3)

CTA

CTA did not perform for this species, most likely due to lack of adequate presence data.

GBM

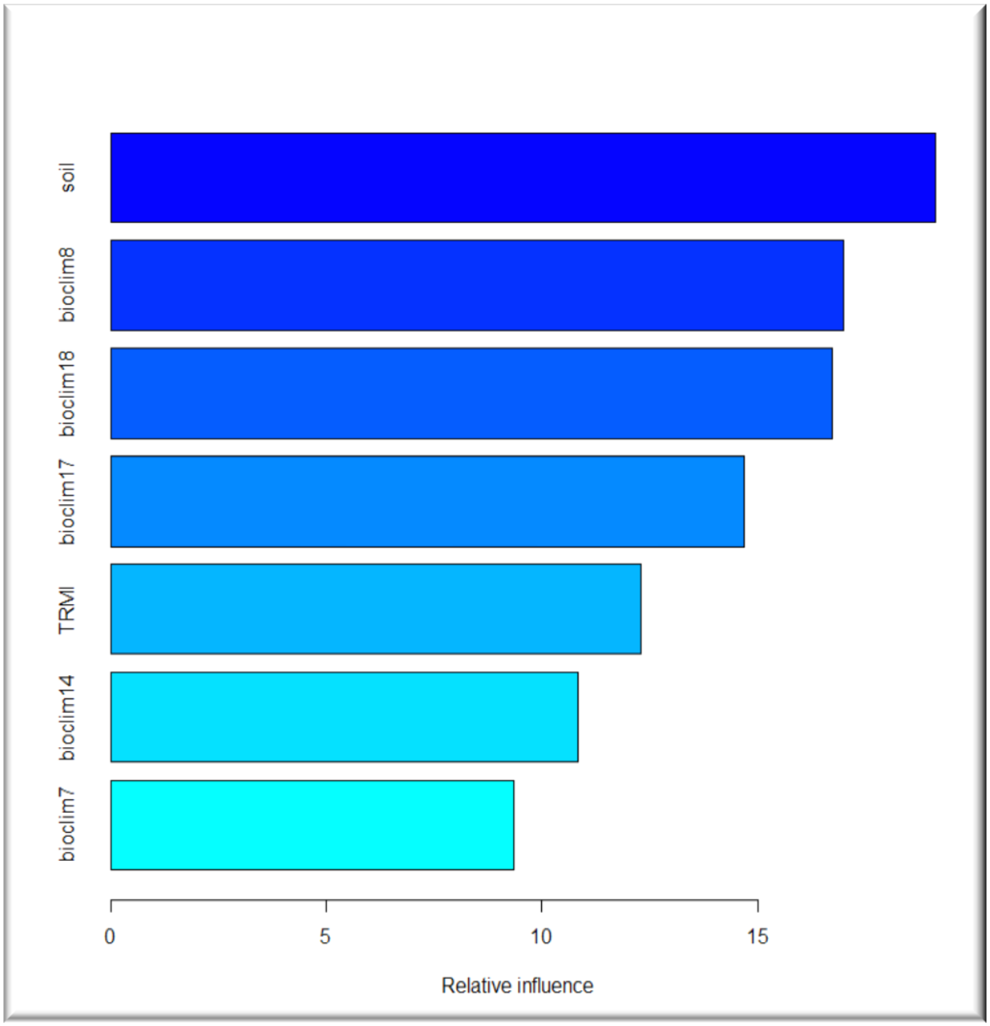


Figure 7: GBM results showing relative influence of each variable on the heartleaf plantain model.

Appendix F: Novel Climatic Conditions

The program MaxEnt generates multivariate similarity surface (MESS) maps that indicate areas where variables fall outside the range of the training data (but not new combinations of variables)[17]. This is especially important when making projections into new spaces – geographic or climatic. MESS maps can be used in conjunction with projections from MaxEnt, and any other models, as long as the same training data is used. Results of projections for green salamander, large-flowered skullcap, southeastern shrew, and heartleaf plantain onto 2050 and 2080 climate surfaces should be interpreted with levels of confidence adjusted to reflect where these surface maps show areas of greatest uncertainty.

Green salamander

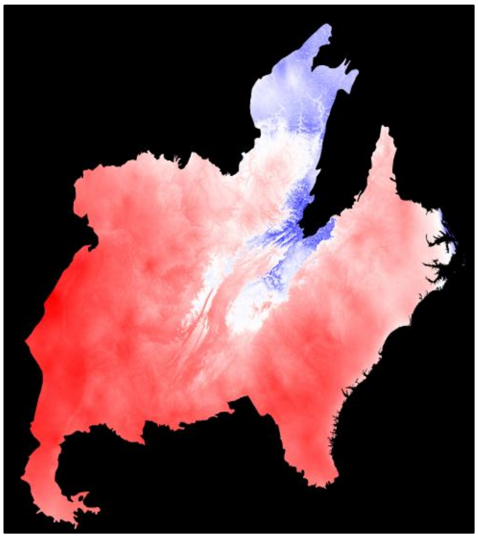


Figure 1: Areas in dark blue indicate variables found at these locations do not exceed the training range of the data for 2050. Areas in dark red indicate one or more variables exceed the training range of the data. Projections into areas in dark red should be interpreted with caution.

