

DEVELOPMENT AND ASSESSMENT OF PREDICTIVE SPATIAL
MODELS FOR A RARE TENNESSEE ANURAN:
BARKING TREEFROG (*HYLA GRATIOSA*)

By

Nyssa R. Hunt

Thomas P. Wilson
UC Foundation Associate Professor of
Biology, Geology, and Environmental Science
(Chair)

David A. Aborn
Associate Professor of Biology,
Geology, and Environmental Science
(Committee Member)

Andrew Carroll
GISP, PG, and Skytec Co-Founder
(Committee Member)

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A Thesis Submitted to the Faculty of the University of
Tennessee at Chattanooga in Partial
Fulfillment of the Requirements of the Degree
of Master of Science: Environmental Science

The University of Tennessee at Chattanooga
Chattanooga, Tennessee

August 2018

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ABSTRACT

In Tennessee, the Barking Treefrog (*Hyla gratiosa*) is listed as both rare and vulnerable, and more field data is needed to elucidate its distribution. Predictive modeling using the program MaxEnt provided results for models that guided field sampling to potential presence locations. From April-August 2017, 126 sites (63 historical; 63 predicted) were visited monthly and sampled for frog calls according to a standardized protocol. Field results revealed *H. gratiosa*'s auditory presence at 23 out of 63 historic sites and at nine out of 63 predicted sites. While other predictive models were also generated, MaxEnt was demonstrated to be most precise in predicting presence likelihood. Weighted regression analysis showed that shrub/scrub and woody wetland coverages were the most positively associated with presence. The results suggest that *H. gratiosa* is not as relatively abundant as some frog species throughout ecologically relevant landscapes in Tennessee.

DEDICATION

This work is dedicated to all who have believed in me, my family and friends, throughout the entirety of this project. I also dedicate this to the memory of my sister, Sara.

ACKNOWLEDGEMENTS

There are many people I have to thank, for their unwavering, steadfast support, encouragement, and patience throughout the many obstacles of this project.

First, I thank Dr. Wilson for all of his sound advising and keeping me grounded, especially when I became overly ambitious on occasions or needed firm guidance. Even more, he has been as supportive and encouraging as a father to me, helping me to feel assured of my abilities and facilitating my growth as a person. He continues to inspire me as a scientist every day and I am deeply honored to have been a member of his lab. Words can only express so much, but I hope he knows how much he has meant to me as an advisor, father-figure, role model and friend.

I thank Andy Carroll for believing in my potential and involving me in amazing opportunities in the GIS lab, which seamlessly complimented the skills needed for this project. As my primary workplace supervisor over the past few years, I've learned more than just technical skills from him; he reflected all of the ideal qualities of a caring and loyal supervisor, and I am glad to have held him as a role model as well. I'm ever grateful for his support on my committee and for all of the thoughtful advice he's given.

I thank Dr. Aborn for his encouragement and support on my committee, as he has provided insight for this project and words of wisdom for the field sampling. His sense of humor was also welcome and I appreciated his down to earth perspectives.

Other professors I must thank are Drs. DeAnna Beasley, Hope Klug, and Jennifer Boyd, for encouraging writing processes and giving thoughtful feedback. Your willingness to guide and assist with the progress of this thesis meant a great deal to me, and the added encouragement along the way helped to cheer me on!

I greatly thank Bob English for his contribution and collaboration with data, because it made a large portion of this project possible! Also, I thank Dr. Joanne Romagni, Dr. Ethan Carver, and the Biology/Geology/Environmental Sciences Department for supplying me with funds to carry out the field portion of my project. All of you helped in a great way to help me accomplish my goal!

To the friends at the University of the South at Sewanee, I must thank Saunders Drukker, Nate Wilson, Bran Potter, and Dr. Kristen Cecala for their help and support in advising my arrival at certain sites – you all were a great help!

While out in the field, I had a select group of individuals that housed me, and so I give a special heartfelt thanks to Jeremy Hooper, Ashley and Nick Tieman, and Susan and Rusty Tuders. All of you were so wonderful to help me out and I will never forget your compassion.

Last, but definitely not least, I want to thank all of my family and friends who supported and encouraged me along the way: my parents, my sisters (Ann, Sara, and Elora), my uncles and aunts, Laura Lee, Rebekah Hildebrandt, Joanna Elmore, Brittany Bird, Paul-Erik Bakland, Elijah Reyes, Kelly Daniels, Tori Roy, Charlie Mix and other graduate colleagues, members of Team Salamander and the IGTLab. You all played a role in helping me get to this point in my life, and I am eternally grateful for each of you.

TABLE OF CONTENTS

ABSTRACT.....	iv
DEDICATION	v
ACKNOWLEDGEMENTS	vi
LIST OF TABLES	x
LIST OF FIGURES	xi
LIST OF ABBREVIATIONS	xii

CHAPTER

I. MODELING AND ASSESSMENT OF SPATIAL STATUS AND ECOLOGICAL TRENDS OF *HYLA GRATIOSA* IN TENNESSEE

Introduction	1
Amphibians: Declining Bioindicators	1
Effects of Urbanization on Anurans.....	2
Climatic Factors Influencing Anuran Distribution	5
Selection of Study Organism and Reasoning	8
Current Spatial Status and Ecology of Barking Treefrog in Tennessee.....	9
Research Objectives and Hypotheses.....	10
Methods and Materials.....	11
Procurement of Spatial Distribution Data.....	12
Acquiring Land Cover Data.....	14
Summarizing Land Cover to Watersheds.....	15
Climatic Data Acquisition and Processing.....	16
Spatial Statistical Analysis.....	16
Results.....	18
Results of Land Cover Analysis.....	18
Results of Climatic Data Analysis.....	21
Documented Distribution in Tennessee	23

Discussion.....	26
Suitable Habitat Implications	26
Limitations and Biases	28
Conclusions.....	30
II. DEVELOPMENT AND ASSESSMENT OF PREDICTIVE SPATIAL MODELS FOR <i>HYLA GRATIOSA</i> IN TENNESSEE WITH CITIZEN SCIENCE DATA	
Introduction.....	31
Conservation and Predictive Modeling	31
Contribution of Citizen Science	34
The Modeling Candidate: Barking Treefrog (<i>Hyla gratiosa</i>)	35
Research Objectives and Hypotheses	36
Methods and Materials.....	37
Data Acquisition and Processing.....	37
Predictive Model Processing.....	39
Selection of Sampling Sites Using MaxEnt.....	41
Mapping Routes With Google MyMaps.....	43
In-Field Sampling Methods.....	44
Postprocessing and Statistical Analyses	45
Results.....	46
Comparison of Predictive Models.....	46
Spatial Results of Auditory Surveys.....	51
Exploratory Regression Results	54
Discussion.....	55
Observations: In and Out of the Field	55
Limitations, Biases, and Reflections	56
Conservation Speculations.....	57
Conclusions.....	58
REFERENCES	59
APPENDIX	
A. PYTHON SCRIPT DEVELOPED FOR “EXTRACT BY MASK” BATCH.....	68
B. PYTHON SCRIPT DEVELOPED FOR TRANSFERRING RASTER TABLE VALUES TO VECTOR TABLE	70
C. DATA SHEETS FROM AUDITORY SAMPLING – 2017.....	73
VITA	77

LIST OF TABLES

1.1 Ordinary Least Squares Statistics Results.....	20
1.2 Geographic Weighted Regression Model Results	21
1.3 Bioclimatic Variable Trends for <i>H. gratiosa</i> in Tennessee.....	22
2.1 Site Descriptions of Predicted Sites with Confirmed Presence	55

LIST OF FIGURES

1.1	The Austin Peay State University distribution map for <i>H. gratioosa</i>	13
1.2	TDEC HUC12 distribution map.....	23
1.3	TDEC and APSU HUC12 distribution map.....	24
1.4	TDEC, APSU, and TAMP combined HUC12 distribution map.....	25
1.5	Citizen science-only HUC12 distribution map.....	25
1.6	Comprehensive HUC12 distribution map of <i>H. gratioosa</i> in Tennessee.....	26
1.7	Concentrations of shrub/scrub land cover proportions by HUC12 Watershed.....	27
2.1	Historical citizen science sampling sites with <i>H. gratioosa</i> Presence.....	39
2.2	MaxEnt Model for <i>H. gratioosa</i> potential distribution	43
2.3	Map of Level III ecoregions with sites	44
2.4	Image of site sampling sections, organized by the Google MyMaps application	45
2.5	BIOCLIM model for <i>H. gratioosa</i> potential distribution	49
2.6	GARP model for <i>H. gratioosa potential</i> distribution	49
2.7	InVEST pilot distribution model	50
2.8	The Jackknife test of variable importance, modeled from MaxEnt	51
2.9	MaxEnt predicted model with 2017 results	52
2.10	Graph of <i>H. gratioosa</i> calling activity during Summer 2017	53

LIST OF ABBREVIATIONS

AIC, Akaike Information Criterion

APSU, Austin Peay State University

AUC, Area Under the Curve

ESRI, Environmental Systems Research Institute

GAP, Gap Analysis Program

GARP, Genetic Algorithm for Rule-set Production

GIS, Geographic Information Systems

GWR, Geographic Weighted Regression

HUC, Hydrologic Unit Code

InVEST, Integrated Valuation of Ecosystem Services and Tradeoffs

MaxEnt, Maximum Entropy

NLCD, National Land Cover Dataset

NAAMP, North American Amphibian Monitoring Program

OLS, Ordinary Least Squares

TAMP, Tennessee Amphibian Monitoring Program

TDEC, Tennessee Department of Environment and Conservation

USGS, U.S. Geological Survey

CHAPTER I
MODELING AND ASSESSMENT OF SPATIAL STATUS AND ECOLOGICAL TRENDS
OF *HYLA GRATIOSA* IN TENNESSEE

Introduction

Amphibians: Declining Bioindicators

Globally, amphibians are experiencing notable population decline due to a variety of environmental and anthropogenic factors (Pounds & Crump, 1994; Lips, Reeve, & Witters, 2003; Stuart et al., 2004). Members of this taxonomic group are known to be biological indicators because of their physiology, reproductive life history, and relative sensitivity to changes in the environment. This knowledge has prompted scientists to ask questions as to what factors contribute mostly to ongoing declines (Stuart et al., 2004). Several involve anthropogenic activities, directly and indirectly, including habitat alteration, spread of disease, and climatic shifts (Mac Nally et al., 2009). Most, if not all, factors causing decline are present in some proportion together, but some are more dominant than others, depending on geography (Mac Nally et al., 2009; Tsuji et al., 2011). At the same time, certain amphibians are affected by specific environmental factors, depending on requirements related to that species' life history.

In North America, two groups of amphibians exist naturally: Salamanders (Order: Caudata) and Frogs/Toads (Order: Anura) (Niemiller, Reynolds, & Miller, 2011). Both groups are responsive to environmental cues for breeding (Stuart et al., 2004; Araujo et al., 2006; Neveu, 2009). Anurans have been of particular research interest in recent decades due to

significant population declines. Absence of anuran breeding and large findings of deceased individuals have repeatedly been documented throughout multiple regions (Tsuji et al., 2011; Araujo et al., 2006).

During breeding seasons, anurans will instinctually seek water bodies to mate and lay eggs. Specific breeding season ranges exist for each species, as determined by the presence of calling males (Oldham & Gerhardt, 1975; Pellet & Schmidt, 2005). Vocalizations are often loud and noticeably audible over distances from the breeding pools, which attract females in the nearby landscape. However, if climatic factors are unusual or habitats disrupted, breeding behavior can be impacted, potentially affecting the populations of the species (Oldham & Gerhardt, 1975; Lemmon, Lemmon, & Cannatella, 2007). The absence of breeding activity may indicate unsuitable habitat or conditions unappealing to these animals (Brand & Snodgrass, 2009; Smallbone et al., 2011). Understanding the landscape ecology and environmental factors at which certain anurans will function is vital to the conservation of these species, especially for those in the face of decline or in need of management (Brand & Snodgrass, 2009).

Effects of Urbanization on Anurans

The geographic extent at which amphibian decline is occurring has been a particularly concerning prospect, especially if the rate continues as it has been observed (Stuart et al., 2004). As reflected in many causes for species extinction, habitat destruction and alteration is also a leading reason for the declines of anurans (Smallbone et al., 2011; Tsuji et al., 2011) However, even in affected landscapes, certain anurans have displayed an ability to adapt, so long as base needs of shelter, prey items, and breeding pools are met (generalists); others have much greater sensitivities to environmental changes (specialists) (Berg et al., 2010). The spectrum of

environmental sensitivity has been a telling factor in predicting which anurans would be more apt to decline due to alteration in the environment (Brander et al., 2007).

Urbanization yields more concentrated impervious or developed surfaces, which may reduce suitable habitat for amphibians by altering local hydrology and wetland recharge (Brand & Snodgrass, 2009). Anurans are relatively mobile and can traverse these landscapes, but might not select to reside in such areas. Many of these species will move throughout the landscape to locate suitable breeding pools or stable shelters in the non-breeding seasons. However, in non-breeding seasons, potential breeding sites may be changed or unavailable due to development, causing potential demise to a local population (Brander et al., 2007). In other cases, new breeding pools may be created by means of retention ponds, swimming pools, or other man-made wetlands (Snodgrass et al., 2000). In general, urbanization introduces new dynamics for breeding pool availability, a resource crucial to the life history and survival of anurans; artificial habitats are at times beneficial, despite the potential of being ecological traps (Brand & Snodgrass, 2009; Birx-Raybuck, Price, & Dorcas, 2009).

In contrast, some anurans may elect to avoid developed areas altogether, seeking undisturbed habitats that still retain more of the original, natural cover (Tsuji et al., 2011). However, while these undeveloped areas may provide suitable habitat, fragmentation can isolate them throughout a landscape, which ultimately has the potential to reduce population viability. Poor water quality in some pools might also deter some species (Riley et al., 2005), though certain species will even breed in puddles or roadside ditches (Homyack et al., 2014). The tolerance level of anurans continues to be a curious and intriguing subject, where studies continue to be carried to further understand this among populations of the same species.

Road mortalities have often been documented in urban landscapes, even for amphibian species (Carr & Fahrig, 2001). Vagility differs between anuran species, where true frogs (members of the family Ranidae) have been found abler to traverse long distances than tree frogs (members of the family Hylidae); (Carr & Fahrig, 2001; Parris, 2006). However, tree frogs are able to latch onto vehicles, which in turn assists dispersal and enhances vagility; this ability has facilitated the movement of an invasive tree frog species (Rodder & Weinsheimer, 2010). How traffic noise may affect species is a phenomenon still being further understood, though hypotheses have been tested in recent years. Some studies hypothesized and observed that modifications of calling behavior would take place, in order to compensate for the ambient level of noise that traffic creates (Bee & Swanson, 2007; Hanna et al., 2014). Researchers have artificially simulated traffic noise, making changes to frequency and decibels, to test the duration, call rate, and peak frequency of males advertising (Hanna et al., 2014). Certain species have been found to not elicit hypothesized responses to introduced noise, where manipulations seemed ignored and the males continued normal calling behavior, but sensitivity to noise seemed dependent on whether males were alone or with a chorus (Lengagne, 2008). Researchers continue to consider noise intensity, types of noise, and responses of different species since such variations exist and remain inconclusive to the direct effects of traffic noise on breeding behavior (Bee, 2015).

In many locations, studies are limited by data gaps pertaining to local species presence and absence. It is often unknown which anuran species are better colonizers than others in the urbanized landscape, though tree frogs have been observed to be more exploitative, suggesting resilience and an ability to adapt to disturbed areas that will need to be investigated further (Tsuji et al., 2011). Even as amphibians are on the decline, base needs for reproductive success have

been found available in suburban landscapes, despite being thought as potential ecological traps (Brand & Snodgrass, 2009). In future studies, large-scale monitoring programs, such as the North American Amphibian Monitoring Program (NAAMP) can provide further insight as to the status of anuran species in developed environments (Patuxent Wildlife Research Center, 2012; Cosentino et al., 2014). Also, citizen science, and its increasing popularity, has the great potential to be utilized for gaining baseline data, where anuran conservation may be better understood and bring about species recovery (Cosentino et al., 2014).

Climatic Factors Influencing Anuran Distribution

An environmental factor that may not be able to be directly controlled within a short window of time is climate change, which has been hypothesized to have large scale impacts (Araujo et al., 2006; Griffiths, Sewell, & McCrea, 2010). For many taxonomic groups, climate change has also been blamed for species and population decline, though it functions with much more subtlety with amphibians (Stuart et al., 2004). Given that many amphibians require a certain amount of moisture and typically prefer certain temperature ranges, even small shifts in climate could influence the suitability of preferred habitat. The gradient of climates in the Great Smoky Mountains National Park and the variety of salamanders found only at certain elevations provides an example of just how particular amphibians can be (Peterman & Semlitsch, 2013). The variation of climatic conditions over landscapes holding suitable habitat provide unique niches for amphibian species, where climatic change or disruption to these places may lead to species decline (Araujo et al., 2006; Fu et al., 2006).

