AN ASSESSMENT OF HABITAT SUITABILITY MODELING USING GEOSPATIAL TOOLS FOR A THEORETICAL RIVER OTTER POPULATION

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ABSTRACT

Predictive niche modeling is an essential tool in effectively managing and conserving wildlife habitats. With environmental and landscape data, we can determine and assign priority areas for conservation efforts targeting the North American river otter (*Lontra canadensis*) in east Tennessee and beyond. The focus of the present study is the relationship between otters and land cover. Using citizen-science, an analysis was conducted using ArcGIS and Maxent to determine potential habitat for river otters using presence-only data. The results of this study detail a habitat suitability map for river otters in east Tennessee, indicating a strong positive correlation between mixed forest land cover and otter presence. This information can be expounded on with further field testing and utilized by state officials in managing wildlife. As river otters are indicators of stream ecosystem health, maintaining habitat that is suitable to *L. canadensis* would also mean providing quality habitat for many riparian species.

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only through this research and writing process, but also through every aspect of life. He always pushes me to do my best, pursue what I think is unachievable and care for myself through rest and reflection along the way.

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CHAPTER I

INTRODUCTION

Predictive niche modeling is an essential tool in effectively managing and conserving wildlife habitat and populations. It utilizes presence-only occurrence data, along with larger scale environmental factors that meet the ecological needs of a given species over large spatial extents, to predict the relative suitability of a habitat for that species (Woolf et al. 1997; Rotenberry et al. 2006; Warren and Seifart 2011; McCallen et al 2018). The loss of any species and its value is incalculable, due to the important and complex role biodiversity plays in ecosystem function; and therefore, any tool aiding in conservation effort is important (TVA v. Hill 1978; Groombridge and Jenkins 2002; Alvey 2006). The Anthropocene extinction – Earth's "sixth extinction wave," driven by humans and resulting in a decrease in biodiversity and elevated extinction rates – has demonstrated that the primary predators that threaten many mammals are human beings (Dirzo et al. 2014; Pievani 2014; Bellamy et al. 2020;). Anthropogenic threats include habitat loss and degradation, over-exploitation, and pollution (Pievani 2014; Solari et al. 2016). Prior to the 20th century, extending as far back as the earliest human colonization of the continent, North American mammals have been overharvested and eradicated from their former ranges by humans (Alroy 2001; Mosimann and Martin 1975; Ceballos and Ehrlich 2002; Reid 2006). In the southeastern U.S., these species included cougar, red wolf, black bear, and the North American river otter (*Lontra canadensis*) (Phillips and Parker 1988; Van Dyke et al. 1986; Simek et al. 2012; Bluett et al. 1999; Raesley 2001; Reid 2006).

Using predictive ecological niche modelling, species distribution and habitat suitability can be estimated and modelled using GIS analysis (Woolf et al., 1997; Rotenberry et al. 2006; Warren and Seifart 2011; Holland & van der Merwe 2016; McCallen et al 2018; Freeman et al. 2019; Bellamy et al. 2020). Niche modeling is useful in guiding conservation and management for mammalian species, as it provides a tool with which to determine areas of focus for conservation efforts, allowing for the most efficient use of time and money (Rotenberry et al. 2006; Warren and Seifart 2011; McCallen et al 2018; Freeman et al. 2019; Bellamy et al. 2020). This tool can be used for Environmental Impact Statements under the National Environmental Policy Act (NEPA), as it is stated in Section 101 “to use all practicable means and measures, including financial and technical assistance, in a manner calculated to foster and promote the general welfare, to create and maintain conditions under which man and nature can exist in productive harmony, and fulfill the social, economic, and other requirements of present and future generations of Americans" (NEPA 1970, p. 1).

Additionally, we can use this as a tool to determine habitats under threat by development, agriculture, etc. These can be singled out to help mitigate ongoing and future threats to species, as well as to identify areas that are potentially suitable for reintroduction programs and expansion of current populations (Woolf et al. 1997; Thierry & Rogers 2020).

A niche model is created by combining presence-only occurrence data with larger scale environmental factors that relate to the species’ ecological requirements over large geographic areas, to predict the relative suitability of a habitat and its potential significance for that species (Rotenberry et al. 2006; Warren and Seifart 2011; McCallen et al 2018; Freeman et al. 2019;

Bellamy et al. 2020). This differs from a range-map in that it delineates habitat where the species *may* or *could* occur, rather than where it is already known to occur (USDA NRCS 2009). Environmental factors are chosen based on prior niche modeling studies, as well as a review of literature pertaining to the known ecology of the species (Rotenberry et al. 2006; Warren and Seifart 2011; McCallen et al 2018; Freeman et al. 2019; Bellamy et al. 2020). Through the analysis of environmental factors, e.g., elevation, climate, land cover, vegetation, etc., that are particularly important for a given species' success, a model can be created using ArcGIS Pro (2019) that delineates the degree of suitability on a linear scale across a given geographic range, and plots this on a detailed map (Woolf et al. 1997; Rotenberry et al. 2006; Warren and Seifart 2011; McCallen et al 2018; Freeman et al. 2019; Bellamy et al. 2020).

Study Organism

Lontra canadensis is a cryptic, medium-sized semi-aquatic mammal in the Family Mustelidae, occurring throughout much of the Pacific northwest and the eastern United States, extending northwards into Canada and Alaska (Reid 2006). In the 19th and early 20th centuries, river otters and other furbearers were eliminated from much of North America due to fur trapping and to human population expansion and accompanying land use changes, which led to habitat loss (Toweill and Tabor 1982; Bluett et al. 1999; Raesley 2001; Reid 2006). Ongoing threats to the river otter include anthropogenic issues such as pollution, reduced prey availability due to overharvest, and habitat destruction, whereas non-anthropogenic issues are limited (Gomez et al. 2014).

River otters are considered apex predators in the stream and riparian zone ecosystems that they inhabit (Holland & van der Merwe 2016). Given this status, river otters have the potential to be ecologically important in their riparian ecosystems (Holland & van der Merwe 2016). Apex predators play a crucial role in the systems in which they exist, strongly influencing trophic dynamics and thereby affecting overall biodiversity (Estes et al. 1998; Palomres and Caro 1999; Terborgh et al. 2001; Heithais et al. 2008; Sergio and Hiraldo 2008; Ritchie and Johnson 2009). Unfortunately, population sizes among apex predators have decreased globally due to anthropogenic effects (Berger et al. 2001; Ritchie and Johnson 2009). Adverse consequences from this worldwide decline are likely to occur due to top-down effects in individual ecosystem on trophic dynamics and community organization, including increases in mesopredators, pest problems, and threats to and extinction of vulnerable prey species (Polis and Holt 1992; Courchamp et al. 1999; Baum and Worm 2009; Ritchie and Johnson 2009; Morris 2017). These effects have been noted for other mammalian predator species, e.g., gray wolves in Yellowstone and sea otters in the Pacific northwest (Estes et al. 2016; Boyce 2018). Additionally, as apex predators, river otters can also serve as indicator species, with the bioaccumulation of toxicants and pollutants, along with the biomagnification of some heavy metals, including mercury (Sleeman et al. 2010; Carpenter et al. 2014), in their tissues serving as a measure of the prevalence of these chemicals in the ecosystem and therefore of overall ecosystem health (Carpenter et al. 2014; Crowley and Hodder 2019).

For these reasons, understanding river otter occurrence and habitat use can have important implications not just on reintroduction efforts for this species, but also on more general efforts at habitat restoration or biodiversity conservation (Glen and Dickman 2005; Sergio et al. 2008; Probst and Gustafon 2009; Ritchie and Johnson 2009).

Conservation and management of this species could be critical for maintaining the health of riverine and riparian ecosystems in east Tennessee. However, given the absence of sufficient detailed information regarding river otter populations in this area, conservation and management goals are difficult to achieve (Field 1978; Eagar and Hatcher 1980). Yet, due to the difficulty of detecting the presence of the cryptic river otter, state and local agencies in east Tennessee do not keep a record of the distribution and abundance of this species (Field 1978; Eagar and Hatcher 1980; Ellington et al. 2018).

In 1979, river otters were added to Appendix II by the Convention on International Trade in Endangered Species (CITES), prompting state governments in the U.S. to assess the status of river otters within their political boundaries (Griess 1987). Many states began restoration and reintroduction programs, including Tennessee, prompted by the National Park Service's initiative to reintroduce once native species to the Great Smoky Mountains National Park (GSMNP) region (Wright and Thompson 1935). The Tennessee Valley Authority (TVA), the Tennessee Wildlife Resources Agency (TWRA), the University of Tennessee, and the National Park Service (NPS) all participated in planning the river otter reintroduction program to GSMNP, using a previous study on North American beaver reintroduction from NPS, in which potential habitat was assessed for river otter (Griess 1987). In proceeding with the otter reintroduction program, the collaborating organizations aimed to not only monitor and maintain the newly introduced population, but also create guidelines for future river otter management throughout the GSMNP (Griess 1987).

Presently, there are few data available to inform managers and the public about the occurrence of *Lontra canadensis* in most of east Tennessee (R. Applegate and J. Akins, personal communication, 2019; Georgia Museum of Natural History 2019). As niche models can mitigate the lack of information available through predictive analysis, the creation of a niche model for this species would serve as a novel and important tool for management and conservation professionals in proactive measures (Woolf et al., 1997; Holland & van der Merwe 2016; Freeman et al. 2018). This model could be used to determine where surveying efforts can be focused to determine population presence and abundance; identify suitable habitat where the population is likely to expand on its own and identify sites where a reintroduction effort is likely to be successful.

Hypotheses

The hypotheses of this study are as follows:

(I) Water quality will be high where otters occur, i.e. low turbidity, low salinity, relatively low conductivity and total dissolved solutes, high dissolved oxygen and neutral pH;

(II) Environmental factors, such as land cover and geographical features, necessary to provide suitable habitat for *Lontra canadensis* in east Tennessee can be identified and used to create a habitat suitability model and

(III) Environmental data collected at sites where otter presence has been confirmed through citizen science and manipulating ArcGIS layers to obtain data on land cover and other physical and ecological aspects of each site will provide key components of the habitat suitability model; and

(IV) Using these data to create a habitat suitability model for *L. canadensis* in east Tennessee using ArcGIS and Maxent will provide useful information for the future conservation and management of river otters in Tennessee.

This study is significant, in that it will provide a useful tool for conservation managers so that they can determine the most efficient use of time and money in any efforts to survey for current populations, manage those populations, and perhaps even reintroduce *L, canadensis* to new areas in Tennessee, although there are not currently any such efforts underway (TWRA 2007). *L. canadensis* is not currently listed as a species of concern according to the Tennessee Wildlife Resources Agency, U.S. Fish and Wildlife Service, or IUCN Red List, but it was listed as endangered or extinct in certain regions of the U.S. as recently as the 1980s, including Tennessee (Griess 1987). My approach will allow for proactive management and conservation measures to be taken at the local level, rather than relying on outdated or continent-level data (Griess 1987; TWRA 2007; USFWS; Serfass et al. 2014; Serfass et al. 2015). This research can show where otter population and other ecological surveys should be conducted. These surveys may then allow refinement of the model presented here, because as we better understand the factors important in determining otter habitat choice in east Tennessee, we can start to look at differences in various environmental factors between areas where they are and are not found.