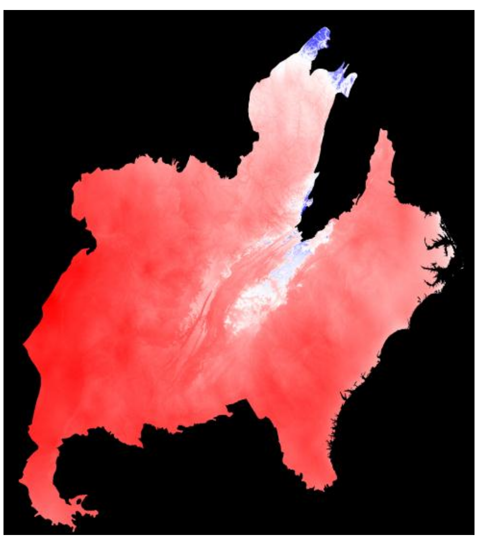


Figure 2: Areas in dark blue indicate variables found at these locations do not exceed the training range of the data for 2080. Areas in dark red indicate one or more variables exceed the training range of the data. Projections into areas in dark red should be interpreted with caution.

[17] See: http://www.cs.princeton.edu/~schapire/maxent/

Large-flowered skullcap

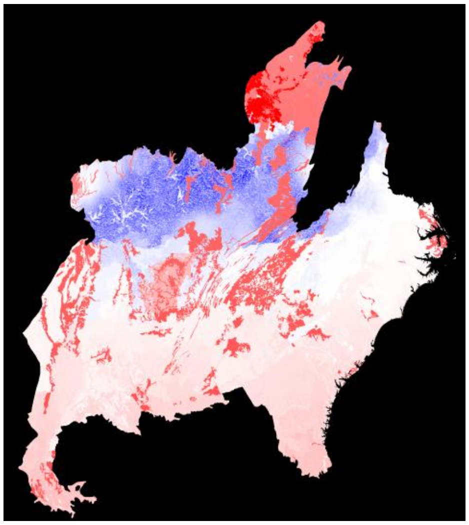


Figure 1: Areas in dark blue indicate variables found at these locations do not exceed the training range of the data for 2050. Areas in dark red indicate one or more variables exceed the training range of the data. Projections into areas in dark red should be interpreted with caution.

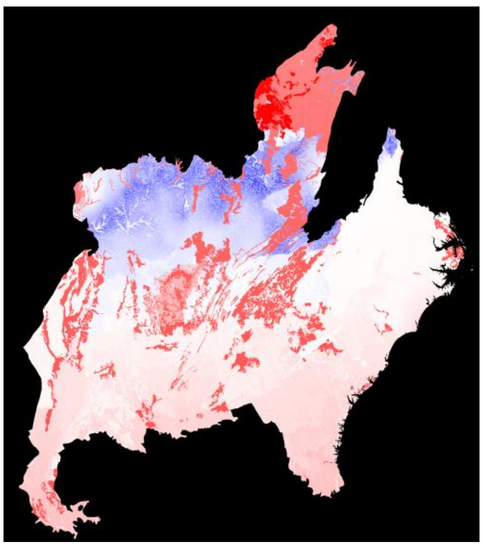


Figure 2: Areas in dark blue indicate variables found at these locations do not exceed the training range of the data for 2080. Areas in dark red indicate one or more variables exceeds the training range of the data. Projections into areas in dark red should be interpreted with caution.

Southeastern shrew

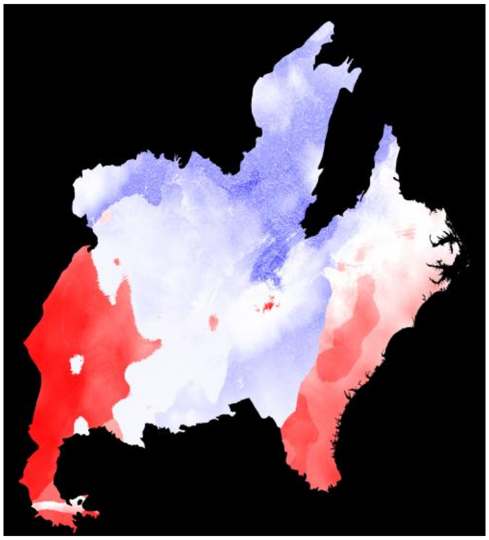


Figure 1: Areas in dark blue indicate variables found at these locations do not exceed the training range of the data for 2050. Areas in dark red indicate one or more variables exceed the training range of the data. Projections into areas in dark red should be interpreted with caution.

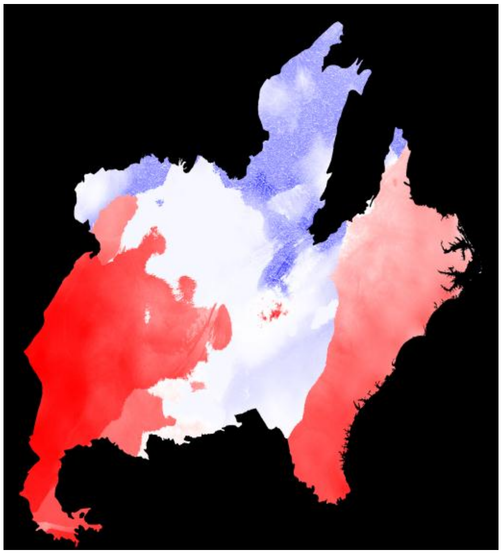


Figure 2: Areas in dark blue indicate variables found at these locations do not exceed the training range of the data for 2080. Areas in dark red indicate one or more variables exceeds the training range of the data. Projections into areas in dark red should be interpreted with caution.