Anurans exist in a wide range of geography and have displayed some level of resiliency throughout a variety of habitat types. Even as this group is facing declines, certain species have

been found to adapt to changes and persist in manipulated environments (Mac Nally et al., 2009; Griffiths, Sewell, & McCrea, 2010). At the same time, other species have been noted to drop out, which leads to a decrease in biodiversity and increases concern for anurans as a whole (Araujo et al., 2006). As anurans have long been considered environmental indicators and are rather sensitive to climate, decreases in their presence and abundance have made researchers question how climatic factors may influence survival and distribution (Berg et al., 2010; Peterman et al., 2013).

Direct impacts of climate change tend to affect abiotic variables, mainly temperature and precipitation, where availability of resources associated with these may be affected. Increased temperatures have been shown to reduce reproductive potential (Saenz et al., 2006), which ultimately could cause extinction if no adaptive strategies (relating to behavior, phenotype and/or genetic plasticity) take place (Newman & Rissler, 2011). Thermal sensitivity can also affect the metabolic rate of anurans, where overheating can be detrimental to their bodies and induce stress (Berg et al., 2010). The amount of land mass available for these species to disperse upon plays a subtle role, as climate change can limit suitable habitat sizes and cause more competition to take place; this approach, however, cannot be applied to all regions, which the researchers of the study noted (Blaustein et al., 2010). Developed landscapes can often introduce changes to abiotic factors, such as increasing temperatures or adding new breeding pools to an area, though fragmentation of habitat is often found detrimental to communities (Mac Nally et al., 2009). At the same time, the survival of certain anurans becomes very dependent on the presence of pools and moisture for reproduction, where new pools potentially decrease chances of local extinction (Walls, Barichivich, & Brown, 2013). Abiotic factors may vary with climatic changes, where certain species may respond differently to extreme cases (Walls, Barichivich, & Brown, 2013),

but the response of species in the same family are not always the same. Several researchers acknowledge that long-term effects must still be monitored in order to understand the rates at which the subtleties of climate change affect these species (Ochoa-Ochoa et al., 2012).

Changes in abiotic variables have the tendency to influence biotic factors in the environment, such as food availability, structure that may be used for shelter, or the spread of diseases (Araujo & Luoto, 2007). The fungal disease *Batrachochytrium dendrobatidis* has been increasingly decimating anuran populations, where researchers believe that climate may influence its occurrence on various landscapes (Berg et al., 2010). Available vegetation may also be impacted by climate change, especially if certain types have evolved specially to an area's thermal and precipitative capacity; some insects or other prey items may feed on certain plants, where the disappearance of such could lead to a lack of food for anurans (Blaustein et al., 2010). Other organisms in the area might manipulate ecosystem processes, such as beavers, which potentially shift the microhabitat; some anuran species are sensitive to the slightest changes, which might deter them from residing in an area disturbed (Popescu & Gibbs, 2009). Even invasive species present an underlying issue, as some are more adapted to warmer conditions, where certain native species may not compete as well with such changes (Tsuji et al., 2011). These biotic factors all interact at the community level, which can strongly influence each other at the trophic scale if faced with environmental changes.

Humans often are unaware of the effects to microclimate that development creates, where shifts in communities, diversity, and resource availability may occur. In Australia, where climatic conditions are already quite harsh, changes in land-use can have drastic effects on species (Mac Nally et al., 2009). Fragmentation often decreases habitat connectivity, which can isolate populations from each other and possibly cause local extinctions. Some species prefer

largely undisturbed plots of land, while others might thrive in agricultural plots. Despite the varying effects of development, the presence of water in the form of pools becomes a crucial component to survival, as it provides the possibility for anurans to reproduce. How some anurans are able to withstand such disturbed conditions has yet to be further understood, especially as some species are more tolerant than others (Mac Nally et al., 2009).

Climate change and anthropogenic development can be modeled together using geospatial platforms, yielding results that may elucidate potential interactions or effects (Pilliod et al., 2015). This approach can also be used to simulate how a human-introduced invasive species might function on the landscape, especially in human disturbed areas which invasive species have the tendency to exploit (Rodder & Weinsheimer 2010). Invasive species also have the ability to reduce resource availability to natives, where the presence of invasive species can further be driven by climate change. Thus, modeling the extent at which each of these factors occur together may reveal further correlations that otherwise are subtle or unnoticed (Tsuji et al., 2011; Terrado et al., 2016).

Selection of Study Organism and Reasoning

When considering anuran species of conservation concern, federal listings are often consulted, though some species at the state level are less understood and perhaps need some level of protection locally. For the state of Tennessee, the Barking Treefrog (*Hyla gratiosa*) has a conservation status of ‘Vulnerable’ due to its specific habitat requirements and a discontinuous, poorly understood distribution across the state. As an apparent specialist, this species prefers open canopy wetlands or pools that are fish-free, but also require trees in proximity to the breeding site to reside on during non-breeding seasons (Oldham & Gerhardt, 1975). Alterations to these conditions could harm local populations and possibly cause declines (Borzee et al.,

2016). Hence, the need to further investigate the circumstances at which this species occurs and survive in the Tennessee landscape is paramount due to the potential of further decline. Are Tennessee's populations of *H. gratiosa* in need of management, or is the species merely undersampled and in need of spatial understanding?

Current Spatial Status and Ecology of Barking Treefrog in Tennessee

Academic institutions, federal agencies, and citizen scientists have all provided data on species presence, but not all parties actively document or seek *H. gratiosa*. In Tennessee, published maps in amphibian field guides and online resources often display clusters of distribution largely in the Coastal Plain of the western region, north-central region near Clarksville, and on the Cumberland Plateau of the eastern region. While each of these populations are apparently well established, the cause of these separate occurrences has yet to be truly elucidated, especially in the face of potential decline. Within known range, *H. gratiosa* is said to be fairly "common", yet on a state-level is classified as "rare" due to being a habitat specialist (Dorcas & Gibbons, 2008; Niemiller, Reynolds, & Miller, 2011).

Tennessee is unique in many regards, with a varying geography throughout the state that presents a vast multitude of habitats. This variety may provide *H. gratiosa* a spectrum of suitable habitats throughout the state, but habitat connectivity and accessibility are added obstacles that could hinder species distribution. Floodplain wetlands, ephemeral pools and wetlands, and even flooded ditches are all potential breeding habitat, but the criteria of breeding pools having an open canopy and being fish-free must also be met. During non-breeding seasons, *H. gratiosa* is arboreal and seeks shelter in tree canopies, meaning that forests must be approximate to breeding areas. Alternatively, they will burrow into soil during dry seasons, to retain moisture. The animal

tends to favor warmer temperatures, being primarily a summertime breeder in Tennessee; activity often coincides with rain events, typically in late spring and into summer. Breeding tends to begin in lower latitudes of Tennessee in earlier parts of summer, with more northern latitudes experiencing it in later summer, showing that *H. gratiosa* activity does vary throughout the state (Dorcas & Gibbons, 2008; Niemiller, Reynolds, & Miller, 2011).

These specifications clarify why *H. gratiosa* can be rare to find in respect to all of Tennessee, since the varying landscape and local climates may not consistently facilitate the needs of the species. For the locations that the species has been documented, it is natural to next question whether the habitat components present are consistent throughout its known Tennessee range.

Research Objectives and Hypotheses

The primary research questions investigated in this study were:

1. What are the land cover conditions at which *H. gratiosa* is documented approximate to throughout Tennessee, and does that vary greatly across the landscape or are these areas consistent?
2. On average, what are the ranges of documented precipitation and temperature that are found with *H. gratiosa* presence?
3. Can citizen science data assist in mending data gaps and supplement federal and institutional presence data?

To understand the factors that may contribute to the spatial distribution of *H. gratiosa*, one must consider how species presence is influenced by the landscape. Reviewed literature revealed that climatic factors and anthropogenic disturbance compound upon each other, where

habitat destruction typically poses an immediate threat to species presence, while shifts in temperature and/or precipitation may gradually cause decline if unfavorable to the species. The species is able to find suitable habitat throughout Tennessee, but not all regions possess the same habitat conditions.

As the species is largely found along the Coastal Plain of the southeastern United States, the climatic conditions of this region must also be considered. Breeding in Tennessee typically occurs between the months of April – August, with the peak being in late summer for the more northern latitudes, indicating a need for milder temperatures. As it prefers pools (as opposed to puddles or streams) and calls from the water, some amount of standing water must be present for breeding, even in the form of temporary pools. Lowland elevations also typically play a role, which permit flood events to occur and expand breeding pool options. However, overflowed areas introduce the risk of aquatic predators such as fish, where *H. gratiosa* would select against breeding in these environments (Dorcas & Gibbons, 2008; Niemiller, Reynolds, & Miller, 2011).

Over the past several decades, documentation of species presence has been gathered by federal workers and citizens alike. However, citizen science data does not always get processed into updated species distribution models, which may lead to data gaps. Given that citizen science has played a role in amphibian monitoring in Tennessee, the results of many years of sampling may reveal new information to contribute toward further conservation and spatial understanding.

Methods and Materials

Addressing questions regarding apparent spatial preferences of *H. gratiosa* in Tennessee requires somewhat fine scale presence data and relevant environmental data to analyze. Because the state of Tennessee was the region of concern for the species, this extent functioned as the

spatial scope. Restricting the scope to the state enabled the environmental data to be confined to a very precise extent, creating an element of consistency between data layers.

Procurement of Spatial Distribution Data

Acquiring presence data involved consulting government, academic, and citizen science sources to determine which would be usable for spatial analysis and to what scale.

The Tennessee Department of Environment and Conservation (TDEC) has compiled a dataset of “Rare Species by HUC 12”, where *H. gratiosa* is a species included. This data is in tabular format and was freely available and downloadable, presenting watersheds in which *H. gratiosa* has been confirmed present by federal or academic personnel. Alongside the table, a data layer of HUC 12 watersheds was acquired, so that the species location table and watershed locations could be joined. After these two datasets were joined, a visualization of watersheds containing *H. gratiosa* resulted. Because TDEC’s finest scale of distribution was at the HUC 12 level, this landscape scale was to be kept consistent for other distribution data gathered.

Another official source of distribution information for the state is the Austin Peay State University (APSU) Amphibian Atlas, which has accumulated presence data throughout the state through multiple sources, including the Tennessee Wildlife Resource Agency (TWRA) and students. The points are presented on a map on the Amphibian Atlas, with the actual coordinates reported through journal articles sourced with the map (Figure 1.1). Many of the points in the Atlas aligned with the TDEC watersheds, while others were mapped accordingly with associated watersheds.

Hyla gratiosa - Barking Treefrog

Solid red circles represent records published since 1996 that are vouchered in the APSU Museum of Zoology.
Red symbols other than circles represent records published since 1996 that are either unvouchered or vouchered elsewhere.

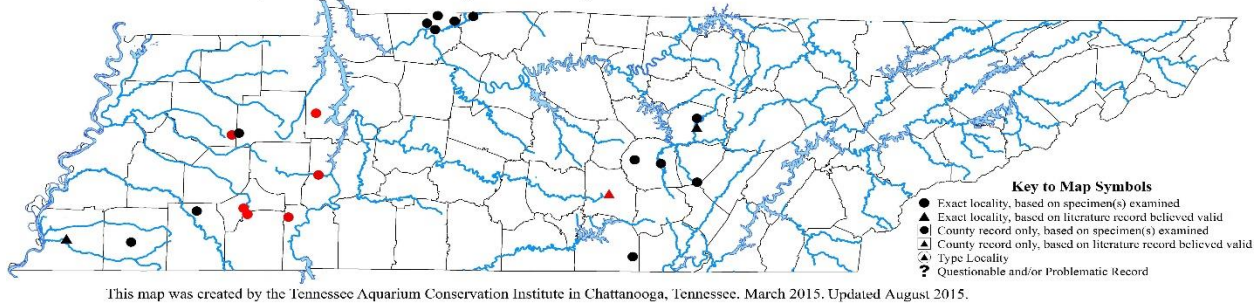


Figure 1.1 The Austin Peay State University distribution map for *H. gratiosa* (solid red circles represent records published since 1996 that are vouchered in the APSU Museum of Zoology; red symbols other than circles represent records published since 1996 that are either unvouchered or vouchered elsewhere)

While TDEC and APSU's data provided some sense of *H. gratiosa* distribution in Tennessee, citizen science data was also investigated for the potential of additional presence findings. Throughout the past couple decades, the Tennessee Amphibian Monitoring Program (TAMP) has assessed Anuran presence and diversity throughout the state via citizen science volunteers along assigned routes. Auditory call surveying has been the primary monitoring method utilized, which required volunteers to be trained to identify calls with great accuracy. All TAMP volunteers adhere to protocols defined by the North American Amphibian Monitoring Program (NAAMP), which yielded consistent methods with gathered presence data in the field. Bearing this in mind, TAMP data was a valid candidate to consider for presence data, given how often data are gathered in precise locations. Data from this source was acquired by contacting Bob English, the TAMP coordinator, as he possessed a comprehensive spreadsheet of coordinates from all routes in the state. After acquiring the points, this data was aligned with HUC 12 watersheds and additional areas with documented presence were added with the TDEC and APSU watersheds.

Another avenue of citizen science explored was an application called iNaturalist, which was launched in 2008. The purpose of iNaturalist has been to enable citizen scientists to document biological findings on a map casually, which has the potential to aid in research and conservation. While iNaturalist's openness may be viewed as a risk of data integrity, the application developers allowed for observations to be identified appropriately by individuals of certain expertise. These individuals can also be contacted directly to gain more information regarding observations posted. For gaining data on *H. gratiosa*, the species was searched for on iNaturalist and observations were documented for use after ensuring accuracy of the data.

Acquiring Land Cover Data

The distribution of amphibians is hardly ever random, where habitat types influence where they select to breed and reside. With the known watersheds in which *H. gratiosa* has been documented to occur, trends in habitat types were sought to be assessed in these areas.

The National Land Cover Dataset (NLCD) was used to acquire land cover classifications, utilized because it is free and readily available for spatial research. Due to the NLCD 2011 dataset being the most recent land cover product available, it was selected for this portion of the project. The spatial resolution of the data is 30 meters, a grade fine enough to account for habitat definition on a broad scale while not too fine to hinder computer processing. NLCD was categorized into 15 classes, ranging from developed, urbanized surfaces to wetland cover types (Homer et al., 2015).

Summarizing Land Cover to Watersheds

To gain an understanding of the distribution of certain land cover types, I sought to summarize NLCD 2011 by HUC 12 watershed. Given that there are hundreds of watersheds at the HUC 12 level in Tennessee, this task was more efficiently executed by developing a Python programmed script that automated an extraction process per watershed (see Appendix A). A shapefile of all HUC 12 watersheds in Tennessee was used to select and extract specific pieces of the NLCD raster. The script automates the tasks of: select a row in the HUC 12 attribute table, Extract by Mask based on the selection, save the extracted piece of raster in a geodatabase, move to the next row in the HUC 12 table. This process looped until the end of the table, when all HUCs would have a land cover raster extraction associated with the watershed.

Next, to transfer all of the NLCD values to the HUC 12 shapefile attribute table, another Python script was developed (see Appendix B). This script automated the process of creating land cover category columns in the attribute table, reading the categories and pixel values in each raster, and writing the values to the respective category column and to the respective HUC 12 in the attribute table. After all values were transferred, proportions of each cover type category were calculated to normalize the weights of pixel representation in each watershed. This was done by totaling all land cover pixels in each watershed and subsequently calculating the proportion of each category pertaining to that total. As a result, all HUC 12 watersheds in Tennessee had land cover proportions calculated, allowing for further spatial analysis to be performed.

Climatic Data Acquisition and Processing

Several studies that consider climatic modeling utilize data from WorldClim's set of global climate layers, which influenced its usage for this project. This data is freely available to use for mapping and spatial modeling, and has been generated by climatic averages of temperature and precipitation over the past several decades. Because *H. gratiosa* is said to be particular with climatic tolerance, several aspects of both temperature and precipitation were assessed. While there are 19 categories of variables available to use, literature stated that extreme values may be most influential of distribution, though annual averages may attribute to baseline stability. Thus, for temperature, the variables selected were: Annual Mean Temperature, Maximum Temperature of Warmest Month, and Minimum Temperature of Coldest Month. For precipitation, the variables selected were: Annual Precipitation, Precipitation of Wettest Month, and Precipitation of Driest Month (Groff et al., 2014; Fourcade et al., 2014).

Each of the bioclimatic variables were downloaded and processed through ArcGIS to match the extent of the Tennessee study region. Pixel values near *H. gratiosa* presence were extracted, so that temperature and precipitation values in association with presence could be analyzed. The minimum, maximum, mean, median, and mode were documented for the areas with presence, and compared to the overall possible range of values in Tennessee.

Spatial Statistical Analysis

When searching for trends in attributes to a spatial phenomenon, linear regression analysis has often been a viable option (Snodgrass et al., 2008; Hartel et al., 2010; Stapanian, Micacchion, & Adams, 2015). In this study, a couple of spatial tools contained in the ArcGIS 10.

* software called Exploratory Regression and Ordinary Least Squares (OLS) were used to

process regression analyses, which require a dependent variable and explanatory variables as inputs. The HUC 12 layer with land cover proportion attributes would be the source input for this tool, to compare proportions in watersheds with presence to those without presence. Based on the points found from the accumulated species presence data, a new attribute would be added that accounts for *H. gratiosa* presence per HUC, and this would function as the dependent variable and allow for weighting to occur among watersheds. The value of presence was defined by how many historic presence sites were represented in a HUC.