CHAPTER II

MATERIALS AND METHODS

Initial Efforts

Before conducting the field work that was ultimately used to create the niche model and conduct statistical analysis, I aimed to use camera trapping as a means to determine otter presence at potential suitable habitat sites in the Greater Chattanooga Area. Camera trapping has been shown to produce higher detection rates than physical survey data alone (i.e., physical trapping, searching for and recording sign, etc.), and I was interested in the effect of water quality of the Lower Tennessee River Watershed on otter presence (Rovero et al. 2014; Trolliet et al. 2014; Day et al. 2016).

After seeking out current data from state managers, as well as historical museum data and raw data from similar previous studies, I was unable to identify any usable material for this project (R. Applegate and J. Akins, personal communication, 2019; Georgia Museum of Natural History 2019). Therefore, I sought out citizen science through word-of-mouth reports of otter presence from professional colleagues, though these were quite limited and left me with only 6 sites to examine.

Citizen science is the collection of additional data from the public or participating volunteers that helps researchers collect more data (increasing geographic and temporal coverage) than they could alone (MacPhail et al. 2019). This information can be shared among researchers and the public alike, reporting sightings of various plant and animal species, often accompanied by pictures, descriptions, and detailed locality information (Black 2009; MacPhail et al. 2019). Similar studies using locality information have successfully employed citizen science to monitor and collect information that many be unprocurable through field work alone, especially in regards to a cryptic species such as *L. canadensis* (Newman et al. 2003; Black 2009). Even with the error that can be introduced through citizen science, it has the potential to fill gaps in knowledge and sampling effort, which likely compensates for reduced accuracy in many cases (Gardiner et al. 2012; Specht and Lewandowski 2018).

In an effort to increase sample size, I randomly generated 24 more sites in the Greater Chattanooga Area using ArcGIS Pro 2.4 to reach a total of 30 sites (T. Gaudin, personal communication 2019). After testing water quality (see methodology below) and setting up cameras at 5 of the sites – 4 random and 1 site where otters were reported– I found no confirmation of otter presence, despite reviewing some 20,000 pictures obtained with the trail cameras over the span of one month. Due to the lack of success with this study design, I needed to alter my approach and field methods to complete my thesis project in a timely manner. Therefore, the remainder of this paper will focus only on the revised project, in which I relocated my study to the Great Smoky Mountains National Park and vicinity.

Study Site

This study utilizes riverine and riparian sites in the Great Smoky Mountains National Park (GSMNP) and surrounding areas of Blount and Sevier Counties to create a habitat suitability map for east Tennessee. GSMNP lies on the border of Tennessee and North Carolina and consists largely of mountains and valleys with slopes varying from 26.7 degrees to 80.1 degrees (NPS 2019). Aspect ranges between 0 and 120 degrees on eastern-facing slopes, 120 and 240 degrees on southern facing slopes, and 240 and 360 degrees on southeastern facing slopes (NPS 2019). The region gets between 124.5 and 241.3 cm of rain annually, with higher elevations receiving greater precipitation (NPS 2019). The majority of the region receives 1K to 1400KWH/m^2 of solar radiation, and land elevations in the study area range from 265.7 to 2024.6 m above sea level (NPS 2019).

River otters are typically found in low elevation, riparian forests of GSMNP, consisting of oak , hickory, maple, pine, spruce, fir, tulip poplar, mountain laurel, rhododendron, and hemlock (Miller 1992; GRSM GIS 2016; NPS 2019; GRSM GIS 2020). As noted above, there are no current official state records of *L. canadensis* abundance or distribution in this area. Therefore, my locations were selected based on observation data available through the citizen science program Otter Spotter on iNaturalist (Figure 1; GSMIT et al. 2015). Most of the observed sites were classified as “Research Grade,” meaning a picture of a river otter or associated sign is provided with the GPS coordinates and is then confirmed by at least two-thirds of the iNaturalist community of identifiers to be “river otter”. Additionally, I was able to view the associated photographs and confirm these as river otter or river otter sign myself. Using GPS points collected from these citizen science observations (Figure 1), I conducted field surveys in order to confirm otter presence at each location using sign survey, as both of these are nonintrusive methods in wide use for direct data gathering (Wilson et al. 1996; De Bondi et al. 2010; Roberts 2011; Findlay et al. 2017).

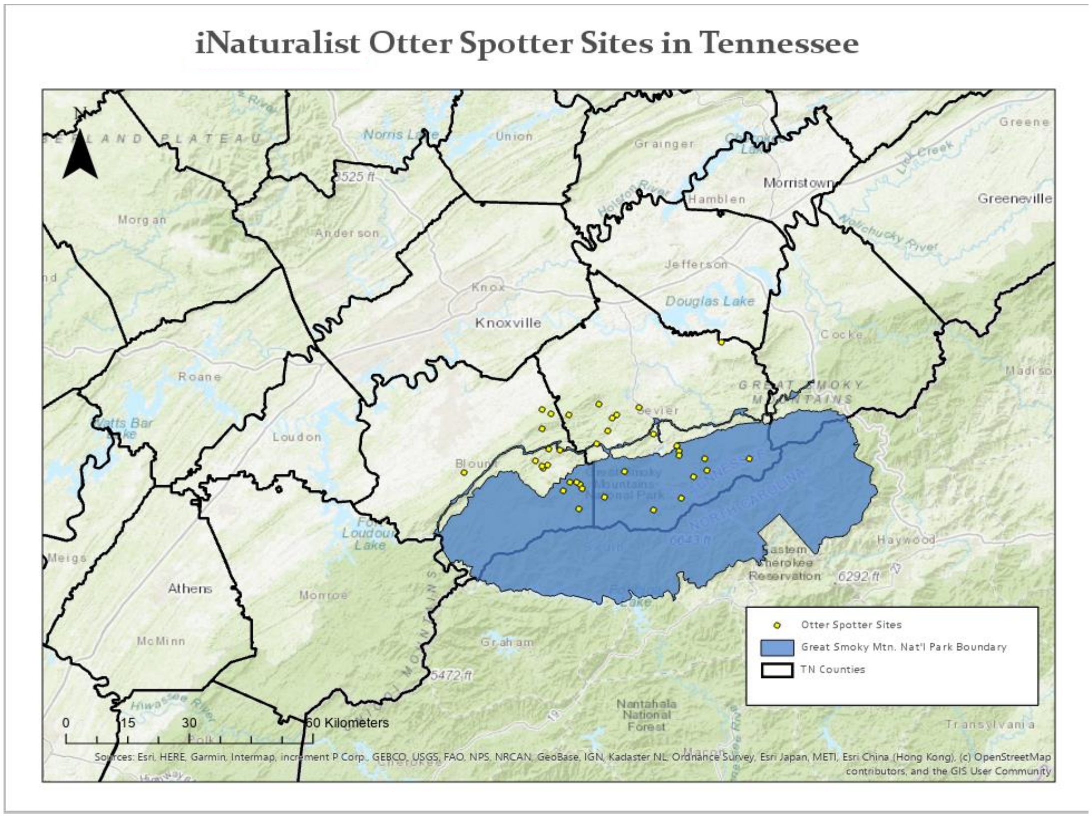


Figure 1 Map of western North Carolina and far eastern Tennessee (with counties delineated in the latter), and the Great Smoky Mountains National Park highlighted in blue. The yellow dots represent the location of river otter observations identified by the citizen science program, Otter Spotter on iNaturalist in and around Great Smoky Mountains National Park in Tennessee

Environmental Factors

Five environmental factors were examined in the present study: land cover, water quality, aspect, elevation and slope. Additional data such as bank cover and stream width were also collected at the survey sites. Water quality metrics, including salinity, pH, conductivity, total dissolved solutes, dissolved oxygen and turbidity, were measured one time per survey site , within a one month timeframe to mitigate seasonal variation, to determine their relationship to river otter habitat selection (detailed below). The remaining environmental factors – land cover, aspect, elevation, slope – were available as GIS layers, and were used to create a habitat suitability model for east Tennessee with ArcGIS and Maxent (Phillips et al. 2006).

Environmental factors measured at each of the survey sites comprised bank and land cover, aspect, slope, elevation, water quality, as each of these metrics have been widely used to determine habitat preference in other river otter studies, and were obtainable in our limited time frame (Griess 1987; Gomez et al. 2014; Godwin et al. 2015; Holland and van der Merwe 2016; Holland et al. 2016). I identified bank cover at each of the survey sites via direct observation, classifying cover type based on the primary plant species present (Woolf et al. 1997; Holland and van der Merwe 2016). GAP land cover, aspect, slope and elevation for the state of Tennessee were obtained from Hunt (2018).

Water quality and pollution have also been found to influence otter presence, suggesting the need for high water quality as an important factor in habitat suitability (Crowley & Hodder 2019; Woolf et al. 1997). Water quality was determined at each site by measuring pH, conductivity, total dissolved solutes, dissolved oxygen, and turbidity, as these are indicators of system health (Miller 2007). A multiparameter water quality meter (Apera Instruments PC60

Premium 5-in-1 Waterproof pH/Conductivity/Total Dissolved Solutes/ Salinity/Temp. Multi-Parameter Pocket Tester, Replaceable Probe) was used to determine pH, total dissolved solutes, conductivity, dissolved oxygen, and turbidity. The latter is particularly important because river otters are visual predators, and it has been suggested that turbidity and sediment pollution can play a role in diminishing predation efficiency, though whiskers can aid in predation in murky waters (Prigioni et al. 2006; Pennsylvania Game Commission 2014). Turbidity likely does not affect their food availability itself, though, as they have a varied diet from mussels and fish to frogs and small mammals (Griess 1987; Pennsylvania Game Commission 2014). The other factors were chosen following Gomez et al. (2014) and Prigioni et al. (2006), who showed that these water quality metrics affect otter habitat selection. To collect the metrics, I took small water samples from the survey sites using the collection cap of the meter (approximately 20 mL). I then inserted the measurement probe on site. Three samples were obtained at each site, one to measure pH, conductivity, total dissolved solutes and salinity; one to measure turbidity; and one to measure dissolved oxygen. Measurements were taken along the bank in undisturbed water to minimize suspended sediment levels. I did not collect data on stream flow, steam depth, or flow velocity, though stream width was noted, although this metric ended up not being used subsequently in the analyses or models.

Presence Detection

To evaluate the hypothesis that river otters prefer high quality habitat, i.e., habitat that is less disturbed by human development and has higher water quality factors, I sampled 21 riparian sites where otters have been reported in and around GSMNP, in Sevier and Blount counties in Tennessee, using the application Otter Spotter on iNaturalist which facilitates citizen science (Figure 2; GSMIT et al. 2015). All river otter sightings on iNaturalist in the state of Tennessee have occurred in and around Great Smoky Mountains National Park. This is likely due to the reintroduction program instituted there in the 1980s (Griess 1987).

Using the Otter Spotter, otter presence was indicated for 39 sites (Figure 1; GSMIT 2015). Twelve of these sites were located in inaccessible areas within the boundaries of the Great Smoky Mountains National Park, which had many entrances closed due to construction on a vehicular tunnel; therefore, these sites were not visited. Assuming there may be human error associated with this type of citizen science database, I eliminated those sites I could not visit personally from the analysis (Aceves-Bueno 2017; Specht and Lewondowski 2018). Visits to the remaining 27 sites revealed that only 21 of these actually represented habitat an otter could inhabit, i.e., were riparian sites on or near a stream (Figure 2). Each of the 21 sites used in the final analysis recorded otter presence in the past 2 years, according to citizen science and my own personal interviews with local business owners, fishermen and hunters in the area (Personal Communication 2020). Knowing this, I searched for otter sign, including latrines, dens, tracks, etc. to confirm reported sightings and investigate continuing presence at each site (Woolf et al. 1997; Schooley et al. 2012; Gomez et al. 2014; Scorpio et al. 2016). Additionally, I noted signs for the presence of mink and/or beaver, because the presence of these species is a good indicator of river otter presence (Woolf et al. 1997; Holland & van der Merwe 2016); and, therefore, can provide useful data.