Heartleaf Plantain

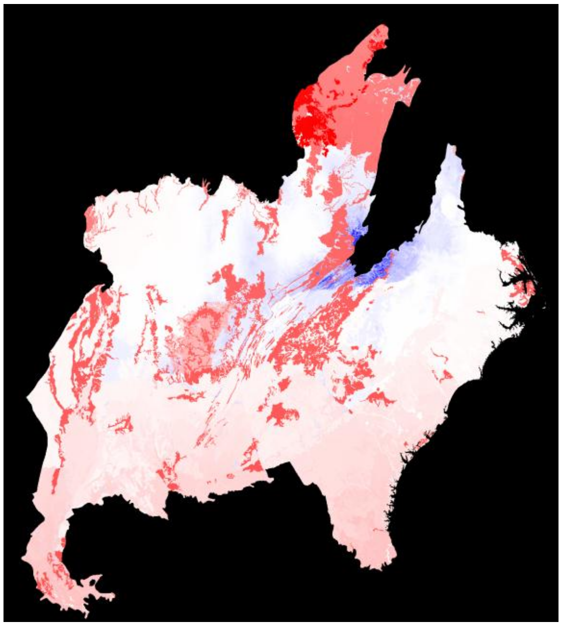


Figure 1: Areas in dark blue indicate variables found at these locations do not exceed the training range of the data for 2050. Areas in dark red indicate one or more variables exceed the training range of the data. Projections into areas in dark red should be interpreted with caution.

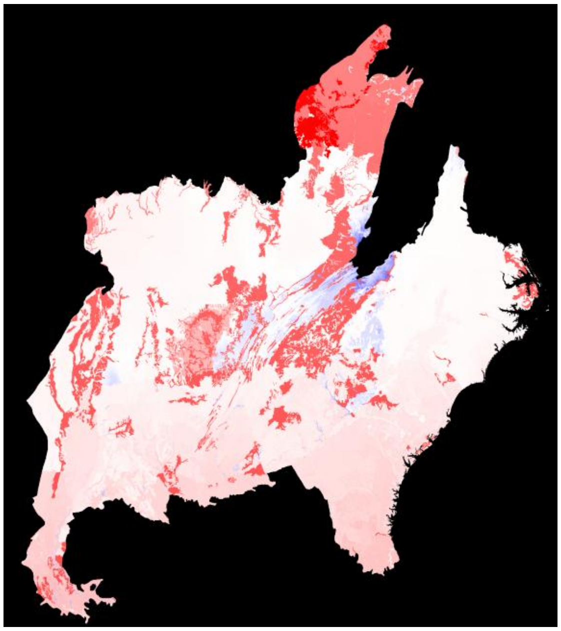


Figure 2: Areas in dark blue indicate variables found at these locations do not exceed the training range of the data for 2080. Areas in dark red indicate one or more variables exceeds the training range of the data. Projections into areas in dark red should be interpreted with caution.

Appendix G: Client Deliverables

Green Salamander:
An Assessment of Climate Change Vulnerability

Species Background

The green salamander's (*Aneides aeneus*) range extends widely throughout the Appalachian Mountains, from southwestern Pennsylvania to Central Alabama, but is mostly characterized by scattered and disjunct populations. Fully-grown adults measure from 8 to 14 cm. As an environmental specialist, the amphibian resides in dark, damp rock outcrops and ledges. Less frequently, loose bark of standing or fallen trees may also serve as habitat. This species is found at elevations ranging from 140-1350 meters, and they are the only members of the "climbing family" of salamanders east of the Rocky Mountains. As the only truly green salamander in North America, this nocturnal amphibian eats small invertebrates, including snails, slugs, spiders, that are found in damp sections of forests and rock outcrops. This species hibernates in the winter and mates in late spring or early fall, resulting in egg clutches of around 10-30 eggs.
Natureserve ranks this as an S2 and S3, G3G4 species.

Descriptive Photo

Climate Change Vulnerability Index

NatureServe recently developed the Climate Change Vulnerability Index (CCVI) to identify and evaluate species that are most vulnerable to the impacts of climate change. The CCVI takes into account a species' exposure and sensitivity to changes in climate, as well as adaptive capacity to disturbances (Young et al. 2010).

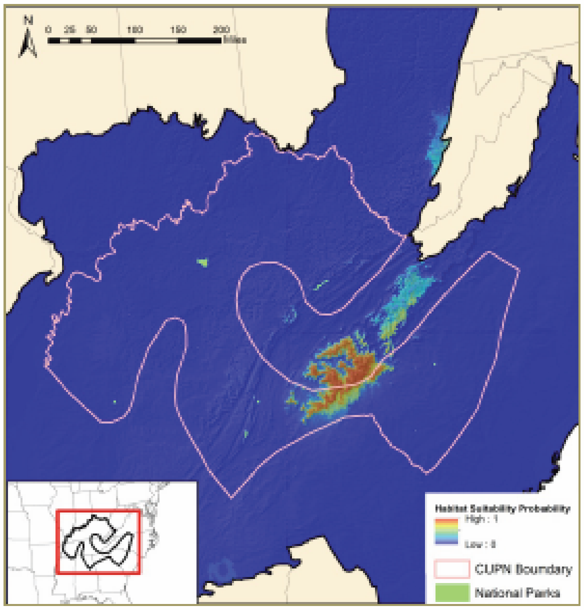
According to the CCVI, this species has been classified as **Moderately Vulnerable**. This is due to anthropogenic barriers, low dispersal potential, historic and physiological hydrologic niche, and physical habitat requirements.