Exploratory Regression was executed first, to address potential redundancy between variables and to identify which land covers appeared most significant in explaining *H. gratiosa* distribution. Initially, all 15 NLCD land cover types were considered for explanatory variables for *H. gratiosa* presence; the top seven significant were noted. From those noted cover types, OLS was executed to assess the strength of significance between the top ranked cover types. Multiple statistical values were computed by the tool to further indicate significance, such as Adjusted R-Squared (R^2), corrected Akaike Information Criterion (AICc), Jarque-Bera p-value (JB), Koenker's studentized Breusch-Pagan p-value (BP), Variance Inflation Factor (VIF), Joint F-Statistic, and Joint Wald Statistics. While each of these values give some indication of strength and significance, the R^2 and AICc were primarily sought for identifying model fitness and performance. The Joint-F and Joint Wald values were also reviewed for validating the land cover significance, which were based on built-in F and Chi-squared tests respectively.

After running OLS and finding landscape variables that were consistently significantly associated with *H. gratiosa* presence, running Geographic Weighted Regression (GWR) was the next step to produce more localized models to assess the regional importance of certain variables. The outcome of this tool has the potential to result in somewhat different results than

OLS, since the variables are able to vary regionally and display local trends. This tool was also considered for its potential in making a lite predictive model, to possibly explain *H. gratiosa* presence in certain watersheds further.

In the process of running OLS and GWR, Akaike Information Criterion corrected (AIC_c) values were generated, which indicate the best models that pertain to the dependent variable. The values are corrected due to the smaller sample size, which normalized the results. The AIC_c values generated with each model are relative to each other, where some combinations of variables performed better in predicting species association than others; if one model's AIC_c value is lower than another's, the lower valued model is viewed to be better. Only variables from the NLCD were considered for the AIC_c models, as they were selected in both OLS and GWR. These values were reviewed to discern whether certain land cover types or combinations of types possessed any significant association with presence.

Results

Results of Land Cover Analysis

Executing Exploratory Regression analysis in ArcGIS with all 15 NLCD land cover proportions revealed that certain cover types are either positively or negatively associated with *H. gratiosa* presence, and some more than others. The cover type that was most important was “Shrub/Scrub”, a land cover type that tends to coincide with shrub/scrub type wetlands; this variable was the most important, with a value of 99.82%, in explaining species presence and was 100% positively associated. The “Woody Wetlands” and “Cultivated Crops” were the next most positively associated land cover types with over 80% positive association, but were less than 80% significant in explaining presence. The most negatively associated land covers were

“Evergreen Forest”, “Developed, Open Space”, “Open Water”, and “Barren Lands”, with each being over 80% negatively associated with presence; however, all were less than 80% important in explaining presence, according to the results from the tool. All other cover types were split between negative and positive associations and received low significance scores. The top seven contributing land cover variables were selected for Ordinary Least Squares regression, for further investigation of statistical significance, which were: “Shrub/Scrub”, “Woody Wetlands”, “Evergreen Forest”, “Developed, Open Space”, “Deciduous Forest”, “Cultivated Crops”, and “Hay/Pasture”.

Initially, all seven top scoring land cover types were used to in executing OLS. The following iterations of the tool removed the lesser important land covers one by one, to reveal the best models according to AIC_c values (Table 1.1). None of the adjusted R^2 values were above 0.5, showing weak connection to the fitted regression line. However, the Joint F-Statistic and Joint Wald Statistic indicated significance in almost all renditions, as “Shrub/Scrub” repeatedly was significant in each model. As a lone variable, “Shrub/Scrub” did not score as well with the AIC_c as when modeled with other variables. The best scoring AIC_c of 1861.837, being relatively less than the other scores, occurred when “Shrub/Scrub” was modeled with “Woody Wetlands” and “Evergreen Trees”. Those same two also stood out as significant to the model, when other variables were added; however, the “Shrub/Scrub” remained consistently significant.

Table 1.1 Ordinary Least Squares Statistics Results

Model	AIC_c	Adj R²	Joint F-Statistic	Joint Wald Statistic
+ Shrub/Scrub + Woody Wetlands - Evergreen Forest	1861.837063	0.051064	p < 0.01*	p < 0.01*
+ Shrub/Scrub + Woody Wetlands - Evergreen Forest - Developed, Open Space	1863.541026	0.050498	p < 0.01*	p < 0.01*
+ Shrub/Scrub + Woody Wetlands	1863.555019	0.048809	p < 0.01*	p < 0.01*
+ Shrub/Scrub + Woody Wetlands - Evergreen Forest - Developed, Open Space - Deciduous Forest	1865.515929	0.049709	p < 0.01*	p < 0.01*
+ Shrub/Scrub + Woody Wetlands - Evergreen Forest - Developed, Open Space + Deciduous Forest + Cultivated Crops	1866.660800	0.049608	p < 0.01*	p < 0.01*
+ Shrub/Scrub + Woody Wetlands - Evergreen Forest + Developed, Open Space + Deciduous Forest + Cultivated Crops + Hay/Pasture	1868.525902	0.048914	p < 0.01*	p > 0.05
+ Shrub/Scrub	1878.322797	0.035679	p < 0.01*	p < 0.01*

Models produced by GWR produced somewhat different results than OLS, in regard to how each of the parameters interacted with each other. A single explanatory parameter, “Shrub/Scrub” proportion, performed best in predicting watersheds with *H. gratiosa* presence, based on the available data and having the lowest AIC_c score. As the amount of parameters increased, the AIC_c values increased, where strength of progressing models decrease from the one prior to it (Table 1.2).

Table 1.2 Geographic Weighted Regression Model Results

Model	AIC_c	Adj R²
Shrub/Scrub	1590.530852	0.402236
Shrub/Scrub Woody Wetlands	1721.703324	0.307611
Shrub/Scrub Woody Wetlands Evergreen Forest	1845.775961	0.051064
Shrub/Scrub Woody Wetlands Evergreen Forest Developed, Open Space	1857.504235	0.214686
Shrub/Scrub Woody Wetlands Evergreen Forest Developed, Open Space Deciduous Forest	1863.704249	0.066052
Shrub/Scrub Woody Wetlands Evergreen Forest Developed, Open Space Deciduous Forest Cultivated Crops	1865.701639	0.051133
Shrub/Scrub Woody Wetlands Evergreen Forest Developed, Open Space Deciduous Forest Cultivated Crops Hay/Pasture	1868.120919	0.050072

Results of Climatic Data Analysis

Of the point presence data found, points from TAMP, iNaturalist, and APSU’s documentation were able to be used; TAMP data yielded the most out of the three. Annual Mean Temperature (BIO1) displayed values that accounted for the entire year, which indicated what overall temperatures could be tolerable to *H. gratiosa*. Maximum Temperature of the Warmest Month (BIO5) values unveiled the warmest extreme that *H. gratiosa* is drawn toward. Minimum Temperature of the Coldest Month (BIO6) values show the coldest extreme that this species is

able to endure. Compared to the entire spectrum of values throughout the state, BIO1, BIO5, and BIO6 values all fell to the warmer side, with the three central tendencies being very close in value (Table 1.3). The mean, median, and mode were also of warmer values within the range of temperatures associated with species presence (Table 1.3).

Precipitation levels displayed moderately close tendency, where Precipitation of the Driest Month (BIO14) had nearly equal mean, median, and mode, while the Annual Average Precipitation (BIO12) had slight variation. In comparison to the statewide ranges, BIO12 leaned more toward a moderately less amount of precipitation possible, but still favored more than the statewide minimum. The range of Precipitation of the Wettest Month (BIO13) associated with presence was a bit broad, but central tendencies were clearly visible at 140mm-142mm of rainfall (Table 1.3). Last, the Precipitation of the Driest Month (BIO14) showed ~78mm being the apparently preferred minimum precipitation.

Table 1.3 Bioclimatic Variable Trends for *H. gratiosa* in Tennessee

Bioclimatic Variable	Mean	Median	Mode	Minimum	Maximum	TN Overall Range of Values
BIO1	15.13°C (59.2°F)	15.3°C (59.5°F)	15.3°C (59.5°F)	13.1°C (55.58°F)	15.6°C (60.08°F)	6.4°C - 16.3°C (43.52°F-61.34°F)
BIO5	32.15°C (89.87°F)	32.2°C (89.96°F)	32.2°C (89.96°F)	28.9°C (84.02°F)	32.8°C (91.04°F)	20.2°C - 33.4°C (68.36°F-92.12°F)
BIO6	-2.64°C (27.25°F)	-2.4°C (27.68°F)	-2.3°C (27.86°F)	-4.7°C (23.54°F)	-1.9°C (28.58°F)	-8.9°C - -0.4°C (15.98°F-31.28°F)
BIO12	1363.63mm	1375.5mm	1380mm	1259mm	1576mm	1079mm - 2073mm
BIO13	140.40mm	142mm	142mm	127mm	172mm	110mm - 208mm
BIO14	78.40mm	78mm	78mm	70mm	101mm	63mm - 157mm

Documented Distribution in Tennessee

According to TDEC, 29 HUC 12 watersheds have been documented with *H. gratiosa*, with 11 HUCs in the eastern region, five HUCs in the north-central region, and 13 HUCs in the western region (Figure 1.2). Data from APSU revealed three additional HUCs to TDEC's data, with one in the eastern region and two in the western region (Figure 1.3). Overlaps of presence existed for several watersheds between these two data groups. However, the distribution data from these resources solely displayed the discontinuous range that has been understood to occur at this point in time.

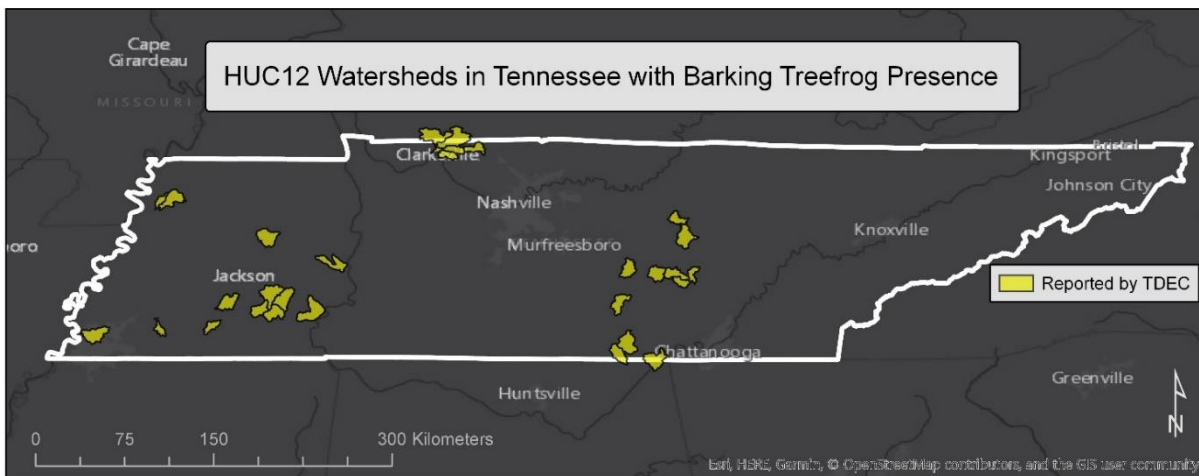


Figure 1.2 TDEC HUC12 distribution map (Datum: GCS_North_American_1983; Spatial Extent: Top 36.681860 dd, Bottom: 34.887339 dd, Right: -85.740875 dd, Left: -89.739759 dd)

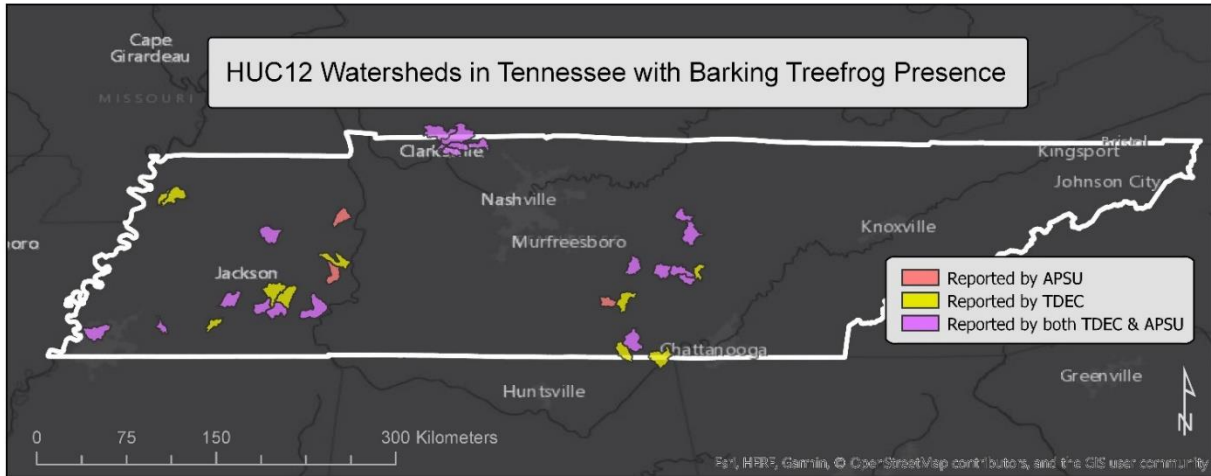


Figure 1.3 TDEC and APSU HUC12 distribution map (Datum: GCS_North_American_1983; Spatial Extent: Top 36.681860 dd, Bottom: 34.887339 dd, Right: -85.740875 dd, Left: -89.739759 dd)

Presence data from TAMP unveiled 19 more HUCs in addition to TDEC and APSU, which complimented previous areas of known presence by displaying continuity between watersheds. Solo, TAMP accounted for 23 HUCs with presence, where some of these watersheds overlapped with TDEC and APSU data as well (Figure 1.4). In addition to TAMP, iNaturalist indicated presence in one HUC in eastern TN, bringing citizen science data to contributing a total of 24 HUCs (Figure 1.5). No other citizen science sources provided additional information to these, showing that TAMP and iNaturalist were productive programs for accumulating information for *H. gratiosa* on a citizen level.

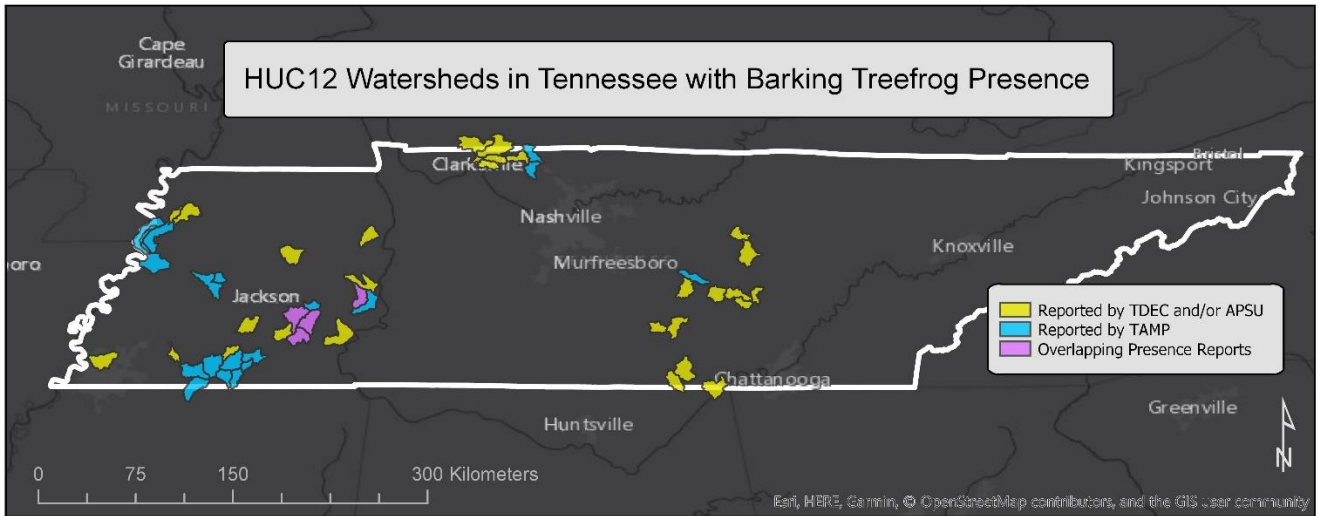


Figure 1.4 TDEC, APSU, and TAMP combined HUC12 distribution map (Datum: GCS_North_American_1983; Spatial Extent: Top 36.681860 dd, Bottom: 34.887339 dd, Right: -85.740875 dd, Left: -89.739759 dd)

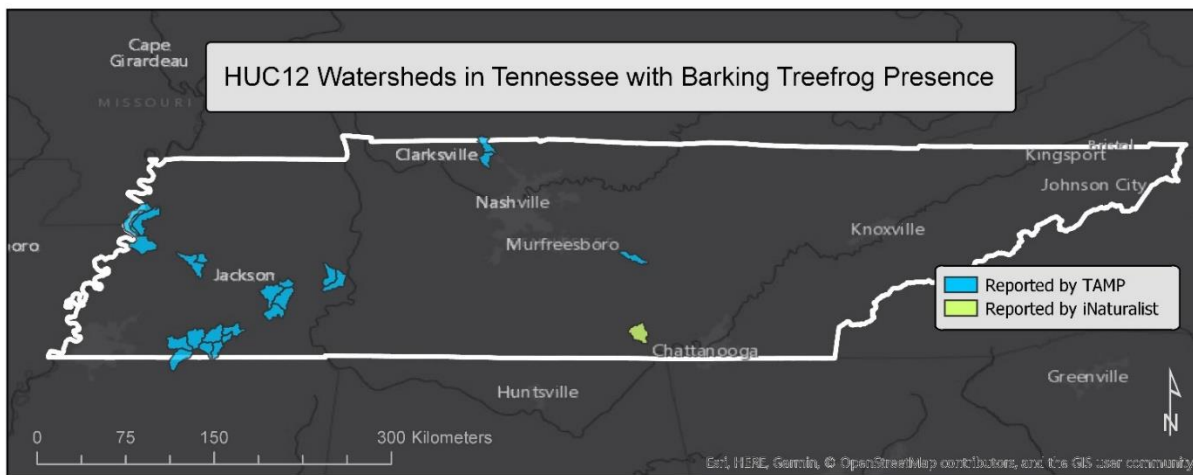


Figure 1.5 Citizen science-only HUC12 distribution map (Datum: GCS_North_American_1983; Spatial Extent: Top 36.681860 dd, Bottom: 34.887339 dd, Right: -85.740875 dd, Left: -89.739759 dd)

Overall, 52 HUC 12 watersheds were found to account for historic *H. gratiosa* presence in Tennessee. In the eastern region, 14 HUCs in all have been documented with presence, ranging from the AL state border up to just south of Cookeville, TN. In the north-central region,

7 HUCs have been documented with presence, ranging from west of Springfield, TN to north of Clarksville, TN. Last, in the western region, 31 HUCs have been documented with presence, having the majority between the regions; these HUCs ranged just north of the MS state border, toward the western border of TN, and areas encircling Jackson, TN. Apparent distribution clusters throughout these three regions and displays largely discontinuous range, but connectivity between local ranges (Figure 1.6).