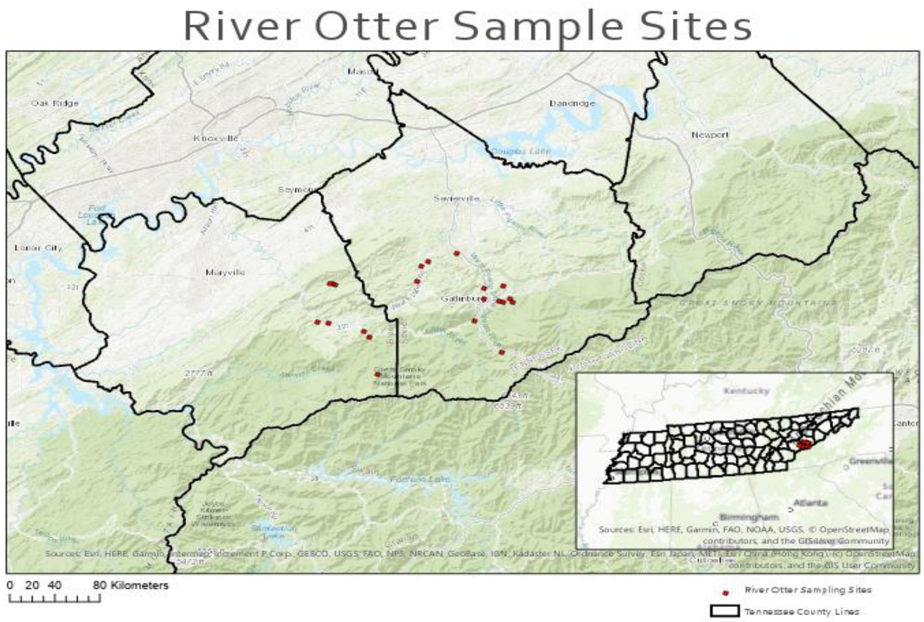


Figure 2 Map of east Tennessee counties, centered on Sevier and Blount counties, showing the 21 River otter observation sample sites (red circles) utilized in the present study. The inset map indicates the location of Sevier and Blount counties within the larger geographic scale of Tennessee

Creating the Models

Modeling ecological niche and distribution of a species requires both environmental data and georeferenced species occurrence data (Rotenberry et al. 2006; Warren and Seifart 2011; McCallen et al 2018; Freeman et al. 2019). Therefore, using the occurrence data collected from Otter Spotter, an ecological niche model can be created for the river otter in the east Tennessee. According to Woolf et al. (1997), PATREC, a pattern recognition habitat modeling method, allows the classification of habitat within the study site as either suitable or unsuitable for *L. canadensis* based on a specific set of environmental factors (Holland & Van Der Merwe 2016).

Using the locality data from iNaturalist and the aforementioned GIS layers, I created a suitability model using ArcGIS Pro and Maxent. Because Maxent is a useful tool when analyzing presence-only data, it is a good fit for this project (Elith et al. 2011). GPS coordinates with metadata including water quality measurements were added to ArcGIS Pro. Each layer – GAP land cover, elevation, slope, aspect and riparian habitat from the National Wetland Inventory– were clipped to include only Tennessee data, in order to reduce processing time, and resampled to ensure all layers were set to 30x30-meter cell size and projected on NAD 1983 Albers coordinate system (Hunt 2018). It should be noted that GAP land cover is used in the Maxent model, while NLCD land cover is used in our statistical analysis. This is because GAP provides a wider array of more specific land cover categories, allowing a finer model output. For use in Maxent, the raster layers were converted to ASCII format; the locality points were converted into .csv format, and a bias layer was created including Blount and Sevier counties, as they were the only counties sampled (Phillips et al. 2006; Young et al. 2011).

To render the Maxent model, it was necessary to ensure the locality coordinates of otter presence sites were in habitat (according to the land cover layer) that would be utilized by otters. For example, if a point fell on a land cover pixel that indicated development, the point was moved in ArcGIS Pro to the nearest pixel with the proper land cover, i.e. water. In addition to this data clean up, it was necessary to retrofit points that were not close enough to the water, as the citizen science users likely input the information from their car, rather than the actual site, rendering the GPS coordinates inaccurate. These steps were taken if a point fell on a road or parking lot, rather than in or near the waterway, to prevent land cover data from causing the model to be biased towards development and roads. Cross-validation was used to compensate for the small sample size, though a bootstrapping analysis was also run to resample the data randomly to confirm significant differences. Maximum iteration was set to 5000. Jackknifing was conducted to ensure the results were not dependent on one site. Response curves for each environmental variable were also generated for the output (Appendix A; Young et al. 2011). A 100-meter buffer was used around the riparian habitat in the map to provide a better visual aid.

Following the rendering of the model for east Tennessee, I also created a map for Blount and Sevier counties to provide a less biased and better visual representation of suitable otter habitat for the area, as all sample points were collected in these counties. I ran a model using cross-validation and another using bootstrapping, in order to compare the outputs (Appendix E). Again, a 100-meter buffer was used around the riparian habitat in the map to present a better visual representation on the map of potential habitat.

Statistical Analysis

Due to lack of knowledge regarding otter presence throughout east Tennessee, and lack of time and resources, I did not have the opportunity to construct a control sample or random samples for water quality data to compare streams with otter presence versus random streams or streams where otters were known to be absent. Instead, using the data collected at the observation sample sites, the Grubbs' Test for Outliers was run using R-4.0.0 software to detect outliers of for each of the water quality metrics – salinity, conductivity, total dissolved solutes, pH, turbidity and dissolved oxygen (Appendix B; Grubbs 1969; Stefansky 1972; R Core Team 2020). Three versions of this test were run: (1) to test for one maximum outlier, in which the null hypothesis is “there are no outliers in the dataset” and the alternative hypothesis is “the maximum value is an outlier;” (2) to test for two opposite outliers, in which the null hypothesis is “there are no outliers in the dataset” and the alternative hypothesis is “the maximum and minimum values are outliers;” (3) to test for two outliers in the same tail, in which the null hypothesis is “there are no outliers in the dataset” and the alternative hypothesis is “the two values are outliers in the same tail.”

With a small sample size and lack of comparative water quality data, I decided to base the primary statistical analysis on land cover ratios in each watershed where otters were present. Using the Hydrologic Unit Code 12 (HUC12), indicating a local sub-watershed level capturing tributary systems (EPA 2016),, in order to provide more polygons for smoother regression analysis, I overlaid the National Landcover Database (NLCD) 2016 layer. Because the watersheds vary in size and area, using proportions allowed me to eliminate bias. After tabulating the area and joining the table to the wetland polygons where otter presence occurred, I calculated the land cover ratios in each HUC12. Using the ArcGIS Pro tool “Exploratory Regression,” I compared land cover ratios within each HUC12 in which otters were present, where otter presence was the dependent variable and land cover categories were the candidate explanatory variables analyzed (Table 4; Appendix D). Using this output, I ran the model again using just the seven most significant land cover categories: mixed forest, shrub scrub, hay pasture, herbaceous, open water, deciduous forest and developed low intensity, respectively (Table 9; Appendix E). Akaike information criterion (AIC) is an approach for determining model selection through unbiased estimation of model performance; it is a relative scale providing each model with a number, the lowest of which indicates the model to be selected (Posada and

Buckley 2014). The model that ran with the lowest AIC in comparison to the other model versions is the one that is used in further analysis and discussion.

Additionally, I used the ArcGIS Pro tool Ordinary Least Squares (OLS), which provides the trend for each variable, the distribution of the values, and whether it exhibits positive and negative correlations, as well as a map output prediction for otter presence (Appendix F).

Lastly, I used Exploratory Regression again to compare land cover ratios of the 21 sample sites and 21 randomly generated points, where otter presence was the dependent variable and land cover categories were the candidate explanatory variables analyzed (Appendix G). This statistical test was devised to bias the analysis against finding significant differences by minimizing the differences in sites through the use of random samples. To elaborate, random samples may or may not have otter presence in reality. Because they were randomly generated through ArcGIS and not field sampled, there is no way of knowing. These 21 random sites could actually have otter presence, meaning the differences found between these sites and the sampled otter presence sites statistically is minimized. In this way, if any differences are found through this test, they are actually significant because the ability to identify significant differences was minimized. Additionally, rather than using the HUC12 as my geographic reference this time, I used a 2.5-km buffer around each point to represent average daily movement of river otters (Griess 1987; Wilson 2012). I used daily movement rather than home range, as it is not uncommon for individuals to have overlapping home ranges (Griess 1987). Additionally, tabulating land cover ratios is made more difficult when many sites overlap, which would be the case if a 16-km buffer were used to represent average home range size (Griess 1987). Fields for each land cover category were calculated to obtain the ratio of each land cover type present in the home range buffer. I then ran the Exploratory Regression tool using the merged buffer layers from the 21 sampled sites and the 21 randomly generated sites throughout eastern Tennessee. Again, the model with the lowest AIC is the one selected for use and later discussion.

CHAPTER 3

RESULTS

Site Observations & Water Quality

Bank cover for the majority of the 21 sites consisted of varying proportions of honeysuckle (*Lonicera* sp.), hornbeam (*Carpinus* sp.), hickory (*Carya* sp.), oak (*Quercus* sp.), sycamore (*Platanus* sp.), privet (*Ligustrum* sp.), hemlock (*Tsuga* sp.) and mountain laurel (*Kalmia latifolia*) (Table 1). Additionally, otters or otter sign, including tracks and dens, were only observed at 4 of the 21 sites. Salinity, turbidity and dissolved oxygen was quite consistent at each site, whereas pH, conductivity, total dissolved solutes varied widely (Table 2). Salinity ranged from 0.01 ppt to 0.24 ppt. pH ranged from 6.85 to 8.76 with a mean of 7.73. Conductivity ranged from 16 µS to 195.9 µS with a median of 54 µS. Total dissolved solutes ranged from 11.3 ppm to 340 ppm with a median of 42.8 ppm. Turbidity was most often 0 JTLJ, with only a couple of sites reaching 10-15 JTLJ. Dissolved oxygen was typically 10 ppm, with 3 sites between 8.4 ppm and 9.1 ppm. Mixed forest, deciduous forest and developed open space occurred at ≥ 76% of the sites (Figure 3).