Other Threats

Declines in green salamander populations are largely attributed to habitat loss. Due to their narrow environmental specificity, land and watershed development have reduced the occurrence of the species within its range. Additionally, some research suggests that the loss of the American chestnut (*Castanea dentate*) due to blight has further reduced habitat availability. Because of the increase in genetically disjunct populations of the salamander due to habitat loss, the species is increasingly vulnerable to potential over collecting and epidemic disease. Prolonged droughts or periods of cold account for historical populations drop-offs.

Descriptive Photo

Distribution Maps



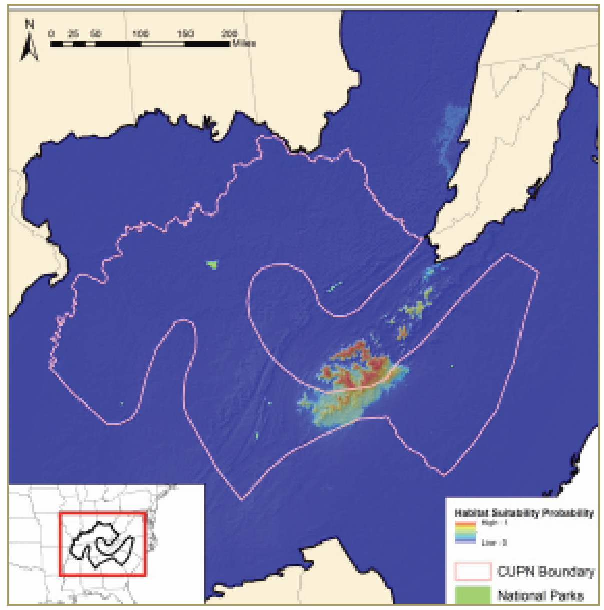


Figure 1: Projected suitable bioclimatic habitat for 2050. **Figure 2:** Projected suitable bioclimatic habitat for 2080.

Suitable bioclimatic habitat for the green salamander is expected to center around the Southern Appalachian Mountains in the year 2050 (Figure 1) and shift outside of the Cumberland Piedmont Network by 2080 (Figure 2). Areas in red indicate high probability of suitable bioclimatic conditions according to projections averaged from five different habitat suitability models. Precipitation of driest quarter was selected by each of the five models as the most important bioclimatic factor in determining the future bioclimatic range of the green salamander. Future climate conditions are based on the IPCC A1B emissions scenario using the Hadley CM3 general circulation model.

Management Summary

Currently, the green salamander is found in two NPS units (Little River Canyon NP and Carl Sandburg Home NHS). However, future predictions show that suitable habitat may remain in Carl Sandburg Home NHS, but will likely be lost from Little River Canyon in the future. There is a possibility that Cumberland Gap may have suitable habitat in the future; however, the ability for this species to reach new parks is questionable. Due to its low dispersal capabilities, this species is highly susceptible to land use impacts adjacent to the NPS units in which it is found.

Among the most important management needs for the green salamander is the maintenance of its habitat in and around moist rocky outcrops. For example, a 100-meter forest buffer surrounding the amphibians' habitat may help prevent disturbance to the salamander's habitat and preserve moisture conditions under the forest canopy. This species requires moist rocky outcrops and woody debris for habitat, and it is possible that these microhabitats may persist in some locations with climate change. Finally, because this species is also sensitive to extreme climate conditions such as severe droughts, monitoring programs that examine population survival, gene flow, and how the disappearance of old-growth forest has affected the species' range extent will help guide further management decisions in the face of climate change.

Contact Information.

Thanks to those at Duke University, NatureServe and NPS who made this project possible. Species information from NatureServe Explorer.

Figure 1. We created page-long informational documents for NPS for each of the four species we modeled. This is an example of the green salamander document.