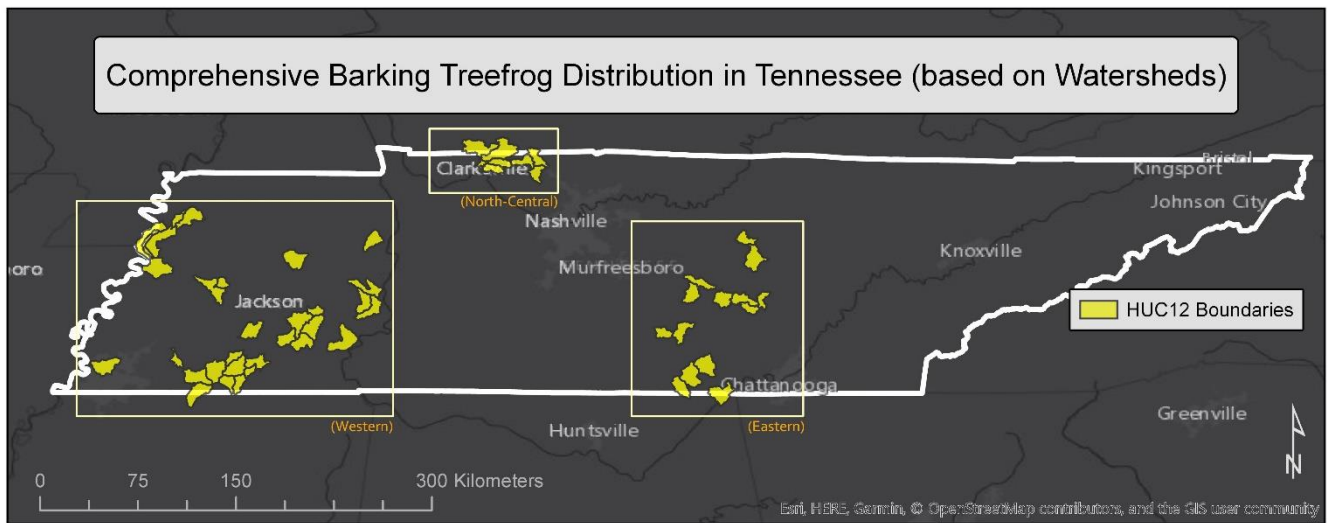


Figure 1.6 Comprehensive HUC12 distribution map of *H. gratiosa* in Tennessee (Datum: GCS_North_American_1983; Spatial Extent: Top 36.681860 dd, Bottom: 34.887339 dd, Right: -85.740875 dd, Left: -89.739759 dd)

Discussion

Suitable Habitat Implications

Knowing that *H. gratiosa* has been documented to favor open canopy wetlands, the shrub/scrub habitat type is a logical match for that criteria. Given that much of western Tennessee is composed of much more grassland, it also makes sense that the species would have a more expansive range in that region if it is utilizing lowland floodplains there. Modeling land cover by smaller regions and assessing presence per watershed allowed for a more weighted

approach that was able to more proportionally analyze pieces of the state. When modeling shrub/scrub land cover by HUC12 on its own, the concentrations do become reminiscent of *H. gratiosa*'s documented range from past distribution models (Niemiller, Reynolds, & Miller, 2011) (Figure 1.7). This land cover type is evidently not consistent throughout the Tennessee landscape, as it occurs primarily in lower latitudes of the state and more so in the western region.

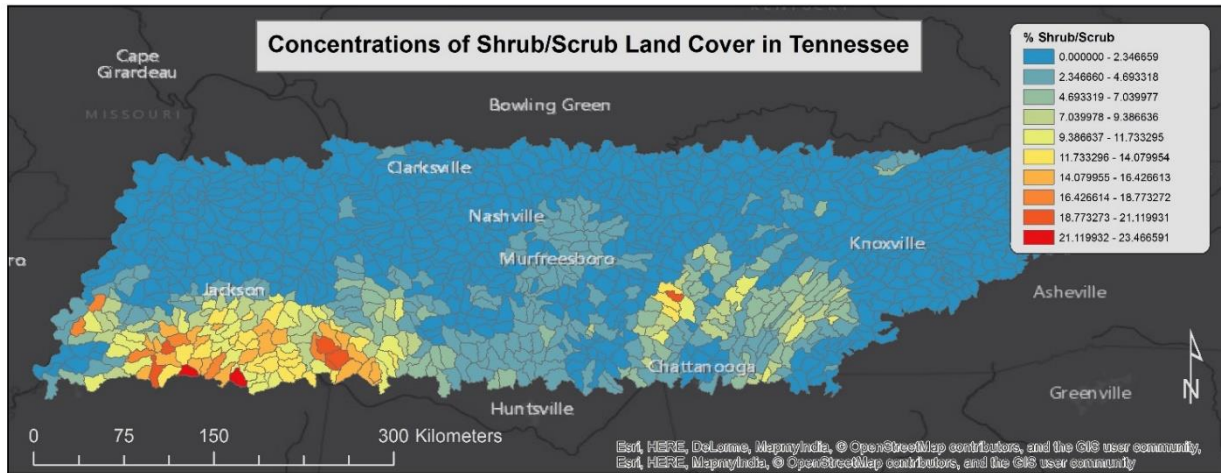


Figure 1.7 Concentrations of shrub/scrub land cover proportions by HUC12 Watershed (Datum: GCS_North_American_1983; Spatial Extent: Top 36.681860 dd, Bottom: 34.887339 dd, Right: -85.740875 dd, Left: -89.739759 dd)

Involving citizen science data, from TAMP especially, not only filled data gaps, but also enabled weighted regression to be a more viable option when modeling (Royle, 2004). Furthermore, gaining precision on climatic trends was possible with the point data provided. While APSU also had point data, the amount was not scattered and the sample size was smaller. Just as NAAMP has been noted productive in other parts of the United States, it was showcased as supplementation of pre-existing public data in Tennessee.

The climatic trends seemed to follow what would be expected, given the frog's nature toward milder conditions. While a certain amount of precipitation seemed variable annually, the range was still restricted to a certain amount. This restriction may have also been due to the sheer number of sites used to extract the climatic data, but having an adequate sample size of 63 points was able to reveal basic trends that coincide with *H. gratiosa* presence. The species has been said to become more active in warmer temperatures, which matched with the temperature values extracted from the WorldClim data. In the future, however, aspects of humidity should be considered, as ambient moisture levels in local climates may influence other trends in presence (Peterman & Semlitsch, 2013). Because Worldclim did not include this parameter, such data would need to be acquired from another available source to be considered in future modeling.

An unexpected result was that the anthropogenic landscapes, which included all of the land covers labeled "Developed", were not as outstandingly negative in association with species presence as they could have been. Many amphibians have been documented as sensitive to habitat alteration and destruction, but some anurans have been able to cope with those circumstances by utilizing manmade structures to fulfill their ecological needs. The dispersal ability of *H. gratiosa* in developed landscapes needs to be addressed further, to assess whether it is a species that is truly impacted or if it is neutral to some degree (Todd et al., 2016). Sister taxa, such as the green treefrog (*Hyla cinerea*) and Cope's gray treefrog (*Hyla chrysoscelis*) have often been noted to be calling in urbanized areas; might *H. gratiosa* also have this potential?

Limitations and Biases

The modeling limitations present in this project are due to the amount of presence data available. While a sample size of 52 HUC12s for spatial modeling was adequate, the results were

not as strong as they could have been, as noted with the small Adjusted R^2 values. Higher sample sizes would be needed to help improve the models, as more data would naturally result in more robust spatial models. Land cover values in association with *H. gratiosa* presence were also not normally distributed; however, this also reflects the reality that a landscape has variation in composition. Assessing presence at an even finer scale than HUC level may improve regression modeling further (Weir et al., 2005; Syphard & Franklin, 2009).

Another limitation that is also due to data availability regards the land cover data and its dating to 2011. Utilizing this data is adequate for basic trends in the landscape, but it is not necessarily reflective of the current landscape, nor able to show the amount of habitat alteration that may have occurred between then and now. When the NLCD 2016 data becomes available, that will be much more suitable to use for the next modeling regimes, given the fast paced development occurring.

While the amount points available from TAMP supplemented presence data, there is an element of bias to consider in its locations. The routes were set all across the state, but not all routes have been monitored as frequently as others. Furthermore, the populations at each of the sites might not represent a population that could be existing across the state. Because of the landscape variability in Tennessee, some populations may be more biased to resources they are familiar with at a certain part of the state, where this may differ in another region. But overall, as *H. gratiosa* tends to be consistent in its selection of breeding pool types, that at least may be reliable for future modelling and assessment of potential habitat, leading to further conservation and management.

Conclusions

This chapter was designed to address the apparent land cover use of *H. gratiosa*, climatic occurrences with presence, and assess the overall spatial status of the species in Tennessee. With the results gained, each of the questions posed earlier are able to be addressed.

First, the significance of the “Shrub/Scrub” land cover proportion supports that the species would be particular to at least one natural land cover, and not partial to developed landscapes. The continuous consistency of that land cover’s significance is worth noting, as it fulfills the lowland, floodplain type of habitat the species is known to be attracted to (Oldham & Gerhardt, 1975). With more presence data, greater specificity of other habitat components can be revealed in the future. Sampling in areas similar to this habitat type may yield other locations of presence to be analyzed in future conservation.

Second, the climatic gradients falling within a specific range in association with *H. gratiosa* points of presence supports that there is a particular climate favored. This species is not one to haphazardly select areas to breed and reside; it is precise and more prone to warmer, rainy conditions. Should sudden microclimate changes occur that are unfavorable, this may force species to migrate or adapt in some way; however, this may be difficult if habitat corridors are not available for their movement (Pilliod et al., 2015).

Last, the addition of citizen science data to federal and academic institution data was able to supplement and expand known distribution on a finer scale, which supported citizen science’s utility in contributing more presence data. One of the purposes of NAAMP was to accomplish the goal of mending data gaps over time. Given the purpose that citizen science data has served for *H. gratiosa*, it will likely be useful for further modeling and for other species in need of management and conservation in the future (Villena et al., 2016)

CHAPTER II

DEVELOPMENT AND ASSESSMENT OF PREDICTIVE SPATIAL MODELS FOR *HYLA GRATIOSA* IN TENNESSEE WITH CITIZEN SCIENCE DATA

Introduction

Conservation and Predictive Modeling

Ongoing development of geospatial technologies and modelling practices have empowered researchers to broadly analyze species populations and ranges, a much needed utility for conservation of declining species. In the early 1990s, climatic envelope modelling, such as with BIOCLIM and DOMAIN, became prominent and was utilized to understand correlations between species presence and persistence in association with environmental conditions (Booth et al., 2014; Carpenter et al., 1993). Over time, profile approaches of modelling were gradually replaced with machine-learning in terms of popular usage, as these modelling algorithms repeatedly displayed greater precision and accuracy in predicting presence based on known locations, even if sample sizes were low (Fouquet et al., 2010). MaxEnt (Maximum Entropy) and GARP (Genetic Algorithm for Rule Set Production) are both capable of creating ecological niche models for species using machine-learning, yet may perform differently at different geographic scales (Pearson et al., 2006; Tsoar et al., 2007). Despite differences in accuracy, both are still widely used and remain dominant in the realm of species distribution modelling because of their general reliability. Newer modelling scenarios are being developed through R programming, a

language that is inclusive of statistical and spatial processing (Hijmans & Elith, 2013), which is presently gaining popularity.

Predictive modeling approaches have been utilized to assess species that fall under a variety of management categories, from invasive to endangered (Iverson, Prasad, & Schwartz, 1999; Giovanelli, Haddad, & Alexandrino, 2007; Groff et al., 2014). Rare species in particular tend to pose prominent conservation challenges (Measey et al., 2016), pushing modelling approaches to continually be developed toward greater accuracy (Groff et al., 2014). There are oftentimes concerns with presence-only data having sampling bias and influencing models (Miller et al., 2011), but for threatened or vulnerable species, utilizing this data becomes crucial for exploratory models (Chandler, 2015; Groff et al., 2014). Certain modelling scenarios, such as in MaxEnt and GARP, have become streamlined, where default settings are capable of creating accurate models with few configurations required for calibration (Phillips & Dudík, 2008). For a rare amphibian in Oregon, MaxEnt was able to assist in guiding exploratory surveys, resulting in the discovery of a previously unknown occurrence (Groff et al., 2014). In larger regions, novel methods had the tendency to outperform older, more established modeling scenarios, where machine-learning methods functioning with presence-only data gave more accurate results (Elith et al., 2006). For species that tend to occur in predictable habitats, presence-only data functions efficiently, but other species may display different dynamics apart from predictive models; the species being modeled becomes of importance when selecting modeling schemes (Segurado and Araujo, 2004). When model customization is more favorable, programming for predictive models in R have become more appealing to allow greater specification (Fiske and Chandler, 2011). An R package known as spThin has the ability to thin clusters of occurrence points in an attempt to reduce spatial bias, allowing models to become less skewed by spatial bias (Aiello-

Lemmons et al., 2015). MaxEnt, however, has been shown to offer a similar capability by allowing the user to indicate where biases may occur and correcting for it (Fourcade et al., 2014). Some of the more established modeling scenarios, such as Generalized Linear Modeling (GLM) and Generalized Additive Modeling (GAM), have been shown to provide comparable results to MaxEnt, but the produced models may vary greatly with complex parameters; models with greater consistency tend to be preferred when being applied toward species assessment (Syphard & Franklin, 2009; Segurado & Araujo, 2004; Elith et al., 2006; Hernandez et al., 2006),

Concerns for amphibians in specific have caught the attention of GIS analysts, where spatial analyses to assess amphibian distribution and range have been performed in recent decades. Multiple researchers in Europe have modeled the effects of a changing environment on amphibian species ranges, displaying shrinking populations and tolerance potential (Arntzen, 2006; D'Amen & Bombi, 2009; Pellet et al., 2006; Schmidt & Pellet, 2005; Joly et al., 2003). Some studies have involved assessing amphibian population connectivity to understand population viability in the impacted landscapes, utilizing GIS packages to produce connectivity models between suitable habitats holding populations (Joly et al., 2003; Decout et al., 2012; Hether & Hoffman, 2012). In various places worldwide, predictive models have been utilized to guide surveys for amphibians or assess population status, such as with: the Syrian Spadefoot Toad (*Pelobates syriacus*) (Tarkhnishvili et al., 2009), the Mountain Yellow-legged Frog (*Rana muscosa*) (Knapp et al., 2003), the Oregon Spotted Frog (*Rana pretiosa*) (Groff et al., 2014), and Hochstetter's New Zealand Frog (*Leiopelma hochstetteri*) (Fouquet et al., 2010). Several of these studies utilized machine-learning modeling schemes in addition to ArcGIS extensions, while others utilized combinations of GLM and GAM modeling, displaying themes of modeling applications in amphibian conservation (Syphard & Franklin, 2009; Groff et al., 2014).