Table 1 Field observations made at river otter presence sites identified by citizen science site "Otter Spotter" on the website iNaturalist. These sites represent 400 meters of stream. Observations including vegetative bank cover (species present indicated by darkened boxes) and otter sign. Field notes left blank indicates no confirmed evidence of otter presence detected by the investigator in the present study

Otter Occurrence Site	**Vegetative Bank Cover**																						**Field Notes**
	Juniper	Sycamore	Privet	Oak	Mtn Laurel	Cypress	Hornbeam	Pine	Redbud	Cedar	Pecan/Hickory	Walnut	Sweetgum	Beech	Tulip Poplar	Hemlock	English Ivy	Smilax sp.	Honeysuckle	Bamboo	Holly	Mimosa	
	Juniperus sp.	*Plantanus* sp.	*Ligustrum* sp.	*Quercus* sp.	*Kalmia latifolia*	*Cupressus* sp.	*Caprinus* sp.	*Pinus* sp.	*Cercis* sp.	*Cedrus* sp.	*Carya* sp.	*Juglans* sp.	*Liquidambar styraciflua*	*Fagus* sp.	*Liriodendron tulipifera*	*Tsuga* sp.	*Hedera helix*	*Smilax* sp.	*Lonicera* sp.	Family Poacae	*Ilex* sp.	*Mimosa* sp.	
1	■	■	■	■	■	■																	
2		■					■		■	■	■	■	■	■									
3			■								■												
4					■			■								■			■				dens, slides
5								■			■				■					■			
6		■			■									■	■	■							
7		■	■										■				■	■					under a bridge, near sightings from locals
8		■			■				■				■		■								
9		■					■				■			■			■						
10		■	■						■		■		■	■		■	■						in a campground
11		■	■		■		■		■		■			■					■				
12		■			■	■										■						■	
13		■					■			■	■										■		
14	■	■			■		■				■					■			■				stream full of trash
15		■	■				■		■		■												saw otter next to den, tracks along bank, near bridge, in a campground
16		■			■	■	■									■							
17		■	■							■	■						■		■			■	
18		■	■						■		■												dens and tracks, in a
19								■								■					■		
20		■		■	■					■				■		■							next to parking lot, culvert emptying runoff into
21		■	■				■				■		■			■							

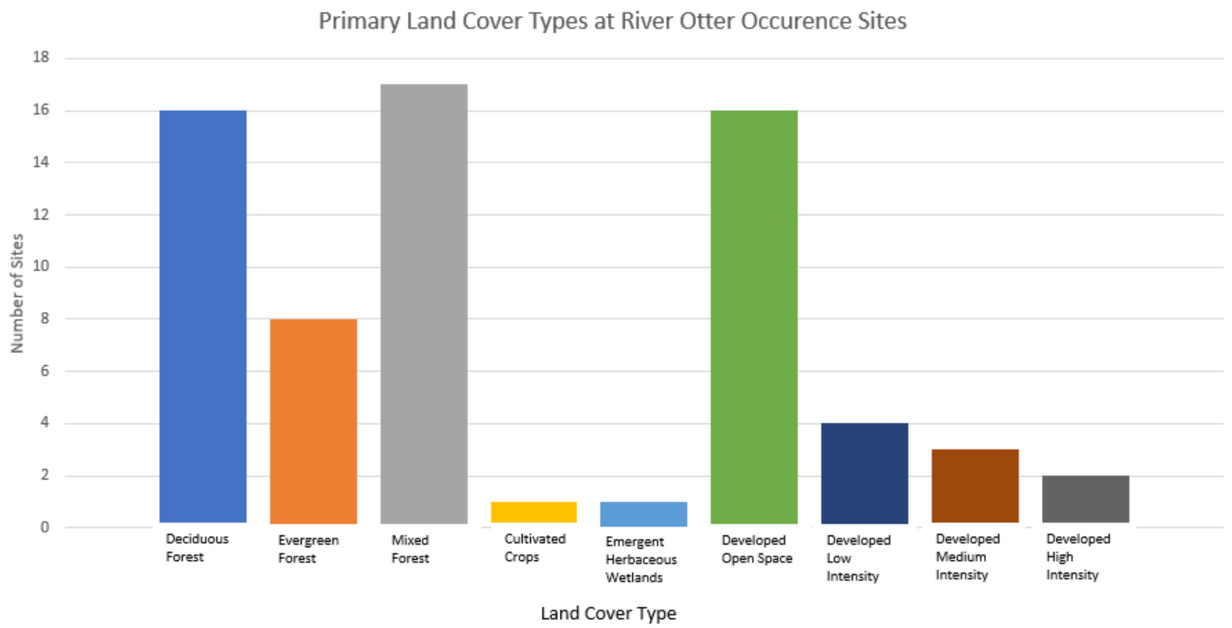


Figure 3 Primary land cover type from the National Landcover Database for the 21 river otter occurrence sites utilized in the present study. Each of the sites can have multiple primary land cover types. The y-axis indicates the number of sites at which each land cover type was found

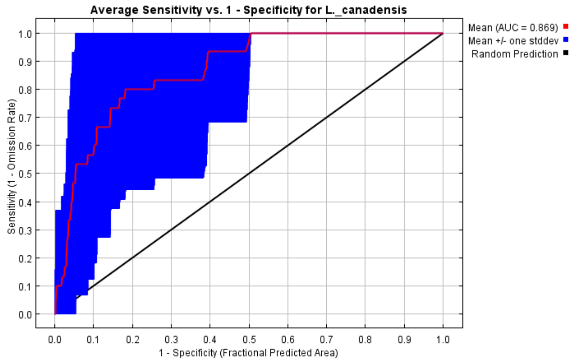
Table 2 Water quality measurements and calculations for 21 river otter occurrence sites utilized in the present study. Salinity is measured in parts per trillion (ppt); conductivity is measured in microsiemens (µS); total dissolved solutes and dissolved oxygen are measured in parts per million (ppm); turbidity is measured in Jackson turbidity units (JTLJ); stream width is measured in meters (m). Mean, median, mode and standard deviation (std. dev.) have been calculated for each metric

Site	Salinity (ppt)	pH	Conductivity (µS)	Total Dissolved Solutes (ppm)	Turbidity (JTLJ)	Dissolved Oxygen (ppm)	Stream Width (m)
1	0.02	7.84	28.8	20	0	10	15
2	0.1	7.98	195.9	139	0	10	4
3	0.11	7.9	224	160	10	8.4	5
4	0.02	7.49	44.4	31.4	0	10	6
5	0.04	7.7	91.7	60.3	0	10	1
6	0.03	6.85	46.6	42.8	0	10	6
7	0.13	8.76	269	185	0	10	15
8	0.01	7.83	29.2	20.2	0	10	2
9	0.01	7.36	16.7	11.7	0	10	3
10	0.03	7.9	54	38.3	6	10	n/a
11	0.01	7.45	16	11.3	0	10	4
12	0.08	8.25	183	130	15	9.1	10
13	0.04	7.79	81	57.6	0	10	1
14	0.03	7.8	66.8	44.2	0	10	2
15	0.02	8.15	42	29	0	10	15
16	0.01	7.2	48.7	34.5	0	10	10
17	0.24	8.09	475	340	0	8.8	2
18	0.05	7.58	103.8	74.2	0	10	5
19	0.02	7.22	37.8	27.7	0	10	1
20	0.05	7.47	102.3	72.8	5	10	2
21	0.02	7.8	37.1	26.2	0	10	8
Mean	0.05	7.73	104.47	74.1	1.71	9.82	5.85
Median	0.03	7.8	54	42.8	0	10	4.5
Mode	0.02	7.9	N/A	N/A	0	10	2
Std. Dev.	0.05	0.41	108.61	77.11	3.93	0.44	4.67

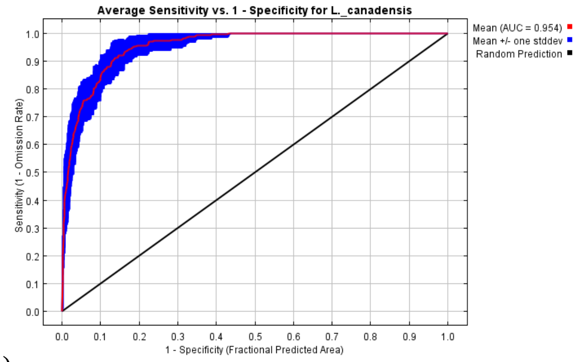
Maxent Models

The Maxent model for east Tennessee (Figure 5; Appendix D) was conducted, yielding an AUC of 0.869 using cross-validation, indicating a successful performance (Figure 4). The bootstrapping analysis produced an even higher AUC score of 0.954. Therefore, the bootstrapping model was used to create the map representing suitable habitat (Figure 5). As seen in Table 3, elevation and land cover, respectively, played the most influential roles in both the cross-validation and bootstrapping model.

The Maxent model for Blount and Sevier counties was conducted with cross-validation, resulting in an AUC score of 0.699, indicating an average performance, whereas the AUC with bootstrapping was 0.892. Therefore, the bootstrapping model was used to create the map representing suitable habitat (Figure 6). As seen in Table 4 and demonstrated through the jackknife output (Appendix D), elevation again played the most significant role in the model, with land cover being the second greatest influencing factor.



(a)



(b)

Figure 4 (a) Performance of the model for east Tennessee represented by the AUC value of 0.869 when conducted with cross-validation; (b) performance of the model for east Tennessee represented by the AUC value of 0.954 when conducted with bootstrapping. These logistic graphs were generated using Maxent 3.4. Each graph indicates receiver operating characteristic curve averaged on replicate runs. The x-axis, specificity, is defined using specificity (fractional predicted area), which is the proportion of absences correctly predicted, rather than true commission. The y-axis indicates sensitivity of the model, defined by sensitivity (omission rate), which is the proportion of presences correctly predicted (Phillips 2010)

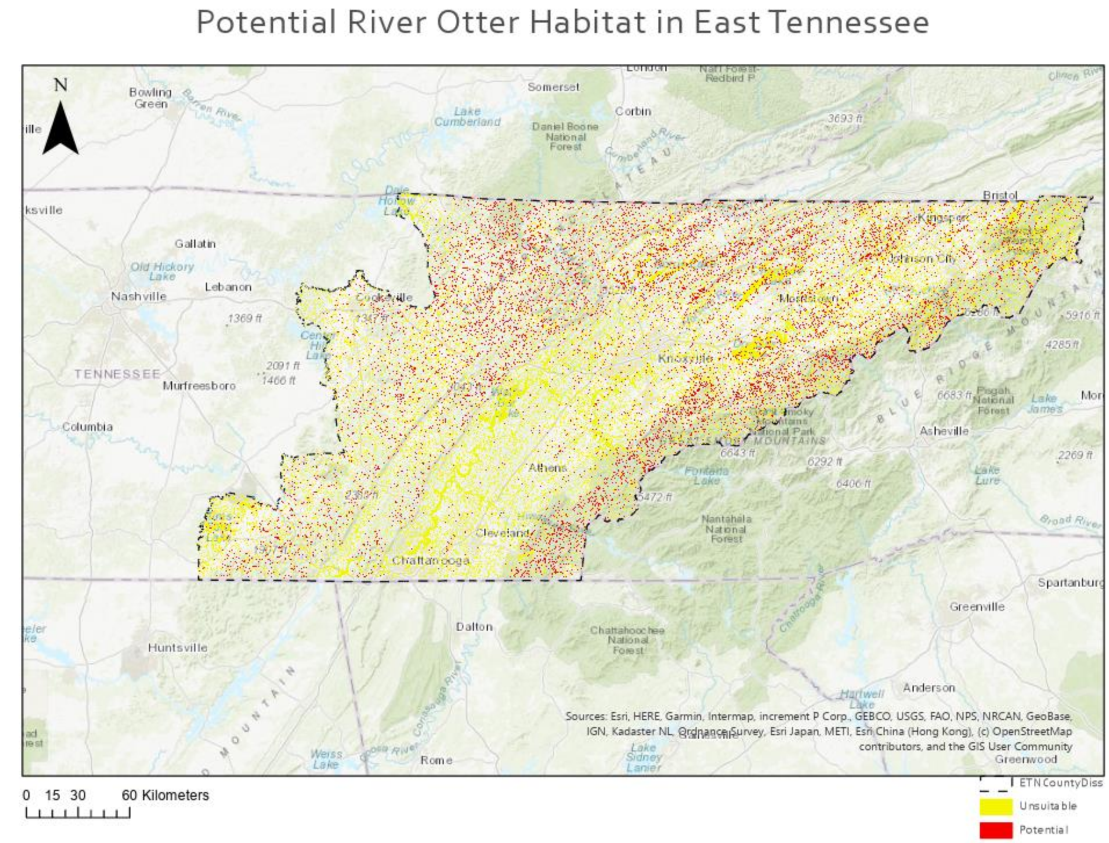


Figure 5 Map of east Tennessee showing potential river otter habitat, where red indicates potential habitat and yellow indicates unsuitable habitat within a threshold of 10% for each environmental factor included in the river otter habitat suitability model developed in Maxent (elevation, aspect, slope, riparian habitat, land cover) (Young et al. 2011; Hunt 2018)