Appendix H: R Scripts

Part I: Exploratory data analysis for large-flowered skullcap

```
################################ *code sourced from Geoffrey Matthews
###    Exploratory Data Analysis     ### (Computer Science Dept. Western
###      Large Flower Skull-Cap*      ### Washington University) via Brenna
################################ Forester or Dean Urban Multivariate Class

### Data Prep

### read in the data (a CSV file with each presence/absence point, site ID
### and the associated environmental variables; no need for spatial data;
### also, a CSV file with just presence/absence and site ID)

skull.habitat <- read.csv("all_presence_pseudo_absence.csv")
skull.presence <- read.csv("just_ID_presence_absence.csv")

### remove ID, CID
skull.habitat <- skull.habitat[,c(-1:-2)]
### check it out
head(skull.habitat)

### remove ID,
skull.presence <- skull.presence[,c(-1)]
head(skull.presence)

###-------------------------------------------------------------------###
### Correlations among environmental variables (2 different methods)
### Note, this is good for ALL OF OUR SPECIES (~10,000 points across the ecoregions)

### Method 1: From Dean Urban Multivariate Analysis class
### This method doesn't produce a nice table like Brenna's

habitat.cor <- cor(skull.habitat)
### type the object name to scan it
habitat.cor
### look at a few as plots
pairs(habitat.cor[,5:7])
### test one correlation
cor.test(sal.habitat$bioclim5,sal.habitat$bioclim12)

### Method 2: From Brenna Forester
### This method produces a nice table

### call in r-code from Brenna
source("correlation.r")
### create correlation matrix; list correlation coefficients and
### list p-values
skull.cor <- correlation.matrix(skull.habitat, method = "pearson")
skull.cor
### look at just coefficients
skull.cor$statistics
### look at just p-values
```

```
skull.cor$p.values
### write to CSV
write.table (skull.cor, "skull.cor_pearson_EDA.csv", row.names=T, col.names=T, sep=",")
### besides method = "kendall", you can use "pearson" (which is the default), or "spearman"

###------------------------------------------------------------------###
### Correlations between environmental variables and species of interest
### Edit for the species of interest: now, GREEN SALAMANDER

### call in the ecodist library (remember to install first)
library(ecodist)

### cross-correlate 2 matrices
cor2m(as.matrix(skull.presence), skull.habitat)

### Which are the variables most correlated? List them here in order to populate box plots:
### DEM, bioclim3, bioclim4, bioclim5, bioclim8, bioclim10, bioclim12, bioclim13, bioclim14,
### bioclim15, bioclim16, bioclim17, bioclim18, bioclim19

### boxplots
### now look at a bunch of variables
par(mfrow=c(2,4))
boxplot(skull.habitat$soil~skull.presence,ylab="soil")
boxplot(skull.habitat$X8~skull.presence,ylab="bioclim8")
boxplot(skull.habitat$X12~skull.presence,ylab="bioclim12")
boxplot(skull.habitat$X13~skull.presence,ylab="bioclim13")
boxplot(skull.habitat$X14~skull.presence,ylab="bioclim14")
boxplot(skull.habitat$X16~skull.presence,ylab="bioclim16")
boxplot(skull.habitat$X17~skull.presence,ylab="bioclim17")
boxplot(skull.habitat$X19~skull.presence,ylab="bioclim19")

### and some more
par(mfrow=c(2,4))
boxplot(skull.habitat$bioclim14~skull.presence,ylab="bioclim14")
boxplot(skull.habitat$bioclim15~skull.presence,ylab="bioclim15")
boxplot(skull.habitat$bioclim16~skull.presence,ylab="bioclim16")
boxplot(skull.habitat$bioclim17~skull.presence,ylab="bioclim17")
boxplot(skull.habitat$bioclim18~skull.presence,ylab="bioclim18")
boxplot(skull.habitat$bioclim19~skull.presence,ylab="bioclim19")
boxplot(skull.habitat$bioclim12~skull.presence,ylab="bioclim12")
boxplot(skull.habitat$bioclim13~skull.presence,ylab="bioclim13")

### another way to look
plot(skull.habitat$bioclim14, skull.presence, xlab="bioclim14", ylab="skull", pch=19)

### test a variable with ANOVA
soil.aov <- aov(skull.habitat$soil~as.factor(skull.presence))
summary(soil.aov)
```

Part II: Generate models using BIOMOD package

```
############################## Thuiller, W., Lafourcade, B., Engler, R. and Arau´jo, M. B. 2009.
###              BIOMOD              ### BIOMOD a platform for ensemble forecasting of species
```

```
###    Large Flower Skull-Cap       ### distributions. Ecography 32: 369-373 (Version 0).
##############################

###-------------------------------------------------------------------------------------------------###

library(BIOMOD)

### load data
### SpEnv is a CSV with column headings: rowID, X, Y, species P/A, and all the environmental variables

SpEnv <- read.csv("all_presence_pseudo_absence_var.csv", header=TRUE)

### this if for modeling future distribution, ignore for now
### data(Future1) #future environmental variables for rendering future projections

#LM: visualize the data to ensure everything looks okay (fix one at a time)
fix(SpEnv)

### Pseudo absences: I generated a random set of ~10,000 points in ArcMap and read them in here as if
### they are true absences. So, I don't think I need the code right below, because this is what I did
### in ArcMap. I will set NbRepPA=0 in the models call.

### Initialize the data: the response variable is simply the presence column; the explanatory variables
### are the columns containing the environmental variables

Initial.State(Response=SpEnv[,2], Explanatory=SpEnv[,3:8], IndependentResponse=NULL, IndependentExplanatory=NULL,
                                    sp.name="CID")

### Run the models. Pick which models you would like to run and how you would like to evaluate them.

Models(GLM=T, TypeGLM="simple", Test="AIC", GBM=T, No.trees=2000, GAM=T,
Spline=3, CTA=T, CV.tree=50, ANN=F, CV.ann=2, SRE=F,quant=0.05, FDA=T,
MARS=T, RF=T, NbRunEval=3, DataSplit=70, Yweights=NULL, Roc=T,
Optimized.Threshold.Roc=T, Kappa=T, TSS=T, KeepPredIndependent=T, VarImport=5)

##############
### Output ###
##############

### GLM---------------------------------------------------------------------------------------------###
### what follows is an explantation of the variables selected by the stepwise procedure and
### residual and null deviances of the model

load("models/CID_GLM_full")
CID_GLM_full
summary(sal_GLM_full)
CID_GLM_full$anova
par(mfrow=c(2,2))
plot(CID_GLM_full)

### GBM---------------------------------------------------------------------------------------------###
### make sure to load the gbm library

library(gbm)
load("models/CID_GBM_full")
```

```
summary(CID_GBM_full)
par(mfrow=c(2,3))
plot(CID_GBM_full, i.var=1)
plot(CID_GBM_full, i.var=2)
plot(CID_GBM_full, i.var=3)
plot(CID_GBM_full, i.var=4)
plot(CID_GBM_full, i.var=5)

### GAM--------------------------------------------------------------------------------------------###
### make sure to load the gam library

library(gam)
load("models/CID_GAM_full")
CID_GAM_full
summary(CID_GAM_full)
CID_GAM_full$anova

### CTA--------------------------------------------------------------------------------------------###
### make sure to load the rpart library

library(rpart)
load("models/CID_CTA_full")
names(CID_CTA_full)
CID_CTA_full$frame
plot(CID_CTA_full, margin=0.05)
text(CID_CTA_full, use.n=T, cex=0.7)

##################
###     Evaluation   ###
##################

### Check the evaluation results for each run
### Need to decide on an evaluation scheme for this

Evaluation.results.TSS
Evaluation.results.Kappa
Evaluation.results.Roc

###-----------------------------------------------------------------------------------------------###
```