For a wide variety of organisms, researchers have utilized these computational tools to address conservation concerns across landscapes in an attempt to improve conservation management practices (Giovanelli, Haddad, & Alexandrino, 2007; Fouquet et al., 2010; Groff et al., 2014). For anurans in the face of decline, this mode of species distribution assessment has great potential to guide conservation along a more efficient path. With this in mind, one may question: which Anuran species are in need of spatial analysis for conservation purposes?

Contribution of Citizen Science

The modern era has access to many technological advancements, allowing knowledge to be quickly available in the palm of one's hand. Whether by a book or a mobile device, citizens have become more empowered in recent decades to be more involved with the gathering of scientific data, whether they realize it or not (Tulloch et al., 2013; Biggs et al., 2015). For programs that do intentionally use citizens as a data source, accommodations for training or data verification are in place (Walls, 2014; Biggs et al., 2015). With citizen science, the flux of information to be gained has great potential to be explored (Devictor, Whittaker, & Beltrame, 2010).

Throughout the decades, monitoring various species through citizen efforts has been underway, ranging from bird counts to tree inventories (Silvertown, 2009; Galloway, Tudor, & Haegen, 2006). The benefits of this effort have been reported as double-sided, where officials in need of data gain a great amount, and citizens receive an opportunity to learn more about ecology and wildlife. Across the board, most any taxa that people are interested in investigating has a citizen science opportunity, allowing international biodiversity monitoring and monitoring across different regions (Chandler et al., 2017; Mair & Ruete, 2016).

As amphibian biodiversity is in a state of decline worldwide, monitoring programs for this taxa have been greatly encouraged through citizen science, which has been evident through online applications such as iNaturalist, HerpMapper, and the Herpetological Education and Research Project. Given the mass concern for amphibians, this avenue of data has been viewed as efficient and creates greater awareness, encouraging the conservation of these species (Theobald et al., 2015). The North American Amphibian Program (NAAMP) began an initiative in the 1990s to expand on awareness, train citizens, and allow in-field opportunities throughout spring and summer seasons. The fruits of this effort have come in the form of usable data for research, as seen in an occupancy studies performed from NAAMP data (Weir et al., 2005; Weir, Fiske, & Royle, 2009). Another study utilized NAAMP data to assess negative effects of road traffic on amphibians, in which they did discover impacts on populations (Cosentino et al., 2009).

With so many different amphibian species that may be at risk, and with many accessible opportunities to contribute data, the time to utilize citizen science data for conservation is upon modern citizens. Spatial modeling and citizen science have the potential to be used together for furthering the conservation of a species of concern (Walls, 2014).

The Modeling Candidate: Barking Treefrog (Hyla gratiosa)

Amphibians are often low hanging fruits for spatial modeling, given their predictable ecological needs and typically limited geographic ranges. Throughout the United States, many amphibian species are in need of management, where researchers have adopted spatial modeling to efficiently assess habitat requirements and remediate impacts potentially lead to declines. Within the state of Tennessee, one such species that has remained poorly understood is Barking

Treefrog (*Hyla gratiosa*), where this species is also listed as ‘Vulnerable’ due to its nature as a specialist. To understand the needs of this treefrog for further management, more presence data is needed to clarify its habitat preferences in the Tennessee landscape. A way to gain more presence data is to utilize presence data sources already existing alongside environmental parameters and create predictive distribution models to test (Kearney & Porter, 2009).

Tennessee has maintained a citizen science program through the Tennessee Amphibian Monitoring Program (TAMP) since 2004, which involves and trains citizen scientists to perform auditory surveys along assigned routes. Of the species heard in Tennessee, *H. gratiosa* is included, but its distribution from the accumulated data had not yet been fully analyzed.

Research Objectives and Hypotheses

Using presence data from citizen science sources, the objective of this section of the project is to develop and assess spatial predictive models in the field. Predictive modeling also requires environmental parameters with which to model potential habitat, such as land cover, climatic data, topography, and more, which have been utilized in previous studies involving amphibians (Tarkhnishvili et al., 2009; Fouquet et al., 2010; Groff et al., 2014). Some modeling programs have been more popularly used than others, such as MaxEnt and GARP, which are machine-learning algorithms that can function with presence data only (Segurado & Araujo, 2004; Fourcade et al., 2014; Miller, 2014). Testing these modeling methods against each other, and with an older method, such as BIOCLIM, may reveal the usefulness of this modern utility for conservation. In contrast, testing a newer modeling scenario, InVEST, is also of worth to benchmark the future reliability of certain programs. With all of these modeling schemes in mind, I seek to answer these questions: 1) Will one of these modeling programs create a more

accurate model than the others, given the same presence data and similar environmental parameters? 2) Will the predictive models, born of citizen science presence data, be able to accurately locate *H. gratiosa* presence in one or more previously undocumented places in Tennessee? Ultimately, I will use the results to assess potential modeling solutions for *H. gratiosa* and assess how predictive modeling may enhance conservation for the species in Tennessee.

Methods and Materials

To answer the research questions presented, the methods involved computational and in-field phases. The computational aspect required a moderately high-powered computer with at least an Intel i5 processor, 8GB of RAM, adequate graphics capability, over 100GB of storage space for files, and the ESRI ArcGIS 10.* software suite. The in-field aspect required a reliable vehicle for traveling long distances, funds for fuel, and a smartphone with GPS capabilities for navigation.

Data Acquisition and Processing

Based on past studies that have utilized NAAMP data for research (Weir et al., 2005; Weir et al., 2009; Walls, 2014; Villena et al., 2016), data from TAMP was pursued for modelling. The state coordinator for TAMP was contacted he provided the coordinates for all TAMP sites in Tennessee. From those points, the sites having documented *H. gratiosa* presence were analyzed, queried, and separated using ArcGIS software. In addition to NAAMP data, many other citizen sciences sources were analyzed, but only iNaturalist had usable coordinates

for modeling. The resulting amount of presence points numbered to 63, and the coordinates were placed into a *.csv file in preparation for predictive modeling programs (Figure 2.1).

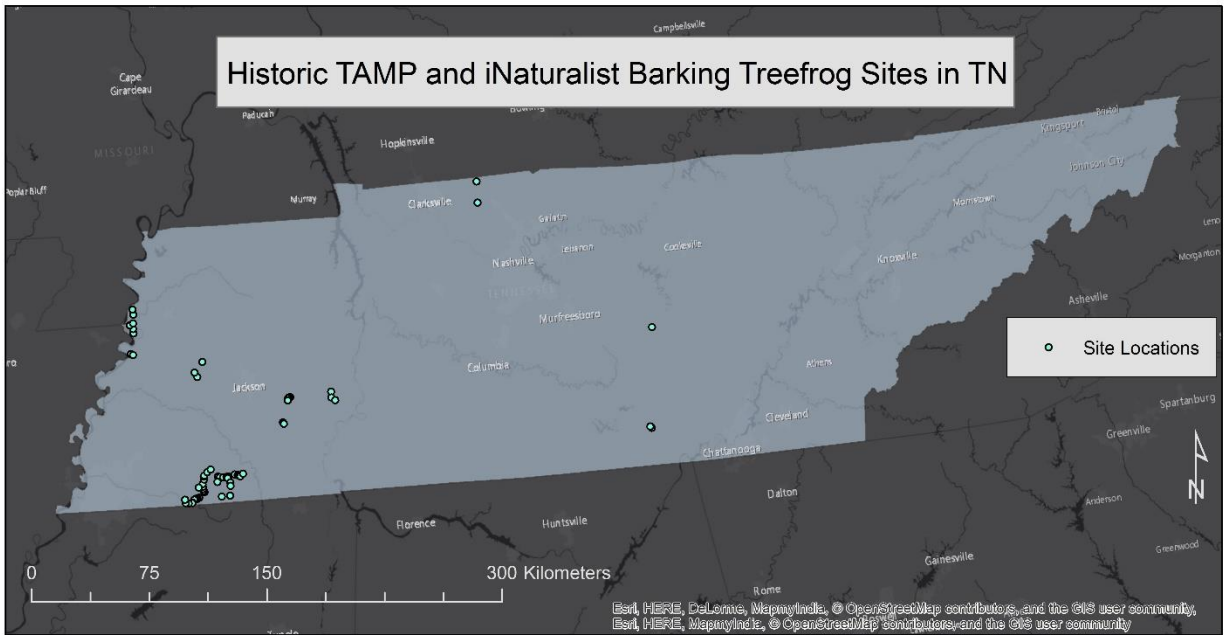


Figure 2.1 Historical citizen science sampling sites with *H. gratiosa* presence (among these points, 61 are from TAMP and 2 are from iNaturalist, totaling 63 sites)

The environmental parameters used in other modeling studies involved land cover, temperature, precipitation, and topographical features. Along with those datasets, wetland proximity and climate resiliency were considered and used, to test if they would be of any importance to the model. The following datasets were located and downloaded: NLCD 2001, 2006, and 2011; GAP land cover; Worldclim Bioclimatic variables Annual Mean Temperature (BIO1), Maximum Temperature of Warmest Month (BIO5), Minimum Temperature of Coldest Month (BIO6), Annual Precipitation (BIO12), Precipitation of Wettest Month (BIO13), Precipitation of Driest Month (BIO14); Nature Conservancy’s Climate Resiliency data; US Geological Survey Slope, Aspect, and Elevation; and the National Wetland Inventory’s wetland dataset. All of these parameters were processed to be at the same exact extent to be used for the

state of Tennessee, rendered to a resolution of 30m. After processing all layers to the same extent, all fourteen (14) were converted to a *.asc file format, in preparation for predictive modeling.

Predictive Model Processing

Literature supports MaxEnt's reliability compared to most other predictive modeling algorithms (Segurado & Araujo, 2004; Tarkhnishvili et al., 2009; Radosavljevic, Anderson, & Araujo, 2014; Groff et al., 2014); for this reason, it was chosen to be the base modeling method for selecting sampling sites.

MaxEnt is an open source modeling program that requires downloading from the internet and need only be extracted and installed on a computer. Once setup, the maxent.bat file must be executed to run the program. Upon the MaxEnt window's opening, the coordinates *.csv file is able to be added to the Samples on the left, and the series of processed Environmental Layers can be added on the column on the right. Environmental Layers are defined as either categorical or continuous, where discrete layers such as land cover would be classified as categorical and numerical layers such as elevation would be continuous. After all of the data was uploaded, a set of guidelines by Phillips & Dudík (2008) and Young et al. (2011) were followed to ensure proper setup of the modeling environment. The output format was set to be Logistic, and the program was instructed to do a jackknife test to measure variable importance. Other settings modified were: the number of replicates (to 15), the random test percentage (to 25), the replicated run type (to Subsample), the maximum iterations (to 5000), and a bias file was input (the HUC 12s with *H. gratiosa* presence were used for this) (Phillips & Dudík, 2008; Young et al., 2011). In addition, the following checkboxes were modified from the default: Random seed (checked);

Write clamp grid when projecting (unchecked); write output grids (unchecked). At this point, the model was to be executed and took a few hours to process. The output was set to be in *.asc format.

To create models for GARP and Bioclim, an open source program called openModeller was used. Similarly, to MaxEnt, the program needed only to be downloaded, setup, and executed. After setup and opening the program, the Data Preparation button was selected and a prompt for Occurrence data and environmental variables appeared. The algorithms Bioclim and GARP were also selected in this window, and the file save location was set up, and the model was then instructed to run. No other modifications were found to be made in the modeling environment. The output for these models were also set to be in *.asc format.

Last, InVEST, a newer modeling scenario, was located and downloaded from the Natural Capital Project website: <https://www.naturalcapitalproject.org/> (Tallis et al., 2011). This modeling scenario was selected as more of an exploratory aspect, as the inputs permitted and set up were different from the other three modeling algorithms. The Habitat Quality tool in InVEST was utilized to model potential suitable habitat for *H. gratiosa*. The inputs required for this model were the most recent land cover, NLCD 2011, and threats that may be present to habitats, such as roads and agricultural impact. All natural land covers were described as suitable potential habitat, such as forests and wetlands, while agricultural areas and lightly developed areas were categorized as mildly potential, and urbanized areas were categorized as not suitable. The sensitivity values to threats are on a scale of 0 to 1, where 1 means a land cover is very sensitive to the threat. The likely suitable habitats were set up to a moderately sensitive value to respond accordingly to threats on the landscape (Tallis et al., 2011).

Selection of Sampling Sites Using MaxEnt

The model resulting from the MaxEnt algorithm was opened in ArcGIS and displayed precise, suitable areas for *H. gratiosa* to be calling from, which indicated potential presence for the species (Figure 2.2). The model ranked the areas on a scale of 0.0-1.0, where 1.0 has a higher probability of presence. According to literature and similar studies, using 0.5 and above is a sufficient for finding areas that can support a rare species. All areas ranking 0.5 and above were selected and converted to a vector shapefile to be used with another spatial tool. Given 63 historic sites used to generate the predictive model, 63 predicted sites based on the MaxEnt model were selected via stratified random sampling. Predicted sites were divided between major ecoregions of Tennessee at the EPA III level, which allowed spatial broadness of sampling areas while also accounting for ecological relevance of the selected sites. Numbers of historic sites per ecoregion were noted, indicating the number of random predicted sites to be selected per region. The ArcGIS tool “Create Random Points” was used alongside the vector of MaxEnt areas ranking 0.5 and above, to ensure random selection of suitable areas in each ecoregion. After random points were laid out, screening was performed to ensure accessibility and plausibility of sites based on environmental appropriateness.

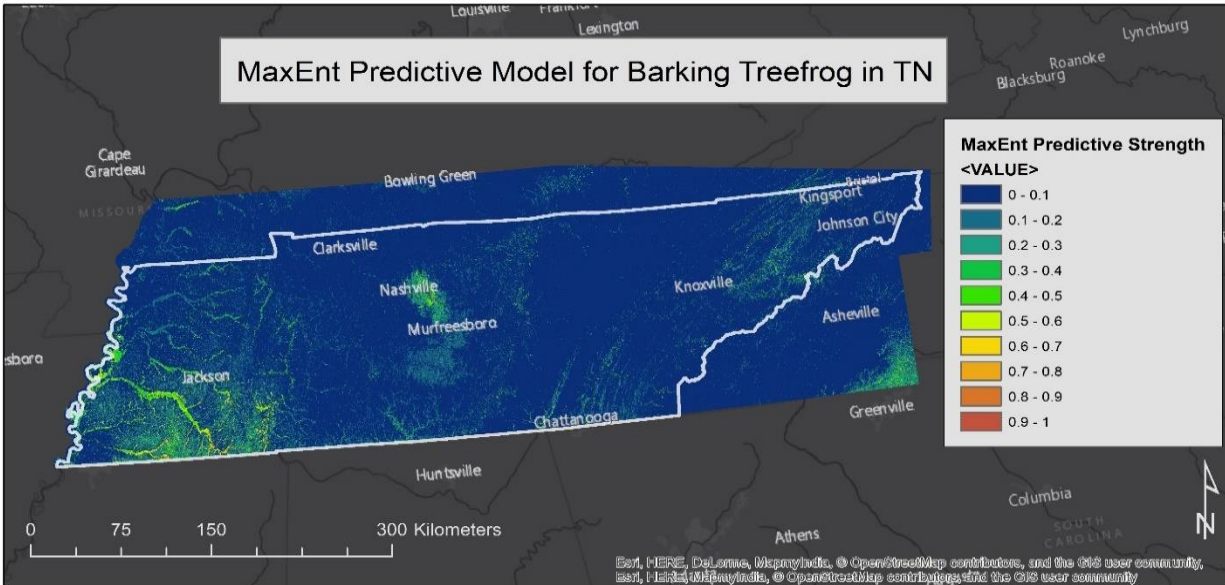


Figure 2.2 MaxEnt Model for *H. gratiosa* potential distribution (Datum: NAD_1983_Albers; Spatial Extent: Top: 1126572.09967543, Bottom: -35062.579798864, Right: 3272352.08455572, Left: 611702.888096803)

Five ecoregions contained historic TAMP points, with the most amount of coordinates being in western Tennessee. The Southwestern Appalachians region had two historic points and was granted two predicted points to sample; the Interior Plateau had three historic points and was granted three predicted points to sample; the Southeastern Plains had 33 historic points and was granted 33 predicted points to sample; the Mississippi Valley Loess Plains had 17 historic points and was granted 17 predicted points to sample; and last, the Mississippi Alluvial Plain had 8 historic points and was granted 8 predicted points to sample (Figure 2.3).