Table 3 Percent contribution, determined by the order variables were input into Maxent code, and permutation importance, an unbiased measure dependent on the final Maxent model to define environmental variables correlated to river otter presence in east Tennessee: (A) Cross-validation (B) Bootstrapping (Figure 5). (elev_tnaii = elevation; gap_tnaii = land cover; aspect_tnaii = aspect; slope_tnaii = slope; nwi_tnaii2 = riparian habitat). The permutation importance is the better estimate of variable correlation to river otter presence, as it is not defined by the user's order of input and the path used to obtain it (Phillips et al. 2010)

(A)

Variable	Percent contribution	Permutation importance
elev_tnaii	62.2	74.8
gap_tnaii	16.5	9.5
aspect_tnaii	8.8	6
nwi_tnaii2	7.6	4.2
slope_tnaii	4.9	5.5

(B)

Variable	Percent contribution	Permutation importance
elev_tnaii	50.3	71.3
gap_tnaii	21.7	10.6
aspect_tnaii	10.2	9.1
slope_tnaii	9.3	6.8
nwi_tnaii2	8.5	2.1

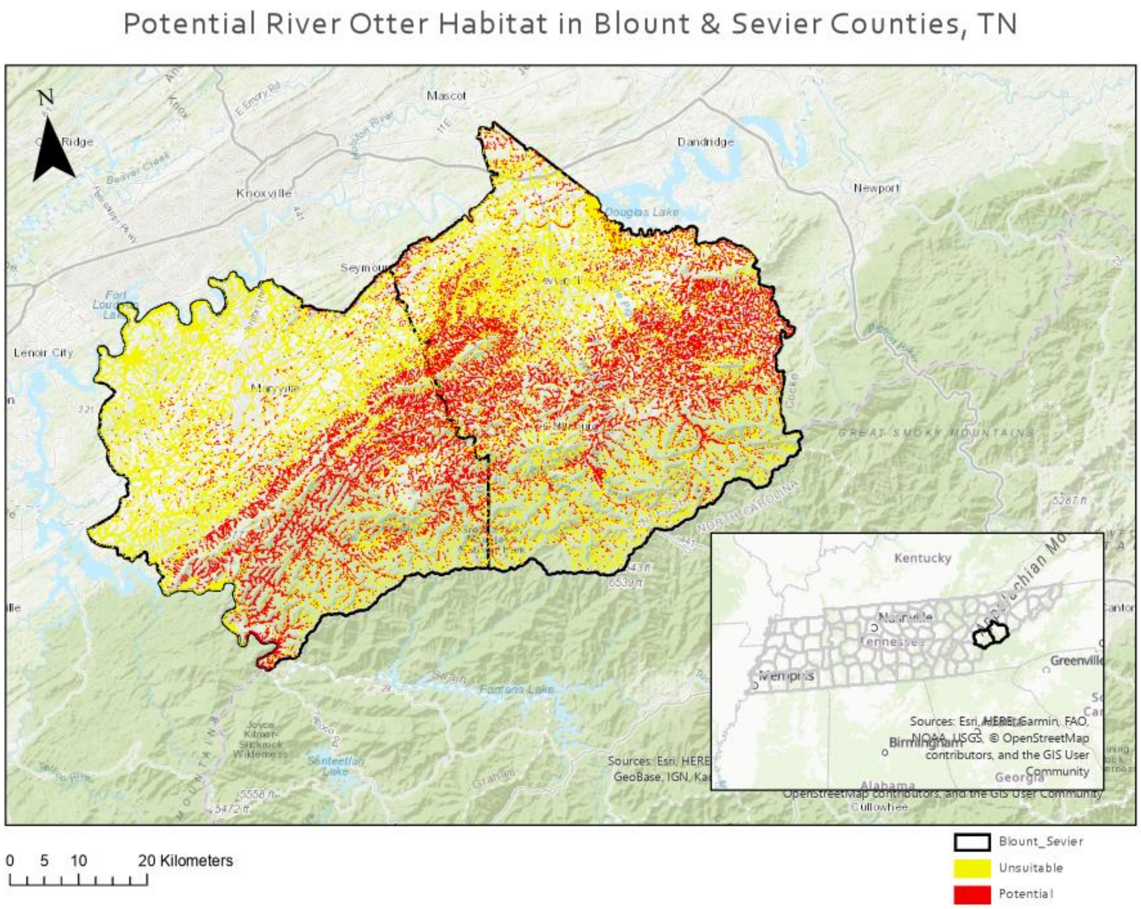


Figure 6 Map of Blount and Sevier counties of Tennessee showing potential river otter habitat, where red indicates potential habitat and yellow indicates unsuitable habitat within a threshold of 10% for each environmental factor included in the river otter habitat suitability model developed in Maxent(elevation, aspect, slope, riparian habitat, land cover) (Young et al. 2011; Hunt 2018)

Table 4 Percent contribution, determined by the order variables were input in to Maxent code, and permutation importance, unbiased measure dependent on the final Maxent model to define environmental variables correlated to river otter presence in Blount and Sevier counties of Tennessee: (A) Cross-validation (B) Bootstrapping (Figure 5). (elev_tnaii = elevation; gap_tnaii = land cover; aspect_tnaii = aspect; slope_tnaii = slope; nwi_tnaii2 = riparian habitat). The permutation importance is the better estimate of variable correlation to river otter presence, as it is not defined by the user's order of input and the path used to obtain it (Phillips et al. 2010)

(A)

Variable	Percent contribution	Permutation importance
elev_bs	45.9	55.5
gap_bs	28.5	12.3
wetlands_bs	14	10
aspect_bs	10.8	17.6
slope_bs	0.8	4.5

(B)

Variable	Percent contribution	Permutation importance
elev_bs	34.2	37.4
gap_bs	29.1	17.9
wetlands_bs	13.5	4.3
aspect_bs	12.4	23.6
slope_bs	10.8	16.8

Statistical Analysis

Using the Grubbs' Test for Outliers, I constructed histograms and boxplots in R-4.0.0 (R Core Team 2020) to determine the outliers for the water quality metrics collected (Table 5; Appendix B). A p-value less than 0.05 indicates significance and acceptance of the null hypothesis. According to results, there were outliers for each water quality metric measured, most commonly found at Site 4, Site 8 and Site 18.

Table 5 Outliers for water quality metrics measured at 21 river otter occurrence sites in Blount and Sevier counties of Tennessee. Salinity is measured in parts per trillion (ppt); conductivity is measured in microsiemens (µS); total dissolved solutes and dissolved oxygen are measured in parts per million (ppm); turbidity is measured in Jackson turbidity units (JTLJ); stream width is measured in meters (m). Mean, median, mode and standard deviation (std. dev.) have been calculated for each metric. "Outlier Value" indicates the value identified amongst the 21 site measurements that represents an outlier(s) based on the Grubbs' Test for Outliers. Three versions of this test were run: (1) to test for one maximum outlier, in which the null hypothesis is "there are no outliers in the dataset" and the alternative hypothesis is "the maximum value is an outlier;" (2) to test for two opposite outliers, in which the null hypothesis is "there are no outliers in the dataset" and the alternative hypothesis is "the maximum and minimum values are outliers;" (3) to test for two outliers in the same tail, in which the null hypothesis is "there are no outliers in the dataset" and the alternative hypothesis is "the two values are outliers in the same tail." "Type of Outlier" indicates which of the three tests was significant ($p<0.05$), therefore indicating where the outlier is in the dataset. "P-value" identifies the significant p-value ($p<0.05$) associated with the test. Site # indicates which site of the 21 sampled, contained the outlier for the respective water quality metric

Water Quality Metric	Outlier Value	Type of Outlier	p-value	Site #
Salinity	0.24 ppt	One Maximum	0.0003283	18
pH	6.85 and 8.76	Opposite (minimum and maximum)	0.04239	7 (minimum) and 8 (maximum)
Conductivity	269 µS and 475 µS	Two maxima	< 2.2e-16	8 and 18, respectively
Total Dissolved Solutes	185 ppm and 340 ppm	Two maxima	< 2.2e-16	8 and 18, respectively
Turbidity	10 JTLJ and 15 JTLJ	Two maxima	< 2.2e-16	4 and 13, respectively
Dissolved Oxygen	8.4 ppm and 8.8 ppm	Two minima	< 2.2e-16	4 and 18, respectively

In the results of the first Exploratory Regression analysis looking at landcover ratios in HUC12 watersheds, mixed forest, shrub scrub, hay pasture, herbaceous, open water, deciduous forest and developed low intensity, respectively, were the most influential of the 15 NLCD land cover categories (Table 8). Though, the model that ran with the lowest Akaike information criterion (AIC), i.e., the best quality of the models run, incorporated just the "developed open," "developed low," "developed medium" and "mixed forest" categories, resulting in an AIC of 332.93 (Table 6). "Developed open," "developed medium" and "mixed forest" all had a positive correlation to otter presence, whereas "developed medium" had a negative correlation.

Using these seven most influential categories from Table 8, Exploratory Regression was run again (Table 9). For this second Exploratory Regression analysis, the model that ran with the lowest AIC of 348.06 incorporated just the "mixed forest" and "shrub scrub" categories (Table 7). "Mixed forest" had a positive correlation, whereas "shrub scrub" had a negative correlation to otter presence.