Part III: Generate rasters using BIOMOD and Raster packages

```
################################ Laura Mendenhall 2/22/12
###         Spatial Component           ### with help from John Fay and
###       Large Flower Skull-Cap       ### Brenna Forester (Duke University)
###                  2050                      ###
################################

library (raster)
```

```
library (BIOMOD)

### note: I quartered the study area to solve our memory problem. I created the models using a CSV of
### presence points and ~10,000 background points using only the variables we hand-picked. I then
### projected the model onto each quarter one at a time and read the results into ArcMap 10.

### load in the current climate zero rasters
### note: remember to Edit>Clear Console between each stack creation (otherwise R moves slowly)

trmi <- raster("EnvVars/zero/zero_trmi_ascii.asc")
X8 <- raster("EnvVars/ascii_2050/zero_bio8_2050_ascii.asc")
X14 <- raster("EnvVars/ascii_2050/zero_bio14_2050_ascii.asc")
X16 <- raster("EnvVars/ascii_2050/zero_bio16_2050_ascii.asc")
X17 <- raster("EnvVars/ascii_2050/zero_bio17_2050_ascii.asc")
soil <- raster("EnvVars/zero/zero_soil_ascii2.asc")

### or load in the current climate one rasters

trmi <- raster("EnvVars/one/one_trmi_ascii.asc")
X8 <- raster("EnvVars/ascii_2050/one_bio8_2050_ascii.asc")
X14 <- raster("EnvVars/ascii_2050/one_bio14_2050_ascii.asc")
X16 <- raster("EnvVars/ascii_2050/one_bio16_2050_ascii.asc")
X17 <- raster("EnvVars/ascii_2050/one_bio17_2050_ascii.asc")
soil <- raster("EnvVars/zero/one_soil_ascii2.asc")

### or load in the current climate two rasters

trmi <- raster("EnvVars/two/two_trmi_ascii.asc")
X8 <- raster("EnvVars/ascii_2050/two_bio8_2050_ascii.asc")
X14 <- raster("EnvVars/ascii_2050/two_bio14_2050_ascii.asc")
X16 <- raster("EnvVars/ascii_2050/two_bio16_2050_ascii.asc")
X17 <- raster("EnvVars/ascii_2050/two_bio17_2050_ascii.asc")
soil <- raster("EnvVars/zero/two_soil_ascii2.asc")

### or load in the current climate three rasters

trmi <- raster("EnvVars/three/three_trmi_ascii.asc")
X8 <- raster("EnvVars/ascii_2050/three_bio8_2050_ascii.asc")
X14 <- raster("EnvVars/ascii_2050/three_bio14_2050_ascii.asc")
X16 <- raster("EnvVars/ascii_2050/three_bio16_2050_ascii.asc")
X17 <- raster("EnvVars/ascii_2050/three_bio17_2050_ascii.asc")
soil <- raster("EnvVars/zero/three_soil_ascii2.asc")

###-----------------------------------------------------------------------------------------------------------###
### project the models according to specified evaluation methods

rStack = stack(trmi, X8, X14, X16, X17, soil)
layers <- c("trmi", "X8", "X14", "X16", "X17", "soil")
layerNames(rStack) <- layers

### remember to change the Proj.name to reflect the quarter
Projection.raster(
	RasterProj = rStack,
	Proj.name='skull_Out_three_2050',
	GLM = T, GBM = T, GAM = T, CTA = T, ANN = F, SRE = F, quant=0.025, FDA =T, MARS = T, RF = T,
```

```
        BinRoc=T, BinKappa=T, BinTSS=F, FiltRoc=F, FiltKappa=F, FiltTSS=F,repetition.models=F,
        stack.out=TRUE)

###---------------------------------------------------------------------------------------------------------###
### Write the raster quarters to geotiff files (note: this code will generate the probability surface rasters;
### need to alter the files in the load and writeRaster commands to generate binary surfaces)

### zero
load("proj.skull_Out_zero_2050/Proj_skull_Out_zero_2050_CID_CTA.raster")
writeRaster(Proj_skull_Out_zero_2050_CID_CTA.raster, filename="CID_Out_CID_zero_CTA_2050.tif")
load("proj.skull_Out_zero_2050/Proj_skull_Out_zero_2050_CID_GLM.raster")
writeRaster(Proj_skull_Out_zero_2050_CID_GLM.raster, filename="CID_Out_CID_zero_2050_GLM.tif")
load("proj.skull_Out_zero_2050/Proj_skull_Out_zero_2050_CID_GAM.raster")
writeRaster(Proj_skull_Out_zero_2050_CID_GAM.raster, filename="CID_Out_CID_zero_2050_GAM.tif")
load("proj.skull_Out_zero_2050/Proj_skull_Out_zero_2050_CID_GBM.raster")
writeRaster(Proj_skull_Out_zero_2050_CID_GBM.raster, filename="CID_Out_CID_zero_2050_GBM.tif")