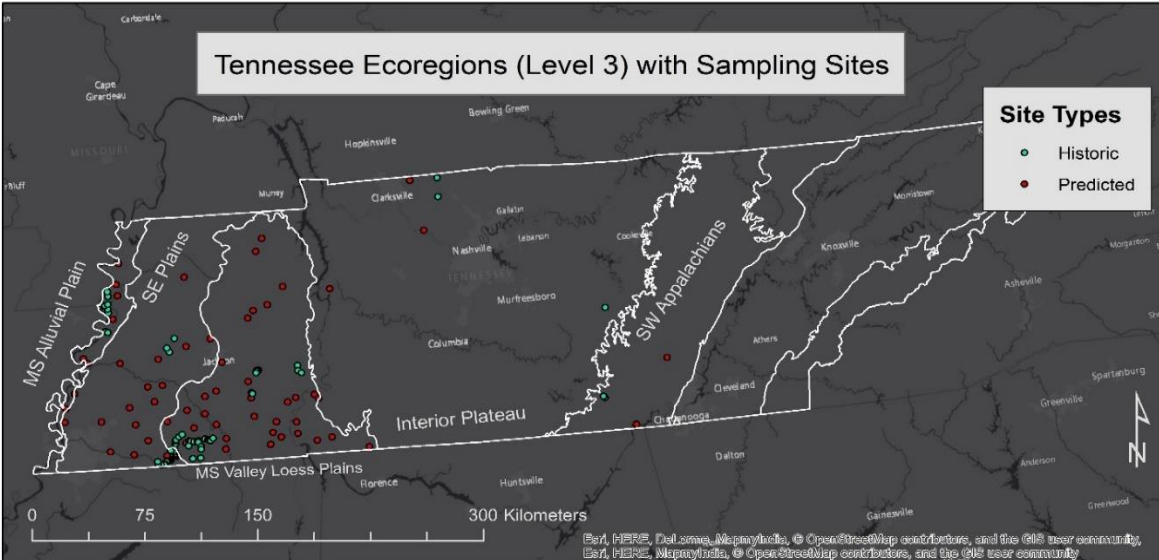


Figure 2.3 Map of Level III ecoregions with sites (Datum: NAD_1983_Albers; Spatial Extent: Top: 1126572.09967543, Bottom: -35062.579798864, Right: 3272352.08455572, Left: 611702.888096803)

Mapping Routes With Google MyMaps

To most efficiently sample all sites, an application called Google MyMaps was used to create routes between the points and to upload the points onto a smartphone. This application assisted in arriving to the locations more precisely, and helped with organizing how many sites to visit per night. Drive times and distances needed to be measured carefully, as time was limited every night for sampling. Sites were broken up into 14 groups, and one group of sites would be completed per sampling night (Figure 2.4).

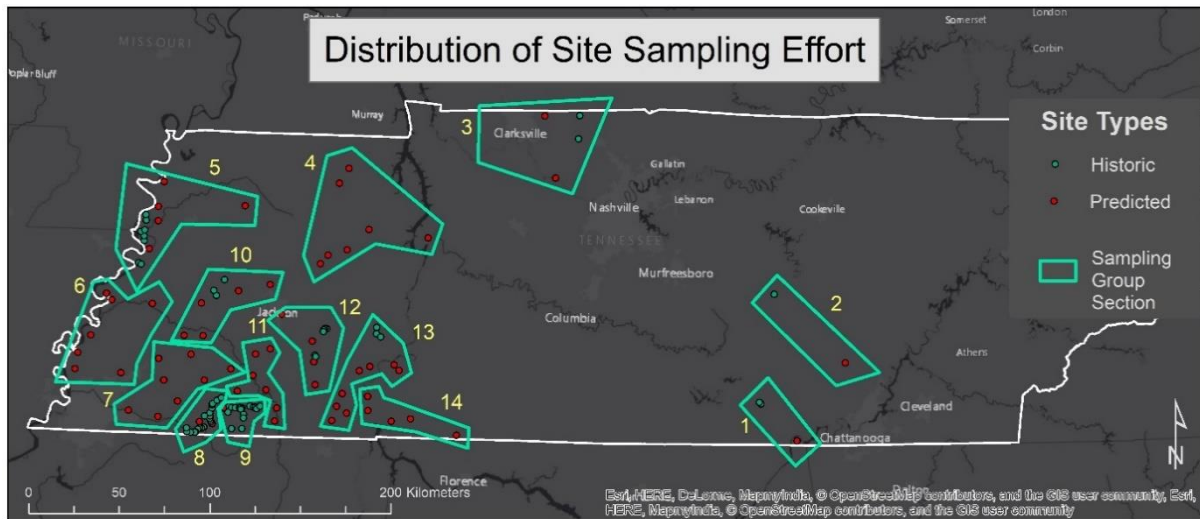


Figure 2.4 Image of site sampling sections, organized by the Google MyMaps application

In-Field Sampling Methods

From the months of April through August 2017, all 126 study sites were visited and surveyed for frog calls according to NAAMP protocol. The generated routes allowed me to efficiently sample a certain number of sites within the time window of 30-minutes-after-sundown to 0100. Distributing site sampling in this manner resulted in a two-week sampling period per month, during which auditory sampling was performed every night. The sites were visited in a consistent order every month, with May having a slight exception due to accessibility issues during a flood event. The latter two weeks of every month were allocated for sampling effort to retain temporal consistency (Bridges & Dorcas, 2000).

If weather was ever a factor, whether windy or rainy, auditory sampling was performed during quieter moments when hearing and calling performance would not be affected. A Kestral® unit was utilized to ensure the wind speeds did not exceed 13 mph, which is a condition that typically deters frogs from usual calling behavior. During flood events in May, some sites

needed to be visited in a different order to maximize accessibility for auditory sampling; if certain sites were inaccessible due to weather hazard during this month, a site very approximate and within hearing range of the original was proceeded to.

Listening locations during sampling were often on the side of the road or from a designated parking area near the sampling sites when available. To maintain safety, listening for frog calls from the vehicle was sufficient and did not interfere with listening ability. Locations were all in public areas, where asking for permissions to enter certain areas were not required. Occasionally, police and citizens approached the vehicle during listening periods, during which the listening session needed to be stalled when explaining the study; people inquired for reasons out of concern for listener safety.

Several environmental and locational parameters were documented at each sampling site, including: start/end time of listening, temperature, moon visibility, car traffic count, and ambient weather. If Barking Treefrog was heard, the intensity was documented on a 1 to 3 scale, according to NAAMP protocol; other frogs heard were also noted at each site to account for general habitat suitability.

Postprocessing and Statistical Analyses

For any sites that were positive for *H. gratiosa* presence, those areas were considered for Exploratory Regression to find habitat trends in those areas. Since sites were visited five times during the season, certain sites were weighted more greatly if *H. gratiosa* was heard calling more than once. Also, the intensity of the choruses was considered for the weighting system. If *H. gratiosa* choruses were a '3' twice over the sampling season, that site received a score of '6', and so on for other sites.

The MaxEnt, GARP, and BIOCLIM models each produced Area Under the Curve (AUC) values, which determines the usefulness of the predicted models and the classes used. The values of those and qualitative use of each model were compared to assess which would continue being useful for conservation management.

Results

Comparison of Predictive Models

While AUC values were only generated from processing MaxEnt, GARP, and BIOCLIM models, those three were assessed in a more statistical manner; comparing InVEST with all of them was done in a more qualitative manner. The three modeling scenarios had similar AUC scores, and yet differing modeling outcomes. MaxEnt had an AUC score of 0.834, GARP received an AUC score of 0.95, and BIOCLIM received an AUC score of 0.83. While each of these models found scored themselves to have fairly modeled the basic distribution of *H. gratiosa*, as a score closer to 1.0 is typically best, not all models appeared equal in prediction. BIOCLIM modeled for large portions of Tennessee to be suitable for *H. gratiosa* habitat, as it creates a bioclimatic envelope. GARP differed from both in its seeking also predict absence values to test alongside the presence values; having the highest AUC of the three, its accuracy may seem the best, though its spatial model too is very broad. MaxEnt's AUC score fell in the middle of the other two, being a high enough score to consider valid, but the mapped model appeared to predict much less than the others (Figure 2.2). All three models were able to run successfully with citizen science data and produce fairly accurate distribution models according to AUC, despite potentially overestimating species presence.

When comparing the four models – Maxent, GARP, BIOCLIM, and InVEST – the amount of overestimating presence becomes more evident in how widespread the potential is. BIOCLIM’s predictive presence values for this model were only on a scale of 0-0.5, only showing areas where *H. gratiosa* presence is somewhat possible (Figure 2.5). GARP produced a similar model to MaxEnt, in terms of where presence likelihood was weighted, but expanded more widely in the western Tennessee region (Figure 2.6). The InVEST model was created as a pilot to test its conservation modeling potential, but its parameters were only able to focus on one environmental aspect and ended up appearing broad as well (Figure 2.7).

With MaxEnt, a Jackknife test was generated automatically, which assessed the most important variables to the predictive model. The test showed that NLCD 2006 land cover was most useful in explaining *H. gratiosa* presence when isolated, yet Slope values cause the entire model to decrease if omitted (Figure 2.8).

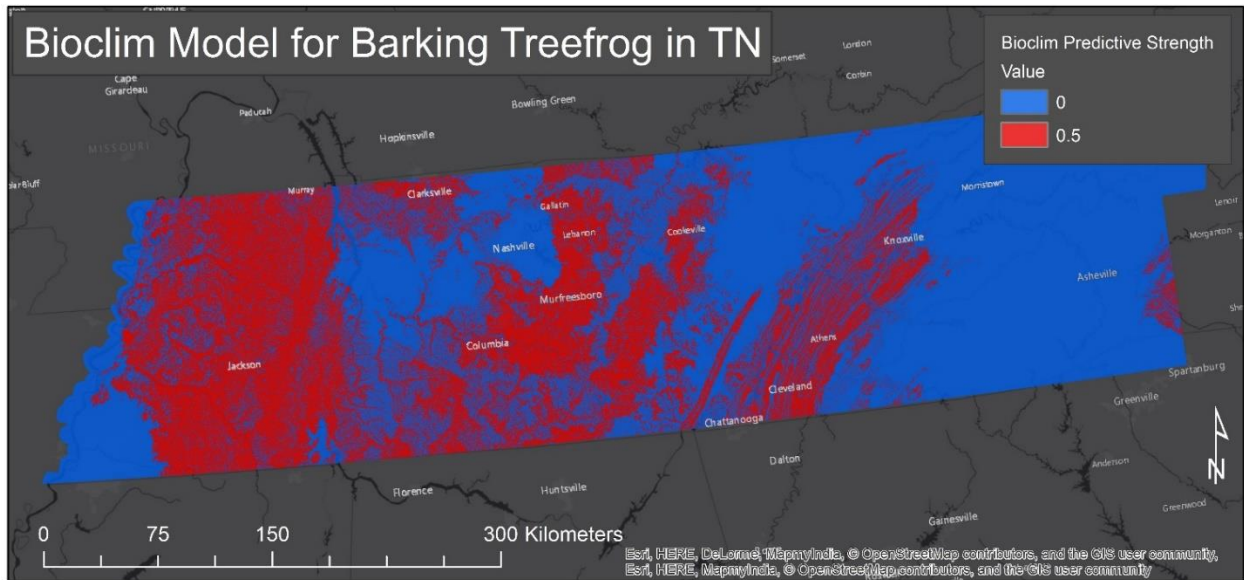


Figure 2.5 BIOCLIM model for *H. gratiosa* potential distribution (Datum: NAD_1983_Albers; Spatial Extent: Top: 1126572.09967543, Bottom: -35062.579798864, Right: 3272352.08455572, Left: 611702.888096803)

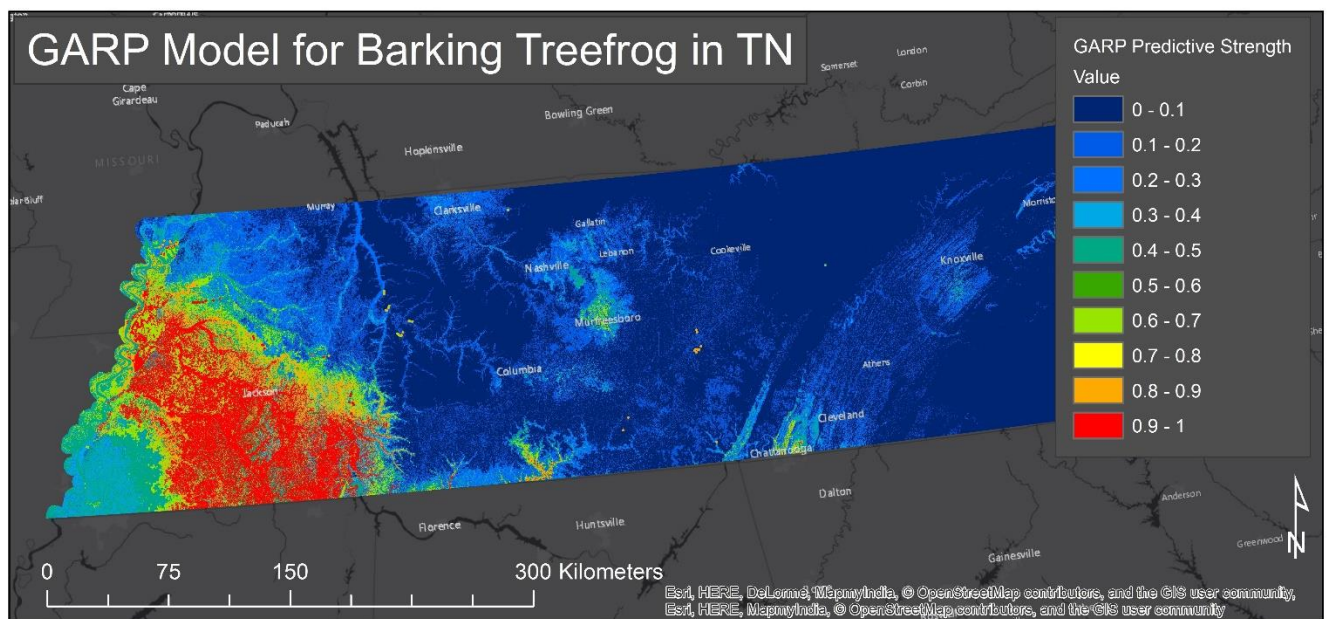


Figure 2.6 GARP model for *H. gratiosa* potential distribution (Datum: NAD_1983_Albers; Spatial Extent: Top: 1126572.09967543, Bottom: -35062.579798864, Right: 3272352.08455572, Left: 611702.888096803)

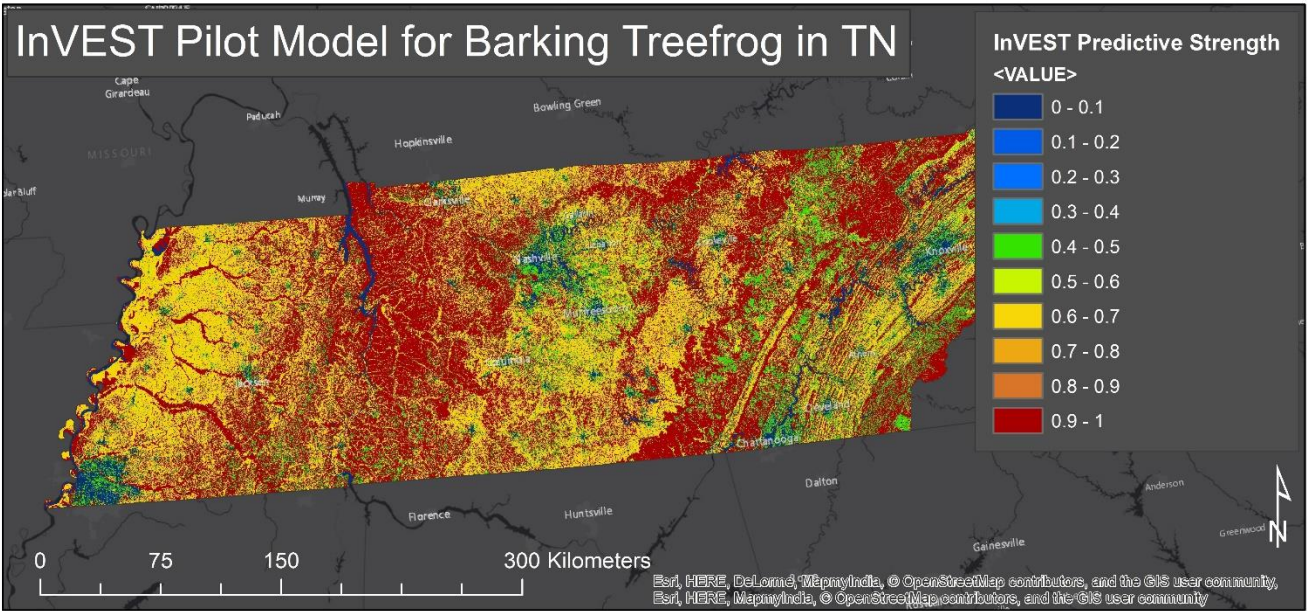


Figure 2.7 InVEST pilot distribution model (Datum: NAD_1983_Albers; Spatial Extent: Top: 1126572.09967543, Bottom: -35062.579798864, Right: 3272352.08455572, Left: 611702.888096803)