Table 6 Akaike information criterion (AIC) results of exploratory regression, conducted using ArcGIS Pro 2.4, regarding relation of land cover (National Landcover Database) type to river otter presence in east Tennessee HUC12 watersheds, analyzing all 15 NLCD land cover categories. "+" indicates positive correlation with river otter presence; "-" represents negative correlation with river otter presence. (MIXFORPR = Mixed Forest; SHRSCRPR = Shrub/Scrub; HAYPASTPR = Hay/Pasture; HERBPR = Herbaceous; OPENWATERPR = Open Water; DECIDFORPR = Deciduous Forest; DEVLOWPR = Developed Low Intensity; EMHERBWETPR = Emergent Herbaceous Wetland; CULTCROPPR = Cultivated Crop; BARRENPR = Barren Land; EVERFORPR = Evergreen Forest; WOODWETLANDSPR = Woody Wetlands; DEVOPENPR = Developed Open Space; DEVMEDPR = Developed Medium Intensity; DEVHIGHPR = Developed High Intensity)

Model	AIC
+MIXFORPR	346.40
-HAYPASTPR	363.83
+EVERFORPR	364.73
+DEVOPENPR +MIXFORPR	345.66
+MIXFORPR -SHRSCRPR	348.06
+MIXFORPR -HERBPR	348.93
+DEVOPENPR -DEVLOWPR +MIXFORPR	335.03
+DEVOPENPR -DEVMEDPR +MIXFORPR	344.55
+DEVOPENPR -DEVHIGHPR +MIXFORPR	345.43
+DEVOPENPR -DEVLOWPR +DEVMEDPR +MIXFORPR	332.93
+DEVOPENPR -DEVLOWPR +DEVHIGHPR +MIXFORPR	334.56
+DEVOPENPR -DEVLOWPR +MIXFORPR -HAYPASTPR	335.84
+DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR +MIXFORPR***	334.09
+DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +MIXFORPR*** -HAYPASTPR	334.17
-OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +MIXFORPR***	334.37
+DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR +EVERFORPR +MIXFORPR***	335.26
+DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +MIXFORPR*** -SHRSCRPR** -HAYPASTPR	335.30
-OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +MIXFORPR*** -HAYPASTPR	335.36
-OPENWATERPR* +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +MIXFORPR** -SHRSCRPR** -HAYPASTPR	335.92
+DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR +EVERFORPR +MIXFORPR*** -SHRSCRPR*	336.05
-OPENWATERPR*** +DEVOPENPR* -DEVLOWPR** +DEVMEDPR -DECIDFORPR** -SHRSCRPR*** -HAYPASTPR***	336.09
-OPENWATERPR* +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +EVERFORPR +MIXFORPR** -SHRSCRPR* -HAYPASTPR	337.22
+DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR +EVERFORPR +MIXFORPR*** -SHRSCRPR +CULTCROPPR**	337.51
-OPENWATERPR* +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR +EVERFORPR +MIXFORPR*** -SHRSCRPR*	337.52
-OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR +EVERFORPR +MIXFORPR*** -SHRSCRPR* +CULTCROPPR*	339.17
-OPENWATERPR* +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +EVERFORPR +MIXFORPR* -SHRSCRPR* -HERBPR -HAYPASTPR	339.24
+DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR* +EVERFORPR +MIXFORPR*** -SHRSCRPR +HAYPASTPR +CULTCROPPR**	339.26
-OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR +EVERFORPR +MIXFORPR*** -SHRSCRPR* +CULTCROPPR* -EMHERBWETPR	341.19
+DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR* +EVERFORPR +MIXFORPR*** -SHRSCRPR* +HERBPR +HAYPASTPR +CULTCROPPR**	341.24
-OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* -BARRENPR +DECIDFORPR +EVERFORPR +MIXFORPR*** -SHRSCRPR* +CULTCROPPR*	341.26
-OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* -BARRENPR +DECIDFORPR +EVERFORPR +MIXFORPR*** -SHRSCRPR* +CULTCROPPR* -EMHERBWETPR	343.29
-OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR +EVERFORPR +MIXFORPR*** -SHRSCRPR* +CULTCROPPR* +WOODWETLANDSPR -EMHERBWETPR	343.29
-OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR +EVERFORPR +MIXFORPR** -SHRSCRPR* +HERBPR +CULTCROPPR* -EMHERBWETPR	343.30
+DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR* +EVERFORPR +MIXFORPR*** -SHRSCRPR* +HERBPR +HAYPASTPR +CULTCROPPR** +WOODWETLANDSPR -EMHERBWETPR	345.40
-OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* -BARRENPR +DECIDFORPR +EVERFORPR +MIXFORPR** -SHRSCRPR* -HAYPASTPR +CULTCROPPR -EMHERBWETPR	345.40
-OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* -BARRENPR +DECIDFORPR +EVERFORPR +MIXFORPR*** -SHRSCRPR* +CULTCROPPR* +WOODWETLANDSPR -EMHERBWETPR	345.40
+DEVOPENPR* -DEVLOWPR* +DEVMEDPR* -BARRENPR +DECIDFORPR* +EVERFORPR +MIXFORPR*** -SHRSCRPR* +HERBPR +HAYPASTPR +CULTCROPPR** +WOODWETLANDSPR -EMHERBWETPR	347.53
-OPENWATERPR* +DEVOPENPR* -DEVLOWPR* +DEVMEDPR -DEVHIGHPR -BARRENPR +EVERFORPR +MIXFORPR* -SHRSCRPR* -HERBPR -HAYPASTPR +CULTCROPPR -EMHERBWETPR	347.53
-OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* -BARRENPR +DECIDFORPR +EVERFORPR +MIXFORPR** -SHRSCRPR* +HERBPR +CULTCROPPR* +WOODWETLANDSPR -EMHERBWETPR	347.53
-OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR -DEVHIGHPR -BARRENPR +DECIDFORPR +EVERFORPR +MIXFORPR** -SHRSCRPR* +HERBPR +CULTCROPPR* +WOODWETLANDSPR -EMHERBWETPR	349.67
-OPENWATERPR** +DEVOPENPR* -DEVLOWPR* +DEVMEDPR -DEVHIGHPR -BARRENPR -DECIDFORPR +EVERFORPR +MIXFORPR -SHRSCRPR* -HERBPR -HAYPASTPR* -WOODWETLANDSPR -EMHERBWETPR	349.67
-OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR -DEVHIGHPR -BARRENPR +DECIDFORPR +EVERFORPR +MIXFORPR -SHRSCRPR -HERBPR -HAYPASTPR +CULTCROPPR -EMHERBWETPR	349.67

Table 7 Akaike information criterion (AIC) results of exploratory regression, conducted using ArcGIS Pro 2.4, regarding relation of land cover type to river otter presence in east Tennessee HUC12 watersheds, based on top 7 most influential cover types from Table 6. "+" indicates positive correlation with river otter presence; "-" represents negative correlation with river otter presence. (MIXFORPR = Mixed Forest; SHRSCRPR = Shrub/Scrub; HAYPASTPR = Hay/Pasture; HERBPR = Herbaceous; OPENWATERPR = Open Water; DECIDFORPR = Deciduous Forest; DEVLOWPR = Developed Low Intensity; EMHERBWETPR = Emergent Herbaceous Wetland; CULTCROPPR = Cultivated Crop; BARRENPR = Barren Land; EVERFORPR = Evergreen Forest; WOODWETLANDSPR = Woody Wetlands; DEVOPENPR = Developed Open Space; DEVMEDPR = Developed Medium Intensity; DEVHIGHPR = Developed High Intensity)

Model	**AIC**
+MIXFORPR	348.40
-HAYPASTPR	363.83
-HERBPR	365.36
+MIXFORPR*** -SHRSCRPR**	348.06
+MIXFORPR*** -HERBPR**	348.93
-DECIDFORPR** +MIXFORPR***	350.08
-OPENWATERPR* +MIXFORPR*** -SHRSCRPR**	349.69
+MIXFORPR*** -SHRSCRPR** -HAYPASTPR	349.80
+MIXFORPR*** -SHRSCRPR** -HERBPR**	349.80
-OPENWATERPR* +MIXFORPR*** -SHRSCRPR** -HAYPASTPR	351.29
-DECIDFORPR +MIXFORPR*** -SHRSCRPR** -HAYPASTPR	351.41
-OPENWATERPR* +MIXFORPR*** -SHRSCRPR** -HERBPR**	351.45
-OPENWATERPR*** -DEVLOWPR*** -DECIDFORPR*** -SHRSCRPR*** -HAYPASTPR**	349.88
-OPENWATERPR* -DECIDFORPR +MIXFORPR** -SHRSCRPR** -HAYPASTPR	352.56
-DEVLOWPR -DECIDFORPR +MIXFORPR -SHRSCRPR** -HAYPASTPR	352.61
-OPENWATERPR*** -DEVLOWPR*** -DECIDFORPR*** -SHRSCRPR** -HERBPR*** -HAYPASTPR**	351.01
-OPENWATERPR* -DEVLOWPR -DECIDFORPR -MIXFORPR -SHRSCRPR** -HAYPASTPR	351.94
-DEVLOWPR -DECIDFORPR +MIXFORPR -SHRSCRPR** -HERBPR* -HAYPASTPR	354.08
-OPENWATERPR* -DEVLOWPR -DECIDFORPR* -MIXFORPR -SHRSCRPR** -HERBPR* -HAYPASTPR	353.01

Table 8 Exploratory Regression, conducted using ArcGIS Pro 2.4. Summary of variable influence on river otter presence in east Tennessee using all 15 GAP National Land Cover Database categories. "% Significant" indicates the overall significance of the land cover type in comparison to each other type. "% Negative" and "% Positive" indicate the specific type of significance each variable played in predicting river otter presence. (MIXFORPR = Mixed Forest; SHRSCRPR = Shrub/Scrub; HAYPASTPR = Hay/Pasture; HERBPR = Herbaceous; OPENWATERPR = Open Water; DECIDFORPR = Deciduous Forest; DEVLOWPR = Developed Low Intensity; EMHERBWETPR = Emergent Herbaceous Wetland; CULTCROPPR = Cultivated Crop; BARRENPR = Barren Land; EVERFORPR = Evergreen Forest; WOODWETLANDSPR = Woody Wetlands; DEVOPENPR = Developed Open Space; DEVMEDPR = Developed Medium Intensity; DEVHIGHPR = Developed High Intensity)

Summary of Variable Significance

Variable	% Significant	% Negative	% Positive
MIXFORPR	86.48	2.55	97.45
SHRSCRPR	55.70	99.71	0.29
HAYPASTPR	46.70	91.38	8.62
HERBPR	43.91	97.97	2.03
OPENWATERPR	27.88	98.13	1.87
DECIDFORPR	23.00	71.98	28.02
DEVLOWPR	20.95	96.07	3.93
EMHERBWETPR	17.95	94.19	5.81
CULTCROPPR	14.24	57.23	42.77
BARRENPR	13.63	98.44	1.56
EVERFORPR	6.61	10.24	89.76
WOODWETLANDSPR	4.68	87.78	12.22
DEVOPENPR	2.11	2.00	98.00
DEVMEDPR	1.88	37.18	62.82
DEVHIGHPR	1.68	57.85	42.15

Table 9 Exploratory Regression, conducted using ArcGIS Pro 2.4. Summary of variable influence on river otter presence in east Tennessee using 7 GAP National Land Cover Database categories. "% Significant" indicates the overall significance of the land cover type in comparison to each other type. "% Negative" and "% Positive" indicate the specific type of significance each variable played in predicting river otter. presence. The 7 variables influence used in this analysis were determined from a previous analysis using all 15 GAP land cover categories. The seven most significant from that output were then used here to further specify the relationships (Table 8) Those seven most significant land cover types were mixed forest, shrub scrub, hay pasture, herbaceous, open water, deciduous forest and developed low intensity, respectively. (MIXFORPR = Mixed Forest; SHRSCRPR = Shrub/Scrub; HAYPASTPR = Hay/Pasture; HERBPR = Herbaceous; OPENWATERPR = Open Water; DECIDFORPR = Deciduous Forest; DEVLOWPR = Developed Low Intensity)

Summary of Variable Significance

Variable	% Significant	% Negative	% Positive
MIXFORPR	89.06	3.12	96.88
SHRSCRPR	81.25	100.00	0.00
HERBPR	67.19	100.00	0.00
HAYPASTPR	50.00	98.44	1.56
DECIDFORPR	28.12	100.00	0.00
OPENWATERPR	21.88	100.00	0.00
DEVLOWPR	21.88	82.81	17.19

The Ordinary Least Squares analysis indicated a negative correlation between otter presence and open water, developed low intensity, developed medium intensity, barren land, deciduous forest, shrub scrub, herbaceous, hay pasture, woody wetlands and emergent herbaceous wetlands (Appendix H). There was a positive correlation between otter presence and developed open, developed high intensity, evergreen forest, mixed forest and cultivated croplands. Figure 7 indicates the otter presence predicted by the OLS analysis, where red indicates the highest probability of presence.