### one
load("proj.skull_Out_one_2050/Proj_skull_Out_one_2050_CID_CTA.raster")
writeRaster(Proj_skull_Out_one_2050_CID_CTA.raster, filename="CID_Out_CID_2050_one_CTA.tif")
load("proj.skull_Out_one_2050/Proj_skull_Out_one_2050_CID_GLM.raster")
writeRaster(Proj_skull_Out_one_2050_CID_GLM.raster, filename="CID_Out_CID_2050_one_GLM.tif")
load("proj.skull_Out_one_2050/Proj_skull_Out_one_2050_CID_GAM.raster")
writeRaster(Proj_skull_Out_one_2050_CID_GAM.raster, filename="CID_Out_CID_2050_one_GAM.tif")
load("proj.skull_Out_one_2050/Proj_skull_Out_one_2050_CID_GBM.raster")
writeRaster(Proj_skull_Out_one_2050_CID_GBM.raster, filename="CID_Out_CID_2050_one_GBM.tif")

### two
load("proj.skull_Out_two_2050/Proj_skull_Out_two_2050_CID_CTA.raster")
writeRaster(Proj_skull_Out_two_2050_CID_CTA.raster, filename="CID_Out_CID_2050_two_CTA.tif")
load("proj.skull_Out_two_2050/Proj_skull_Out_two_2050_CID_GLM.raster")
writeRaster(Proj_skull_Out_two_2050_CID_GLM.raster, filename="CID_Out_CID_2050_two_GLM.tif")
load("proj.skull_Out_two_2050/Proj_skull_Out_two_2050_CID_GAM.raster")
writeRaster(Proj_skull_Out_two_2050_CID_GAM.raster, filename="CID_Out_CID_2050_two_GAM.tif")
load("proj.skull_Out_two_2050/Proj_skull_Out_two_2050_CID_GBM.raster")
writeRaster(Proj_skull_Out_two_2050_CID_GBM.raster, filename="CID_Out_CID_2050_two_GBM.tif")

### three
load("proj.skull_Out_three_2050/Proj_skull_Out_three_2050_CID_CTA.raster")
writeRaster(Proj_skull_Out_three_2050_CID_CTA.raster, filename="CID_Out_CID_2050_three_CTA.tif")
load("proj.skull_Out_three_2050/Proj_skull_Out_three_2050_CID_GLM.raster")
writeRaster(Proj_skull_Out_three_2050_CID_GLM.raster, filename="CID_Out_CID_2050_three_GLM.tif")
load("proj.skull_Out_three_2050/Proj_skull_Out_three_2050_CID_GAM.raster")
writeRaster(Proj_skull_Out_three_2050_CID_GAM.raster, filename="CID_Out_CID_2050_three_GAM.tif")
load("proj.skull_Out_three_2050/Proj_skull_Out_three_2050_CID_GBM.raster")
writeRaster(Proj_skull_Out_three_2050_CID_GBM.raster, filename="CID_Out_CID_2050_three_GBM.tif")

################################ Laura Mendenhall 2/22/12
###        Spatial Component        ### with help from John Fay and
###       Large Flower Skull-Cap    ### Brenna Forester (Duke University)
###                2080             ###
################################

library (raster)
library (BIOMOD)
```

```
### note: I quartered the study area to solve our memory problem. I created the models using a CSV of
### presence points and ~10,000 background points using only the variables we hand-picked. I then
### projected the model onto each quarter one at a time and read the results into ArcMap 10.

### load in the current climate zero rasters
### note: remember to Edit>Clear Console between each stack creation (otherwise R moves slowly)

trmi <- raster("EnvVars/zero/zero_trmi_ascii.asc")
X8 <- raster("EnvVars/ascii_2050/zero_bio8_2080_ascii.asc")
X14 <- raster("EnvVars/ascii_2050/zero_bio14_2080_ascii.asc")
X16 <- raster("EnvVars/ascii_2050/zero_bio16_2080_ascii.asc")
X17 <- raster("EnvVars/ascii_2050/zero_bio17_2080_ascii.asc")
soil <- raster("EnvVars/zero/zero_soil_ascii2.asc")

### or load in the current climate one rasters

trmi <- raster("EnvVars/one/one_trmi_ascii.asc")
X8 <- raster("EnvVars/ascii_2050/one_bio8_2080_ascii.asc")
X14 <- raster("EnvVars/ascii_2050/one_bio14_2080_ascii.asc")
X16 <- raster("EnvVars/ascii_2050/one_bio16_2080_ascii.asc")
X17 <- raster("EnvVars/ascii_2050/one_bio17_2080_ascii.asc")
soil <- raster("EnvVars/zero/one_soil_ascii2.asc")

### or load in the current climate two rasters

trmi <- raster("EnvVars/two/two_trmi_ascii.asc")
X8 <- raster("EnvVars/ascii_2050/two_bio8_2080_ascii.asc")
X14 <- raster("EnvVars/ascii_2050/two_bio14_2080_ascii.asc")
X16 <- raster("EnvVars/ascii_2050/two_bio16_2080_ascii.asc")
X17 <- raster("EnvVars/ascii_2050/two_bio17_2080_ascii.asc")
soil <- raster("EnvVars/zero/two_soil_ascii2.asc")

### or load in the current climate three rasters

trmi <- raster("EnvVars/three/three_trmi_ascii.asc")