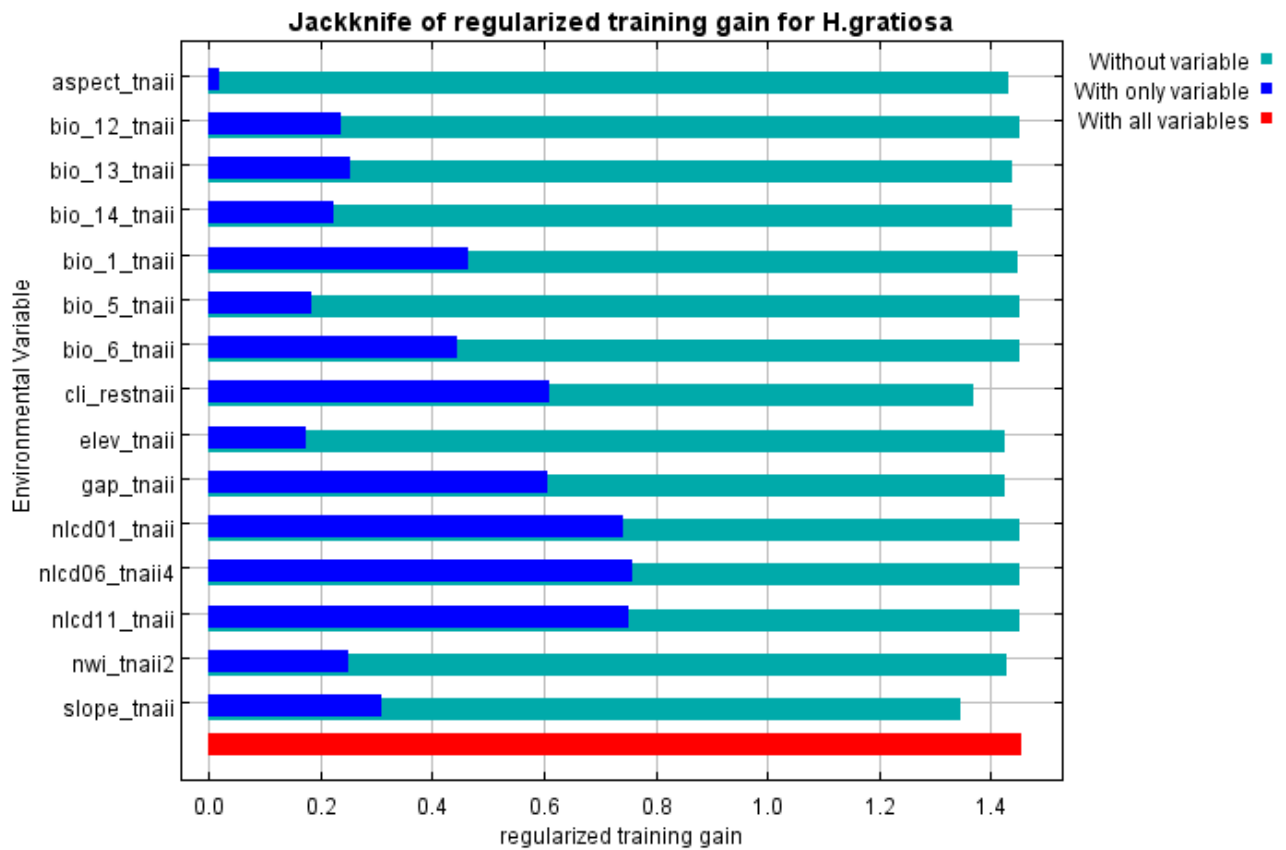


Figure 2.8 The Jackknife test of variable importance, modeled from MaxEnt (the teal color indicates the strength of the overall model when the variable is excluded; if a certain variable's absence causes the model's gain to decrease, it may contribute something in particular; the royal blue color indicates the model's strength when the variable is solely used – the higher the gain, the more important the variable is in contributing to the model)

Spatial Results of Auditory Surveying

Out of the 126 sites sampled for *H. gratiosa* calls, 31 sites overall were positive for *H. gratiosa* presence via calls being heard. There were 23 out of 63 historic sites with auditory presence, and 9 out of 63 predicted sites with auditory presence. Most of the sites with presence were in western Tennessee, though a couple in the eastern and one in the north-central areas also were positive (Figure 2.9). Roughly, *H. gratiosa* was present at 34% of the historic sites; the proportion of positive predicted compared to the number of overall sites *H. gratiosa* was heard at was 29%.

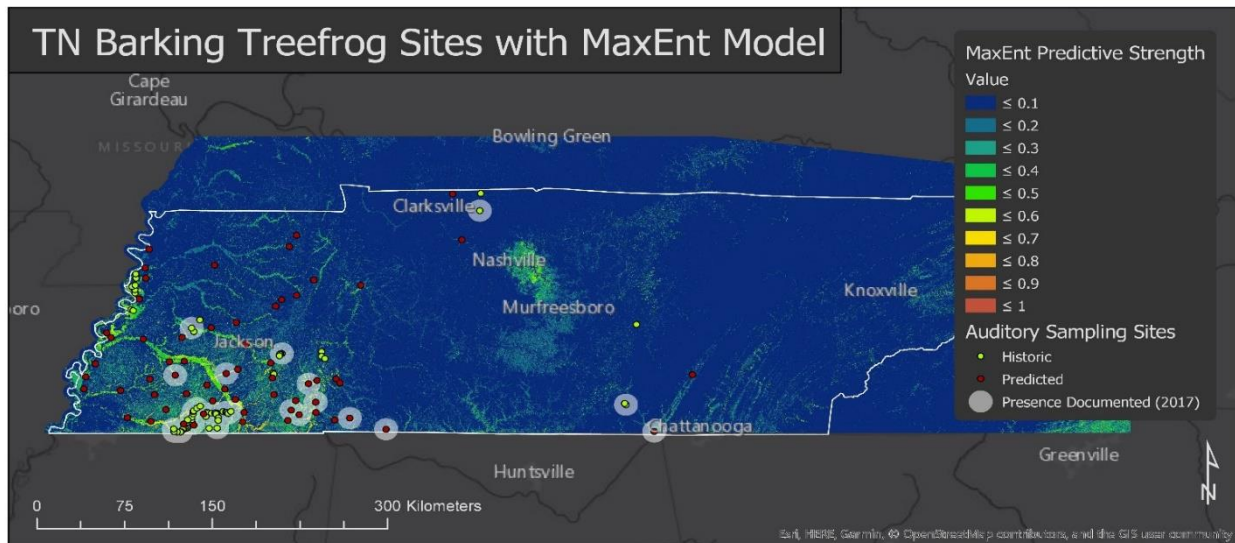


Figure 2.9 MaxEnt predicted model with 2017 results

In April, *H. gratiosa* was heard at three sites, two of which were based on the predicted model. The species was noticed to become more active when temperatures rose and in approximate timing to rain events. In May, temperatures increased and *H. gratiosa* was noted calling at 6 sites; there also was a flood event during that month that may have impacted calling activity. June and July were the peak months of calling, rising to around 20 sites in all each month and a mix of historic and predicted sites were positive (Figure 2.10). Calling activity

occurred at an average temperature of 74°F (23.3°C), with a minimum was 65°F (18.3°C) and maximum of 83°F (28.3°C), again displaying a warm-natured preference.

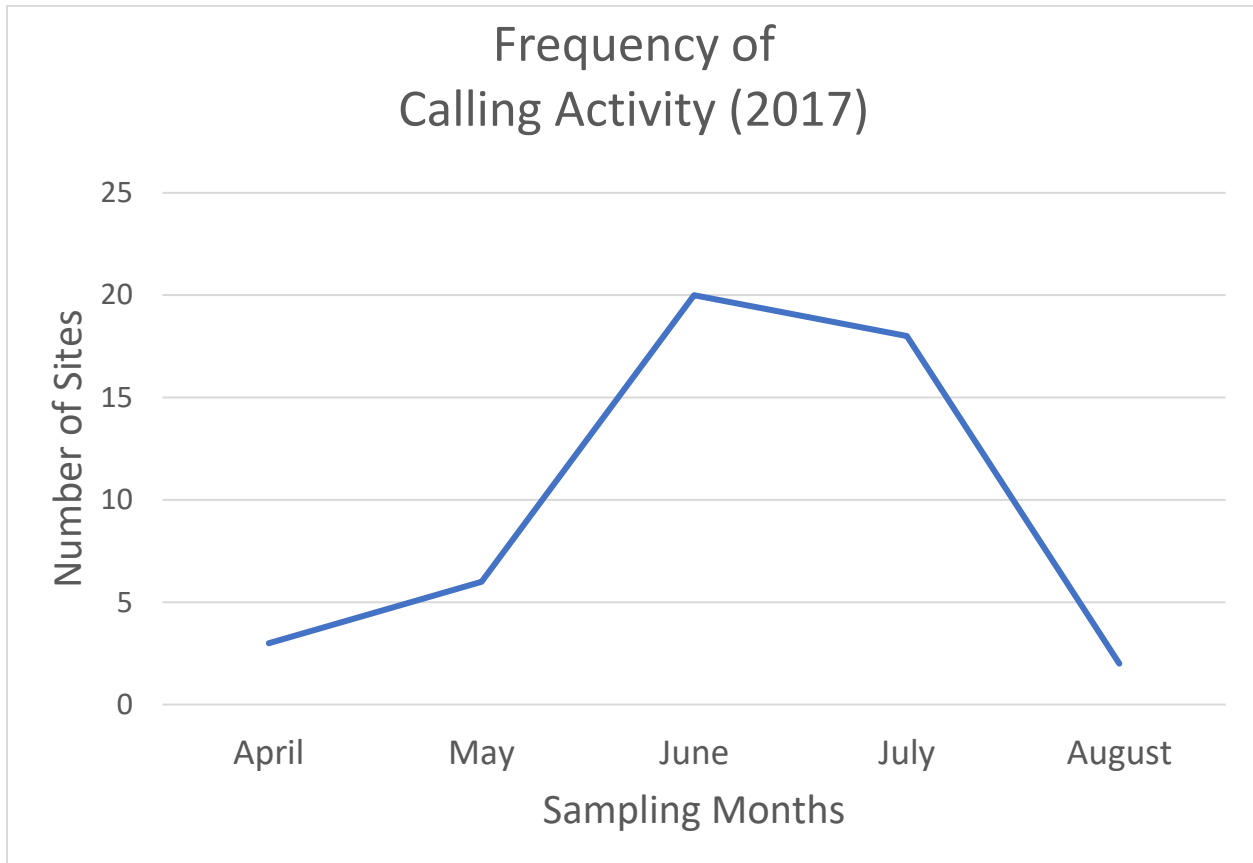


Figure 2.10 Graph of *H. gratiosa* calling activity during Summer 2017

In many cases, if not almost all, *H. gratiosa* was observed to be chorusing with other anuran species, often at least two or more species. Vocal anuran community structures were apparent in association with the presence of the study species. Any breeding territory that did exist approximate to auditory presence were flooded pools, stable ponds, or lowland forest wetlands. At many sites, other anurans were calling without *H. gratiosa*, which showcased that breeding activity was taking place and that the sites were not completely devoid. Breeding

activity typically indicated a level of suitability in general for anurans, that certain pools were usable for them. The tendency for *H. gratiosa* to only be around specific areas was evident, as it was not heard repeatedly at as many sites across the state (see Appendix C). Only in certain regions was *H. gratiosa* heard more regularly, but even then it showcased itself to be much less common than species of sister taxa. The nine predicted sites with newly unveiled presence displayed certain aspects, which may further our understanding of suitable habitats to sustain this species and its communities (Table 2.3).

Table 2.1 Site Descriptions of Predicted Sites with Confirmed Presence

Site Name and Number	TN County	Site Description
1 – NewHope	Marion	Behind a small fire station; at a park that is in lowlands and is flooded; rural neighborhoods approximate; forestry surrounding
35 – Rogers	Fayette	Someone’s farm/agricultural property; pond present in one of the fields that <i>H. gratiosa</i> was calling from
77 - Overton	Hardeman	Big farm field; trees and forest patches nearby <i>H. gratiosa</i> was heard distantly but was a loud chorus
112 - Goadman/Dillon	McNairy	Rural residential; heard <i>H. gratiosa</i> calling from someone’s backyard; pond present and trees nearby
113 – Pickett/TN142	McNairy	Near a suburban neighborhood; very rural; lowland forest and fields nearby, where calling was heard from
115 – McCull	Hardin	Forested lowland; suburban, yet rural area
122 - Lacefield	Hardin	The edge of a residential strip, this had lowland woods near the rural neighborhood
125 – Beulah	Hardin	Very rural neighborhood; pond near house had <i>H. gratiosa</i> calling from; strong chorus
126 – George Olive	Wayne	Residential area surrounded by farm fields; ponds were in the vicinity of the listening location

Exploratory Regression Results

Paralleling Chapter 1, habitat tendencies between sites of species presence were investigated using spatial regression analysis. Exploratory regression showed that “shrub/scrub” land cover was once again 100% associated habitat cover type with *H. gratiosa*. However, due to the small sample size of HUC12s (n=17), significance could not be found between cover types, even with the added weight between watersheds. Given that only HUCs associated with citizen science and areas of new presence were considered for this section, the sheer number of areas for the test to consider were limited. The adjusted R² values were still very low, which indicated non-significance in the models produced by running the statistical tool.

Discussion

Observations: In and Out of the Field

While one of my tasks in this project was to perform a mass test of a predictive spatial model, conservation of this species would benefit from also performing in-depth site selection analysis in Tennessee, to gain a firmer understanding of the habitats this species selects. The usage of the sites discovered from this study may be useful for assessing habitat selection and usage, while also further addressing dispersal abilities and distribution. The species was not heard at 100% of the historic sites, meaning that either migrations have occurred from site to site or local extinctions are occurring. The full story of how this species behaves on the landscape is one that has yet to be explored.

Oftentimes, the sites that *H. gratiosa* was heard around were mainly rural-residential, which was likely due to the lowland condition they tend to be drawn to. These sites were clearly owned by people in the area, but their knowledge of the species existing approximate to them was not investigated. Field sampling with the predictive model sought to merely test and locate potential areas with *H. gratiosa* presence, seeking to address spatial questions. To preserve these habitats for this species even more, federal agencies such as TDEC and TWRA should consider approaching landowners in regard to *H. gratiosa* on their land, to collaborate toward conservation. If *H. gratiosa* is repeatedly residing on their property, the presence is indicative that the habitat is apparently suitable and landowners have not degraded it too severely.

Observing how citizen science data performs in predictive modeling was enlightening and inspiring for future projects. The fact that a model led me to precise locations of *H. gratiosa* presence based off of spatial data revealed that there is always something new to explore with

any amount of information that has been gathered. Modeling and citizen science truly have the capacity to be used together, so long as it is correctly and toward a feasible goal.

Limitations, Biases, and Reflections

The modeling efforts performed in this chapter were useful in being able to broadly assess *H. gratiosa* presence throughout the state of Tennessee. However, while citizen science data provided precise points to utilize, the locations of the points often clustered together (due to the fact that these points were already parts of routes). Spatial clustering can create an element of bias, which does not allow data to be gathered as even or uniform as it could be. For statistical robustness, even more watersheds with *H. gratiosa* presence would be needed to properly assess broad habitat selection and increase the adjusted R^2 values pertaining to models (Bailey et al., 2007).

Going out to randomized locations was one of the potential solutions to mending the bias of clusters (MacKenzie et al., 2003). Even so, the act of carrying out that plan came with a cost, as visiting randomized locations became very time consuming every night. In future attempts of this approach, it may be better to have randomized sites within a certain distance, so as to not create routes that are unfeasible or dangerous to traverse in a limited time window.

Site selection with GARP and BIOCLIM would have caused other issues with sampling, if used instead of MaxEnt. While both programs were able to construct broadly accurate range maps, using those in the field would not have been practical. Similarly, while InVEST has a workable approach in mind for conserving habitat, the result still becomes too broad; the ideal input for the program also must be very precise for the species. MaxEnt was able to point out very precise locations to sample without creating too many complications, hence its usage for the

field testing. But even as MaxEnt is able to direct researchers to particular places, there is still much to learn when actually in the field.

At certain study sites, accessibility was sometimes temporarily an issue or certain aspects of the site became awkward. The act of listening to frogs for 5 minutes is not always seen with understanding eyes by local citizens, though it could be used as an engagement to the public. Otherwise, personal notes were made on how to approach each site in an optimal manner, so as to not be disturbed or to make people feel uncomfortable.

Conservation Speculations

Conservation of biodiversity is one of the most important tasks in amphibian species management, to ensure genetic flow and community survival. At multiple sites, diverse frog choruses were noted to occur alongside *H. gratiosa*, which caused me to ponder its function as an “umbrella species” for conservation purposes. Due to *H. gratiosa*’s particular habitat requirements, according to literature, the species may have the ability to locate habitats also ideal for other species. For future studies, the “umbrella species” nature of *H. gratiosa* needs to be explored and understood further, as it may benefit conservation of multiple species (Fleishman et al., 2005; Hernandez et al., 2006).

Seeing the capacity at which *H. gratiosa* was living in, being in suburban developed landscapes, was enlightening to what the species may be able to tolerate. Compared to other species, their ability to withstand disturbances was questionable, but they may be capable of adapting to human disturbance. Again, gaining a full scope of their dispersal ability and specific requirements other than the status quo would improve the conservation of this species.

Conclusions

The research in this chapter sought to create predictive models from accumulated citizen science data, in an effort to understand the distribution of the rare *H. gratiosa* in Tennessee further. The questions posed earlier are able to be addressed, given the amount of information gathered in the process of this project.