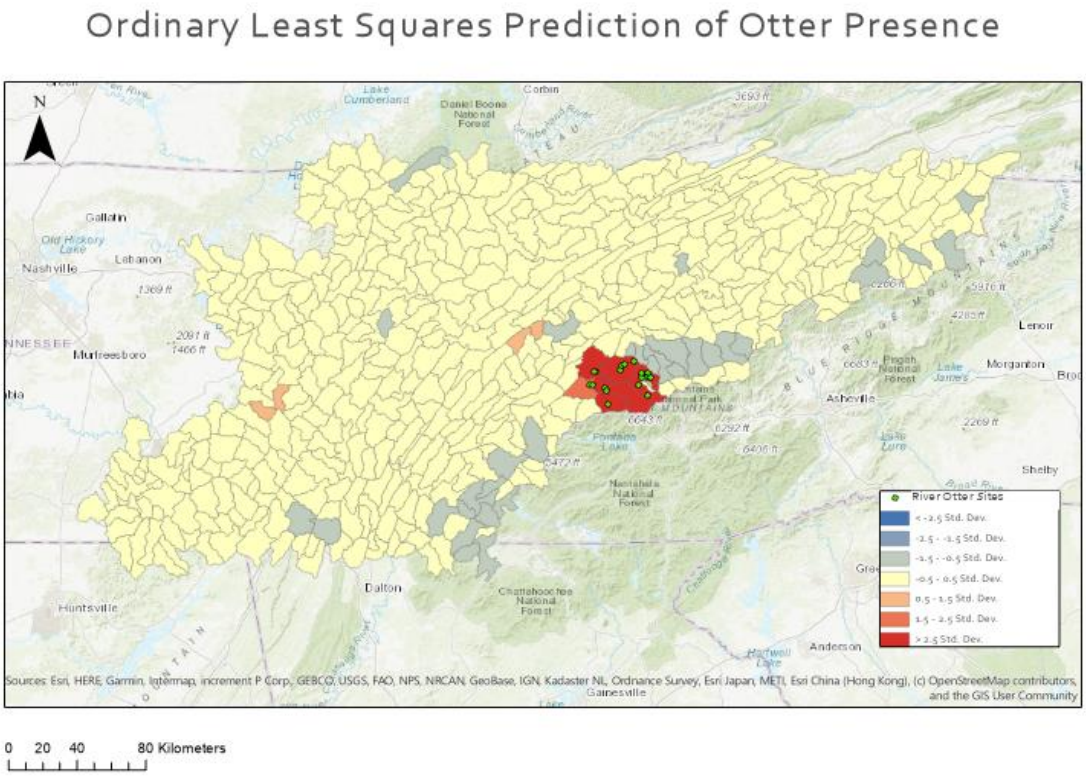


Figure 7 Map of east Tennessee illustrating results of Ordinary Least Squares analysis. Analysis was conducted using ArcGIS Pro 2.4 and was used to predict river otter presence within each Hydrologic Unit Code 12 (HUC12; indicated by the gray lines) throughout east Tennessee. Red HUC12 units indicate likelihood of otter presence is higher than average in those watersheds

Lastly, the daily movement range Exploratory Regression analysis compared my 21 sampled sites to the 21 randomly generated sites throughout eastern Tennessee (Table 10; Appendix G). The model from this analysis that ran with the lowest AIC value (AIC=24.02) incorporated just the “developed open” and “mixed forest” categories (Table 11). “Mixed forest” still had a positive correlation with otter presence, as in the HUC12 Exploratory Regression analysis, though “Developed Open” had a more influential positive correlation.

Table 10 Exploratory Regression conducted using ArcGIS Pro 2.4. Summary of significant land cover categories based on daily movement range of river otter (2.5 km, following Griess 1987; Wilson 2012) for sampled and random sites in east Tennessee. "% Significant" indicates the overall significance of the land cover type in comparison to each other type. "% Negative" and "% Positive" indicate the specific type of significance each variable played in predicting river otter presence. (DEV_OP_PR = Developed Open; MI_FOR_PR = Mixed Forest; PA_HA_PR = Pasture/Hay; DE_FOR_PR = Deciduous Forest; OP_WA_PR = Open Water; DEV_HI_PR = Developed High Intensity; GR_LA_PR = Grassland; DEV_LO_PR = Developed Low Intensity; DEV_ME_PR = Developed Medium Intensity; SH_SC_PR = Shrub/Scrub; BA_LA_PR = Bare Land; WO_WET_PR = Woody Wetlands; EM_HER_PR = Emergent Herbaceous Wetlands; EV_FOR_PR = Evergreen Forest)

Summary of Variable Significance

Variable	% Significant	% Negative	% Positive
DEV_OP_PR	92.60	0.02	99.98
MI_FOR_PR	77.21	11.88	88.12
PA_HA_PR	64.34	95.98	4.02
DE_FOR_PR	48.31	74.51	25.49
OP_WA_PR	18.85	98.88	1.12
DEV_HI_PR	16.39	18.11	81.89
GR_LA_PR	16.23	90.65	9.35
DEV_LO_PR	14.52	53.80	46.20
DEV_ME_PR	13.85	64.63	35.37
SH_SC_PR	12.33	94.40	5.60
BA_LA_PR	7.52	72.38	27.62
WO_WET_PR	7.20	61.04	38.96
EM_HER_PR	7.00	19.14	80.86
EV_FOR_PR	3.16	27.13	72.87

Table 11 Akaike information criterion (AIC) results of exploratory regression, conducted using ArcGIS Pro 2.4, regarding relation of land cover type to river otter presence sites versus random sites, each with 2.5 km buffers around the point to represent the daily average movement of river otters, following Griess (1987) and Wilson (2012). “+” indicates positive correlation with river otter presence; “-“ represents negative correlation with river otter presence. (MIXFORPR = Mixed Forest; SHRSCRPR = Shrub/Scrub; HAYPASTPR = Hay/Pasture; HERBPR = Herbaceous; OPENWATERPR = Open Water; DECIDFORPR = Deciduous Forest; DEVLOWPR = Developed Low Intensity; EMHERBWETPR = Emergent Herbaceous Wetland; CULTCROPPR = Cultivated Crop; BARRENPR = Barren Land; EVERFORPR = Evergreen Forest; WOODWETLANDSPR = Woody Wetlands; DEVOPENPR = Developed Open Space; DEVMEDPR = Developed Medium Intensity; DEVHIGHPR = Developed High Intensity)

Model	**AIC**
+MI_FOR_PR***	45.23
-PA_HA_PR***	55.15
+DEV_OP_PR***	58.31
-DE_FOR_PR*** -PA_HA_PR***	33.69
+DEV_LO_PR** +MI_FOR_PR***	41.76
+DEV_OP_PR*** +MI_FOR_PR*** -PA_HA_PR	25.08
+DEV_OP_PR*** +DE_FOR_PR +MI_FOR_PR***	25.26
+DEV_OP_PR*** -DEV_LO_PR +MI_FOR_PR***	26.29
OP_WA_PR* +DEV_OP_PR*** +MI_FOR_PR*** +EM_HER_PR*	25.17
OP_WA_PR +DEV_OP_PR*** +MI_FOR_PR*** +WO_WET_PR	26.40
+DEV_OP_PR*** +DE_FOR_PR +MI_FOR_PR*** +EM_HER_PR	27.26
OP_WA_PR +DEV_OP_PR*** +DE_FOR_PR +MI_FOR_PR*** +EM_HER_PR*	27.06
-OP_WA_PR +DEV_OP_PR*** +MI_FOR_PR*** -PA_HA_PR +EM_HER_PR*	27.26
-OP_WA_PR* +DEV_OP_PR*** -DEV_ME_PR +MI_FOR_PR*** +EM_HER_PR*	27.67
-OP_WA_PR +DEV_OP_PR*** -DEV_ME_PR +MI_FOR_PR*** -PA_HA_PR +EM_HER_PR*	29.88
-OP_WA_PR* +DEV_OP_PR*** -DEV_ME_PR +DE_FOR_PR +MI_FOR_PR*** +EM_HER_PR*	29.92
OP_WA_PR +DEV_OP_PR*** +DE_FOR_PR +EV_FOR_PR +MI_FOR_PR*** +EM_HER_PR*	29.96
-OP_WA_PR* +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR +DEV_HI_PR +MI_FOR_PR*** +EM_HER_PR*	32.35
+DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR* +MI_FOR_PR*** -PA_HA_PR* +EM_HER_PR	32.54
-OP_WA_PR +DEV_OP_PR*** -DEV_ME_PR +DEV_HI_PR +MI_FOR_PR*** -PA_HA_PR +EM_HER_PR	32.70
-OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR* +MI_FOR_PR*** -PA_HA_PR +EM_HER_PR*	32.75
-OP_WA_PR* +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR* +DE_FOR_PR +MI_FOR_PR*** +EM_HER_PR**	33.10
-OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR* +MI_FOR_PR*** -PA_HA_PR +WO_WET_PR	34.38
-OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR* +DE_FOR_PR +MI_FOR_PR** -PA_HA_PR +EM_HER_PR*	36.44
-OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR* -EV_FOR_PR +MI_FOR_PR*** -PA_HA_PR +EM_HER_PR*	36.46
-OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR* +MI_FOR_PR*** -PA_HA_PR -WO_WET_PR +EM_HER_PR	36.49
-OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR* +DE_FOR_PR +MI_FOR_PR** -PA_HA_PR -WO_WET_PR +EM_HER_PR	40.46
-OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR* -EV_FOR_PR +MI_FOR_PR*** -PA_HA_PR -WO_WET_PR +EM_HER_PR	40.47
-OP_WA_PR +DEV_OP_PR** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR* +DE_FOR_PR +MI_FOR_PR* +GR_LA_PR -PA_HA_PR +EM_HER_PR*	40.48
-OP_WA_PR +DEV_OP_PR** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR +DE_FOR_PR +MI_FOR_PR* +GR_LA_PR -PA_HA_PR -WO_WET_PR +EM_HER_PR	44.80
-OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR -EV_FOR_PR +MI_FOR_PR*** -SH_SC_PR -PA_HA_PR -WO_WET_PR +EM_HER_PR	44.80
-OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR +DE_FOR_PR +MI_FOR_PR* -SH_SC_PR -PA_HA_PR -WO_WET_PR +EM_HER_PR	44.80
-OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR +DEV_HI_PR -BA_LA_PR -EV_FOR_PR +MI_FOR_PR*** -SH_SC_PR -PA_HA_PR -WO_WET_PR +EM_HER_PR	49.46
-OP_WA_PR +DEV_OP_PR** +DEV_LO_PR -DEV_ME_PR +DEV_HI_PR -BA_LA_PR +DE_FOR_PR +MI_FOR_PR* +GR_LA_PR -PA_HA_PR -WO_WET_PR +EM_HER_PR	49.46
-OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR +DEV_HI_PR +DE_FOR_PR +EV_FOR_PR +MI_FOR_PR*** +SH_SC_PR +GR_LA_PR -WO_WET_PR +EM_HER_PR	49.46
+DEV_OP_PR +DEV_LO_PR* DEV_ME_PR +DEV_HI_PR* +BA_LA_PR +DE_FOR_PR +EV_FOR_PR +MI_FOR_PR +SH_SC_PR +GR_LA_PR +PA_HA_PR +WO_WET_PR +EM_HER_PR	54.51
-OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR DEV_ME_PR +DEV_HI_PR BA_LA_PR +DE_FOR_PR +EV_FOR_PR +MI_FOR_PR*** +SH_SC_PR +GR_LA_PR -WO_WET_PR +EM_HER_PR	54.51
-OP_WA_PR +DEV_OP_PR +DEV_LO_PR -DEV_ME_PR +DEV_HI_PR -BA_LA_PR -DE_FOR_PR*** -EV_FOR_PR -SH_SC_PR -GR_LA_PR -PA_HA_PR*** -WO_WET_PR +EM_HER_PR	54.51

CHAPTER 4

DISCUSSION & CONCLUSIONS

Site Observations & Water Quality

Because all the citizen science points in my study were in the Great Smoky Mountain region, within an area approximately 590 km^2 in size, I must address the bias this would exert in predicting otter presence and/or suitability for the entirety of the eastern part of the state. The ability to capture, anesthetize and radio track individuals would aid in better understanding habitat use by these river otters. Unfortunately for this study, funds and time limited me from obtaining the necessary certification, training and permits to use this method.