X8 <- raster("EnvVars/ascii_2050/three_bio8_2080_ascii.asc")
X14 <- raster("EnvVars/ascii_2050/three_bio14_2080_ascii.asc")
X16 <- raster("EnvVars/ascii_2050/three_bio16_2080_ascii.asc")
X17 <- raster("EnvVars/ascii_2050/three_bio17_2080_ascii.asc")
soil <- raster("EnvVars/zero/three_soil_ascii2.asc")

###-----------------------------------------------------------------------------------------------------------###
### project the models according to specified evaluation methods

rStack = stack(trmi, X8, X14, X16, X17, soil)
layers <- c("trmi", "X8", "X14", "X16", "X17", "soil")
layerNames(rStack) <- layers

### remember to change the Proj.name to reflect the quarter
Projection.raster(
        RasterProj = rStack,
        Proj.name='skull_Out_three_2080',
        GLM = T, GBM = T, GAM = T, CTA = T, ANN = F, SRE = F, quant=0.025, FDA =T, MARS = T, RF = T,
        BinRoc=T, BinKappa=T, BinTSS=F, FiltRoc=F, FiltKappa=F, FiltTSS=F,repetition.models=F,
```

```
    stack.out=TRUE)

###------------------------------------------------------------------------------------------------------------###
### Write the raster quarters to geotiff files (note: this code will generate the probability surface rasters;
### need to alter the files in the load and writeRaster commands to generate binary surfaces)


### zero
load("proj.skull_Out_zero_2080/Proj_skull_Out_zero_2080_CID_CTA.raster")
writeRaster(Proj_skull_Out_zero_2080_CID_CTA.raster, filename="CID_Out_CID_zero_CTA_2080.tif")
load("proj.skull_Out_zero_2080/Proj_skull_Out_zero_2080_CID_GLM.raster")
writeRaster(Proj_skull_Out_zero_2080_CID_GLM.raster, filename="CID_Out_CID_zero_2080_GLM.tif")
load("proj.skull_Out_zero_2080/Proj_skull_Out_zero_2080_CID_GAM.raster")
writeRaster(Proj_skull_Out_zero_2080_CID_GAM.raster, filename="CID_Out_CID_zero_2080_GAM.tif")
load("proj.skull_Out_zero_2080/Proj_skull_Out_zero_2080_CID_GBM.raster")
writeRaster(Proj_skull_Out_zero_2080_CID_GBM.raster, filename="CID_Out_CID_zero_2080_GBM.tif")

### one
load("proj.skull_Out_one_2080/Proj_skull_Out_one_2080_CID_CTA.raster")
writeRaster(Proj_skull_Out_one_2080_CID_CTA.raster, filename="CID_Out_CID_2080_one_CTA.tif")
load("proj.skull_Out_one_2080/Proj_skull_Out_one_2080_CID_GLM.raster")
writeRaster(Proj_skull_Out_one_2080_CID_GLM.raster, filename="CID_Out_CID_2080_one_GLM.tif")
load("proj.skull_Out_one_2080/Proj_skull_Out_one_2080_CID_GAM.raster")
writeRaster(Proj_skull_Out_one_2080_CID_GAM.raster, filename="CID_Out_CID_2080_one_GAM.tif")
load("proj.skull_Out_one_2080/Proj_skull_Out_one_2080_CID_GBM.raster")
writeRaster(Proj_skull_Out_one_2080_CID_GBM.raster, filename="CID_Out_CID_2080_one_GBM.tif")

### two
load("proj.skull_Out_two_2080/Proj_skull_Out_two_2080_CID_CTA.raster")
writeRaster(Proj_skull_Out_two_2080_CID_CTA.raster, filename="CID_Out_CID_2080_two_CTA.tif")
load("proj.skull_Out_two_2080/Proj_skull_Out_two_2080_CID_GLM.raster")
writeRaster(Proj_skull_Out_two_2080_CID_GLM.raster, filename="CID_Out_CID_2080_two_GLM.tif")
load("proj.skull_Out_two_2080/Proj_skull_Out_two_2080_CID_GAM.raster")
writeRaster(Proj_skull_Out_two_2080_CID_GAM.raster, filename="CID_Out_CID_2080_two_GAM.tif")
load("proj.skull_Out_two_2080/Proj_skull_Out_two_2080_CID_GBM.raster")
writeRaster(Proj_skull_Out_two_2080_CID_GBM.raster, filename="CID_Out_CID_2080_two_GBM.tif")

### three
load("proj.skull_Out_three_2080/Proj_skull_Out_three_2080_CID_CTA.raster")
writeRaster(Proj_skull_Out_three_2080_CID_CTA.raster, filename="CID_Out_CID_2080_three_CTA.tif")
load("proj.skull_Out_three_2080/Proj_skull_Out_three_2080_CID_GLM.raster")
writeRaster(Proj_skull_Out_three_2080_CID_GLM.raster, filename="CID_Out_CID_2080_three_GLM.tif")
load("proj.skull_Out_three_2080/Proj_skull_Out_three_2080_CID_GAM.raster")
writeRaster(Proj_skull_Out_three_2080_CID_GAM.raster, filename="CID_Out_CID_2080_three_GAM.tif")
load("proj.skull_Out_three_2080/Proj_skull_Out_three_2080_CID_GBM.raster")
writeRaster(Proj_skull_Out_three_2080_CID_GBM.raster, filename="CID_Out_CID_2080_three_GBM.tif")
```