As shown from the qualitative aspects of MaxEnt, GARP, BIOCLIM, and InVEST, one predictive modeling scenario stood out as most precise about the rest: MaxEnt. Literature supported this program being the most reliable, and this study too can fortify that statement. While the other modeling scenarios have potential to be used in research, MaxEnt was practical for taking into the field and for assisting in the conservation of *H. gratiosa*.

The utility of citizen science data can sometimes be viewed with mixed emotions by researchers, but sources that have been gathering data with consistency and precision show themselves as valid options in the field of science. As TAMP has consistently kept its volunteers trained and on protocol, the data hosted becomes ideal for a presence modeling project. With the utility of citizen science data through TAMP and predictive modeling, several previously undocumented locations for *H. gratiosa* in Tennessee were discovered and can be monitored in future research. The continued use of citizen science for modeling should maintain its momentum, as we keep in mind the needs of conservation for the future.

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APPENDIX A

PYTHON SCRIPT DEVELOPED FOR “EXTRACT BY MASK” BATCH


```

import arcpy

workspace = arcpy.GetParameterAsText(0)
raster = arcpy.GetParameterAsText(1)
vector = arcpy.GetParameterAsText(2)
idField = arcpy.GetParameterAsText(3)
extractPrefix = arcpy.GetParameterAsText(4)

rows = arcpy.SearchCursor(vector)
row = rows.next()
i = 0 #Depending on the desired starting position, this number can change.
    #The variable i must match with j for data management purposes.
j = 1100000
while row:
    outname = (extractPrefix + str(j))
    query = (idField + ' = ' + str(i))
    selection = arcpy.SelectLayerByAttribute_management(vector,"NEW_SELECTION",query)
    outraster = arcpy.sa.ExtractByMask(raster,selection)
    outraster.save(outname)
    arcpy.AddMessage(outname + " has been saved in the gdb!")
    i = i + 1
    j = j + 1
    row = rows.next()
arcpy.AddMessage("It's done!")

```

APPENDIX B

PYTHON SCRIPT DEVELOPED FOR TRANSFERRING
RASTER TABLE VALUES TO VECTOR TABLE

```

import arcpy

arcpy.env.workspace = arcpy.GetParameterAsText(0)
arcpy.env.outputOverwrite = True

vectortable = arcpy.GetParameterAsText(1)

rasterList = arcpy.ListRasters()
rows2 = arcpy.UpdateCursor(vectortable)
row2 = rows2.next()
for raster in rasterList:
    try:
        rows = arcpy.SearchCursor(raster)

        for row in rows: #Need to figure out how to iterate through each row in each raster table

            lcover = row.LAND_COVER
            lcount = row.COUNT
            lvalue = row.VALUE
            print (raster, lvalue, lcover, lcount, " data captured.")

            if lcover == 'Open Water':
                row2.Open_Water = lcount
                rows2.updateRow(row2)
            elif lcover == 'Developed, Open Space':
                row2.D_OpenSpace = lcount
                rows2.updateRow(row2)
            elif lcover == 'Developed, Low Intensity':
                row2.D_LowIntens = lcount
                rows2.updateRow(row2)
            elif lcover == 'Developed, Medium Intensity':
                row2.D_MedIntens = lcount
                rows2.updateRow(row2)
            elif lcover == 'Developed, High Intensity':
                row2.D_HighIntens = lcount
                rows2.updateRow(row2)
            elif lcover == 'Barren Land':
                row2.BarrenLand = lcount
                rows2.updateRow(row2)
            elif lcover == 'Deciduous Forest':
                row2.DecidForest = lcount
                rows2.updateRow(row2)
            elif lcover == 'Evergreen Forest':
                row2.EverForest = lcount
                rows2.updateRow(row2)
            elif lcover == 'Mixed Forest':

```

```

        row2.MixedForest = lcount
        rows2.updateRow(row2)
    elif lcover == 'Shrub/Scrub':
        row2.ShrubScrub = lcount
        rows2.updateRow(row2)
    elif lcover == 'Herbaceous':
        row2.Herbaceous = lcount
        rows2.updateRow(row2)
    elif lcover == 'Hay/Pasture':
        row2.HayPasture = lcount
        rows2.updateRow(row2)
    elif lcover == 'Cultivated Crops':
        row2.CultiCrops = lcount
        rows2.updateRow(row2)
    elif lcover == 'Woody Wetlands':
        row2.WoodyWet = lcount
        rows2.updateRow(row2)
    elif lcover == 'Emergent Herbaceous Wetlands':
        row2.EmHerbWet = lcount
        rows2.updateRow(row2)

    name = row2.OBJECTID
    print (name, " row has been updated with ", lcount)
row2 = rows2.next()

except NameError:
    pass
    row = rows.next()
    row2 = rows2.next()
except AttributeError:
    pass
    row = rows.next()
    row2 = rows2.next()

del lcover
del lcount
del row
del rows
del row2
del rows2

```

APPENDIX C

DATA SHEETS FROM AUDITORY SAMPLING - 2017

SITE_ID	SITETYPE	APRL	MAY	JUNE	JULY	AUG	OTHERS?	LONGITUDE	LATITUDE
1-NewHope	Predicted	0	3	2	3	0	Y	-85.658908	35.008169
2-LakeDimmick	Historic	0	3	1	0	0	Y	-85.87631123	35.19077638
3-Appletreewick	Historic	0	0	0	0	0	Y	-85.886197	35.199631
4-OldCreekWay	Predicted	0	0	0	0	0	Y	-85.364744	35.394813
5-Wilson	Historic	0	0	0	0	0	Y	-85.795189	35.736652
6-Chapmansboro	Predicted	0	0	0	0	0	Y	-87.137254	36.308099
7-OldWash	Historic	0	0	0	3	0	Y	-86.999557	36.503868
8-PortersChapel	Historic	0	0	0	0	0	Y	-86.991959	36.619633
9-Ironhorse	Predicted	0	0	0	0	0	Y	-87.20731754	36.61597915
10-LinkRd	Predicted	0	0	0	0	0	Y	-87.91364601	36.00175569
11-Rowland/Main	Predicted	0	0	0	0	0	Y	-88.27554507	36.0369883
12-Palmer22	Predicted	0	0	0	0	0	Y	-88.40723159	35.93363139
13-Ferguson	Predicted	0	0	0	0	0	Y	-88.568248	35.860547
14-US70	Predicted	0	0	0	0	0	Y	-88.52200858	35.90468773
15-HenryParis	Predicted	0	0	0	0	0	Y	-88.46343738	36.26276823
16-OdomParis	Predicted	0	0	0	0	0	Y	-88.40738	36.338657
17-Trimble	Predicted	0	0	0	0	0	Y	-89.0381953	36.1373828
18-TN79Ri	Predicted	0	0	0	0	0	Y	-89.54010468	36.24453128
19-Teemo	Predicted	0	0	0	0	0	Y	-89.5702171	36.11970436
20-Everett	Historic	0	0	0	0	0	Y	-89.643089	36.07827
21-TN104	Predicted	0	0	0	0	0	Y	-89.566129	36.049853
22-GR104	Historic	0	0	0	0	0	Y	-89.640991	36.050289
23-Bradley	Historic	0	0	0	0	0	Y	-89.647278	36.001751
24-GR_B	Historic	0	0	0	0	0	Y	-89.670586	35.992832
25-GR_P	Historic	0	0	0	0	0	Y	-89.650192	35.971279
26-Chic	Historic	0	0	0	0	0	Y	-89.648781	35.948334
27-Suggs	Predicted	0	0	0	0	0	Y	-89.61622297	35.90856828
28-Barr1	Historic	0	0	0	0	0	Y	-89.662849	35.830433
29-Barr2	Historic	0	0	0	0	0	Y	-89.678215	35.837101
30-CrawfordCrutcher	Predicted	0	0	0	0	0	Y	-89.83329386	35.6480035
31-CrutcherLake	Predicted	0	0	0	0	0	Y	-89.86650591	35.68016056
32-Lovelace	Predicted	0	0	0	0	0	Y	-89.584963	35.637047
33-Stewart	Predicted	0	0	0	0	0	Y	-89.760588	35.288403
34-TN59	Predicted	0	0	0	0	0	Y	-89.5355848	35.36515468
35-Rogers	Predicted	0	0	0	2	0	Y	-89.340099	35.39193
36-TN76	Predicted	0	0	0	0	0	Y	-89.2702778	35.48683856
37-TN100	Predicted	0	0	0	0	0	Y	-89.095501	35.325792
38-Armour	Predicted	0	0	0	0	0	Y	-89.253094	35.266049
39-Stevens	Predicted	0	0	0	0	0	Y	-89.499216	35.258531
40-TN193	Predicted	0	0	0	0	0	Y	-89.411415	35.157594
41-Johnson	Predicted	0	0	0	0	0	Y	-89.52674942	35.07693015
42-Bethany	Predicted	0	0	0	0	0	Y	-89.707015	35.102693
43-Bates1	Historic	0	0	0	2	0	Y	-89.351311	35.025749
44-Bates2	Historic	0	0	2	0	0	Y	-89.348389	35.007381
45-Yager1	Historic	0	0	3	0	0	Y	-89.326378	35.004879
46-Yager2	Historic	0	0	1	0	1	Y	-89.300194	35.004841
47-Beas1	Historic	0	0	0	0	0	Y	-89.295128	35.007622
48-Beas2	Historic	0	0	0	0	0	Y	-89.282738	35.022228
49-Beas3	Historic	0	0	0	0	0	Y	-89.2724	35.026939
50-Beas4	Historic	0	0	0	0	0	Y	-89.259781	35.0275
51-Yager3	Historic	0	0	0	0	0	Y	-89.247078	35.031738
52-Sims	Predicted	0	0	0	0	0	Y	-89.275322	35.058626
53-TN57	Predicted	0	0	0	0	0	Y	-89.19744717	35.05132021
54-Buf1	Historic	0	0	1	0	0	Y	-89.204353	35.059689

SITE_ID	SITETYPE	APRIL	MAY	JUNE	JULY	AUG	OTHERS?	LONGITUDE	LATITUDE
55-Buf2	Historic	0	0	0	2	0	Y	-89.208549	35.06744
56-Buf3	Historic	0	0	0	1	0	Y	-89.213608	35.077492
57-Buf4	Historic	0	0	0	0	0	Y	-89.213097	35.089039
58-LaGrange	Historic	0	0	0	0	0	Y	-89.244812	35.087509
59-Buf5	Historic	0	0	2	0	0	Y	-89.213501	35.104328
60-MtCom1	Historic	0	0	0	0	0	Y	-89.201782	35.128109
61-Harvey	Historic	0	0	0	0	0	Y	-89.201767	35.14439
62-MtCom2	Historic	0	0	1	0	0	Y	-89.19767	35.149921
63-MtCom3	Historic	0	0	1	0	0	Y	-89.174133	35.167381
64-Middleburg	Historic	0	0	0	0	0	Y	-89.147713	35.18084
65-VanBuren	Predicted	0	0	0	0	0	Y	-89.05185	35.216589
66-Benjestown	Predicted	0	0	0	0	0	Y	-90.04110223	35.29916085
67-JackHill/RiverBluff	Predicted	0	0	0	0	0	Y	-90.02773467	35.38066756
68-Pryor	Predicted	0	0	0	0	0	Y	-89.95326117	35.46979685
69-TN70_2	Predicted	0	0	0	0	0	Y	-89.38386332	35.48412302
70-Tibbs	Predicted	0	0	0	0	0	Y	-89.28700187	35.64836056
71-Sturdivant	Historic	0	0	0	0	0	Y	-89.196739	35.68782
72-TN54	Historic	0	0	2	2	0	Y	-89.213966	35.712391
73-Randolph	Historic	0	0	0	0	0	Y	-89.150261	35.76783
74-TN88	Predicted	0	0	0	0	0	Y	-89.06357	35.714868
75-DeLoach	Predicted	0	0	0	0	0	Y	-88.871095	35.750154
76-Swink	Predicted	0	0	0	0	0	Y	-88.859666	35.431418
77-Overton	Predicted	0	0	2	1	0	Y	-88.948567	35.403285
78-TN18	Predicted	0	0	0	0	0	Y	-88.959051	35.29689
79-Hornsby	Predicted	0	0	0	0	0	Y	-88.877826	35.226764
80-Hebron	Historic	0	0	2	2	0	Y	-88.912117	35.1446
81-LH1	Historic	0	1	0	0	0	Y	-88.932861	35.13142
82-LH2	Historic	0	0	0	0	0	Y	-88.94162	35.138401
83-LH3	Historic	0	0	2	0	0	Y	-88.951736	35.139778
84-LH4	Historic	0	0	0	0	0	Y	-88.972687	35.143799
85-LH5	Historic	0	0	0	0	0	Y	-89.021423	35.134449
86-LH6	Historic	0	0	0	0	0	Y	-89.025551	35.133862
87-Cal1	Historic	0	0	0	2	0	Y	-89.030746	35.13467
88-Cal2	Historic	0	0	0	0	1	Y	-89.026329	35.126961
89-LH7	Historic	0	0	1	2	0	Y	-89.035347	35.134781
90-LH8	Historic	0	0	2	1	0	Y	-89.060593	35.132881
91-LH9	Historic	0	0	0	0	0	Y	-89.084091	35.1353
92-LH10	Historic	0	0	0	0	0	Y	-89.097351	35.139481
93-Futrell	Predicted	0	0	0	0	0	Y	-89.1216	35.127258
94-Edwin	Historic	0	0	0	0	0	Y	-89.10463	35.10968
95-OldStateLn	Historic	0	0	0	0	0	Y	-89.079353	35.029678
96-Crestwood/OldStateLn2	Historic	0	0	0	2	0	Y	-89.017906	35.030869
97-Cal3	Historic	0	0	0	0	0	Y	-89.008614	35.101921
98-Porter	Historic	2	0	1	2	0	Y	-89.010193	35.083698
99-Peavine	Predicted	0	0	0	0	0	Y	-88.81992632	35.07319546
100-PowellChapel	Predicted	0	0	0	0	0	Y	-88.81054659	35.13783584
101-RoseHill	Predicted	0	0	0	0	0	Y	-88.581815	35.259665
102-Young	Predicted	0	0	0	0	0	Y	-88.592613	35.373669
103-TarCreek	Historic	0	0	0	0	0	Y	-88.58213	35.399288
104-OakGrove	Historic	0	0	0	0	0	Y	-88.588051	35.40641
105-TN200	Predicted	0	0	0	0	0	Y	-88.60593	35.475203
106-Clifford	Historic	0	0	0	0	0	Y	-88.539368	35.523762
107-Tignors	Historic	0	0	0	0	0	Y	-88.536613	35.533901
108-MFR1	Historic	0	0	0	0	0	Y	-88.530312	35.538872

SITE_ID	SITETYPE	APRIL	MAY	JUNE	JULY	AUG	OTHERS?	LONGITUDE	LATITUDE
109-MFR2	Historic	0	0	2	0	0	Y	-88.519913	35.539661
110-Commerce	Predicted	0	0	0	0	0	Y	-88.79567424	35.60396097
111-Olene	Predicted	0	0	0	0	0	Y	-88.47383	35.083303
112-Goadman/Dillon	Predicted	3	0	0	2	0	Y	-88.38668157	35.12240014
113-Pickett/TN142	Predicted	3	1	2	1	0	Y	-88.44835626	35.15403414
114-TN15/64	Predicted	0	0	0	0	0	Y	-88.414387	35.218754
115-McCull	Predicted	0	0	2	0	0	Y	-88.315438	35.333919
116-Sulphur	Predicted	0	0	0	0	0	Y	-88.250651	35.355774
117-CrawfordSchool	Historic	0	0	0	0	0	Y	-88.189827	35.504963
118-JoeTill	Historic	0	0	0	0	0	Y	-88.215614	35.520119
119-MtZion	Historic	0	0	0	0	0	Y	-88.21492	35.551842
120-Oakley	Predicted	0	0	0	0	0	Y	-88.10383637	35.36666615
121-CreekRidge	Predicted	0	0	0	0	0	Y	-88.07422057	35.33965624
122-Lacefield	Predicted	0	2	0	2	0	Y	-88.26040746	35.20810514
123-SunsetDr	Predicted	0	0	0	0	0	Y	-88.25761169	35.13734639
124-Holland	Predicted	0	0	0	0	0	Y	-88.114839	35.086878
125-Beulah	Predicted	0	1	2	1	0	Y	-87.998364	35.09963
126-GeorgeOlive	Predicted	0	0	0	2	0	Y	-87.71965496	35.02299955

VITA

Nyssa Hunt was born in Naples, Italy to the parents of Carl and Esther Hunt. She is the third of four children, having two older sisters and a younger sister. She primarily attended Big Ridge Elementary and continued to Hixson Middle and High Schools in Hixson, Tennessee. After graduation, she attended the University of Tennessee at Chattanooga, where she initially began studies in computer science, but eventually found her niche in Geographic Information Systems and amphibian conservation. Nyssa completed a Bachelor's of Science degree in December 2014 in Environmental Science with a concentration in Cartographic and Geographic sciences before entering the University of Tennessee at Chattanooga's Master of Environmental Science program. Nyssa graduated with a Master of Science degree in Environmental Science in August 2018. She anticipates continued work with conservation GIS and big data analytics.