Understanding the water quality that typifies known river otter habitat in east Tennessee provides the ability to assess future sites for reintroduction or conservation. By testing water quality at novel sites, the averages and ranges obtained in the present study could be used to make a more informed decision regarding the suitability of other habitats being assessed. The Grubbs' Test for Outliers detected many outliers present in the water quality metrics set (Appendix C). Therefore, to prevent skewed results, it is necessary to fix the means for each metric and removing the outliers to get a better idea of suitable water quality related to otter presence. The fixed means for the water quality metrics are as follows: 0.04 ppt for salinity, 7.7 for pH, 76.31 µS for conductivity, 54.27 ppm for total dissolved solutes, 0.58 JTLJ for turbidity and 9.95 ppm for dissolved oxygen (Appendix C). These fixed means give a more accurate representation of potentially suitable water quality for river otters by excluding the outliers. It is also worth noting that sites with outliers were often the same for multiple metrics. Site 4, Site 8 and Site 18 each had multiple outliers. Curiously, these sites did not boast any other identifiably unusual characteristics compared to the other sites, though site 18 was located near a campground where otters are often spotted by locals. However, these sites should perhaps be investigated more thoroughly to try to determine why the water quality results were anomalous.

Model Interpretations

In the model illustrated in Figure 5, many larger bodies of water, such as the Tennessee River and associated lakes, were excluded from "potential habitat." These larger bodies of water are categorized as "open water" in the GAP layer. In similar studies, open water is noted to be the most frequently used land cover type by river otters, with increasing likelihood of presence along shorelines with woody vegetation (Jeffress et al. 2011; Wilson 2012). This could indicate an issue with my model, although a study in Ohio found open water to be the least suitable ranked habitat among riparian systems (Helon et al. 2004). These conflicting results might be explained by differing definitions of open water, e.g., whether or not open water with emergent aquatic vegetation versus deep open water with no vegetation were grouped together (Wilson 2012). Furthermore, other studies have indicated that river otter presence may not be predicted by vegetation and riparian types so much as the presence of urban development, stream size and the presence of mink (*Neovison vison*). This suggests that perhaps these factors should be included in future iterations of the current project (Bennett 2014; Nielsen et al. 2015; Holland and Van der Merwe 2016). Open water was likely excluded from my model due to bias caused by the geographically restricted and rather homogeneous sample. Each of the 21 sample sites where otters were present were found on smaller streams and rivers, making the detection of suitable habitat among larger bodies of water much less likely. Additionally, riparian habitat from the National Wetlands Inventory did not play an influential role in any of the models run. This too ran counter to expectations, since riparian habitats have been found to represent suitable river otter habitat in other studies (Jefferess et al. 2011; Wilson 2012).

The map for Blount and Sevier counties identifies much more potential habitat (Figure 5, in red), relatively speaking, than is the case for the map of east Tennessee, including areas identified for reintroduction by Griess (1987). This is likely because the Blount and Sevier counties map was run without a bias layer. The AUC score for cross-validation was much lower for this two-county model, because AUC scores are typically higher when there is more geographical space for the model to analyze and differentiate where presence is likely and where it is not (Pearson 2010). Finer resolution on the county level would likely aid in specifying suitable habitat in Blount in Sevier counties.

In both the east Tennessee and county-level Maxent models, among the other environmental factors analyzed – i.e., aspect, slope, elevation and land cover –elevation was revealed as a major contributor in determining what areas were selected as "suitable" habitat (Table 3). Elevation at the study sites ranged from 91 to 427-m; for this reason, I believe lower elevation sites were excluded from the models.

HUC 12 Exploratory Regression

Using the Exploratory Regression tool in ArcGIS Pro 2.4, I found that "mixed forest" land cover had the greatest positive correlation with otter presence. Forested aquatic systems are usually associated with river otter habitat (Godwin et al. 2015; Holland and van der Merwe 2016; Holland et al.2016; Griess 1987; Gomez et al. 2014), and so this result conforms with what is known of *L. canadensis* natural history. This analysis distinguished evergreen, deciduous and mixed forest land cover from one another regarding river otter habitat selection, with mixed forest being more influential than deciduous and evergreen forests. That said, both deciduous and evergreen still showed positive correlation with otter presence. The daily movement Exploratory Regression analysis showed that “developed open” and “mixed forest” land cover had the greatest positive correlation with predicting otter presence. This further supports the results of the HUC12 Exploratory Regression analysis that showed positive correlation between mixed forest land cover and otter presence.

Daily Movement Exploratory Regression

In the Exploratory Regression analysis using daily movement ranges, I created 21 random sites to compare to my sample sites where otters have been observed. Because the random sites were not field tested, I can confirm neither otter presence nor absence. Therefore, if all the random streams do in fact have otters present, any significant differences identified among random and sample sites by the analysis may simply reflect the fact that otter habitat is heterogenous to a degree that is undetectable in my small sample of survey sites. This is something that should be explored further in future research to eliminate type I error. By comparing only sites that are known to have otters present to those where detailed field surveys indicate absence, rather than random sites in which presence or absence cannot be confirmed, type I error could be removed. An expansion in the geographic range of sites surveyed for otter presence could better detect habitat heterogeneity for this species in east Tennessee. This could perhaps show some presence in open water or wetland areas, as in previous studies (Jeffress et al. 2011; Wilson 2012). The latter would also correct the some of the biases in the Maxent model of the present study. For example, all observed sites were in the Smoky Mountains at higher elevations. The sample was also biased toward small streams and developed areas.

Ordinary Least Squares

Unfortunately, the Ordinary Least Squares test was not very useful. The results produced a strong, obvious bias towards Blount and Sevier counties when trying to analyze the entire eastern part of Tennessee. Because the sample size was small and all sites were found within these 2 neighboring counties, the analysis was not robust.

Possible Biases

Another important source of bias in this project and analysis is its dependence on citizen science. Most observed sites collected on iNaturalist were classified as "Research Grade" with an accompanying picture for identification. For this reason, I do not think misidentification as mink, beaver or muskrat was an issue, as I and the rest of the iNaturalist community were able to confirm species identity. However, otters will only be detected by humans in areas that humans go; and because areas that humans frequent are often developed, this can skew the data, as seen in the Ordinary Least Squares output (Appendix H). Additionally, most of our sample sites obtained via citizen science observations were near roads and campsites, which appear as varying intensities of developed land cover using NLCD or GAP.

It should also be noted that several of the detection sites were local fishing hotspots, as I discovered when speaking to local businesspeople in the area. The otters reside near bridges that are often used by fishermen/women, and eat bait and scraps left behind. It would be worth further investigating human-otter interaction and its effects on otter habitat selection and the species' adaptation to urban environments in a future study.

Future Direction & Conclusion

Because the present study was, in most respects, a heuristic assessment, generating many ideas for how future models of otter habitat preference could be improved. My goal was to provide a map that allowed areas with suitable river otter habitat to be better visualized for conservation purposes. Environmental factors and habitat features that are specifically tied to otter preferences are needed for an accurate map to be produced. This project paves the way for similar efforts and development of more thorough suitability models. For example, more thorough water quality assessments could be conducted, and additional environmental factors could be added to the analysis to create a more precise predictor of otter suitability, e.g., canopy cover or prey availability (the latter determined by abundance surveys of fish and macroinvertebrates). The study area could also be expanded to include a larger geographic region, such as the entire state of Tennessee, which would be exceptionally useful to state conservation managers. Independently conducted surveys could be sent to registered fur trappers, since the state does not collect this information. Additionally, the use of eDNA may be useful in future studies with more funding. Measuring stream flow volume, flow velocity, bank slope, and stream order are also viable options for analysis. More thorough camera trapping or radio-tracking would be useful tools for this study. The fact that I could not confirm otter presence in the majority of sites where they were reported (Table 1) highlights the difficulty in studying such a wary and cryptic animal, and the need to bring to bear as many tools as possible to the investigator’s toolkit, in order to better understand their ecology and biogeography. There are many aspirational goals I had for this project that were not feasible logistically but would be excellent points to expound upon in future projects.

In general, it is likely that future studies using similar method and building off of this project’s progress would be better suited for species with a more narrow niche or in areas where river otter may utilize a narrower niche (Murphy and Lovett-Doust 2007; Herzel and Le Lay 2008). As discovered through my review of the ecological literature on river otters and my own work on the present study, it is clear that the North American river otter can utilize a variety of spaces, including developed urban areas (Ruiz-Olmo et al. 2005; Bennett 2014). Their wide range of habitat preferences make it much more difficult to identify the environmental parameters that are most important in identifying habitat that is most favorable for otter population expansion or for reintroduction efforts, or even conserving currently occupied areas. Additionally, delving further into the human-otter interaction and the role adaptation to urban environments may play in habitat selection could be a important next step.

Overall, the results of this project can provide a preliminary guide for conservation managers. Because conservation dollars are limited, being able to focus on conserving areas that will provide the greatest amount of protection for the most species is critical. It is important to remember the fact that river otters are indicators of ecosystem health. Assuming the habitat is well managed enough to be suitable for a stable otter population, the habitat should also be suitable for many other aquatic species (Glen and Dickman 2005; Sergio et al. 2008; Ritchie and Johnson 2009; Holland and van der Merwe 2016).

If nothing else, this project reinforces the need for monitoring the North American River otter, as there is little data currently available on the distribution and abundance of this species in

Tennessee. Although the reintroduction of otters into Tennessee was successful (Griess 1987), it is important that we continue to safeguard this species and sustain healthy populations for years to come, especially as a species that can currently be trapped as a furbearer without limitation (TWRA 2007). According to IUCN's Red List, the other 12 extant otter species of the world are listed as "Vulnerable," "Near Risk," or "Endangered." The IUCN's World Conservation Congress published notion 114 on March 23, 2020, indicating the global decline of otter populations due to environmental threats, mostly caused by humans, and the need for maintaining and enhancing otter habitats worldwide (IUCN 2020). Perhaps we should take heed and proactively provide conservation support to our native otter species, *Lontra canadensis.*

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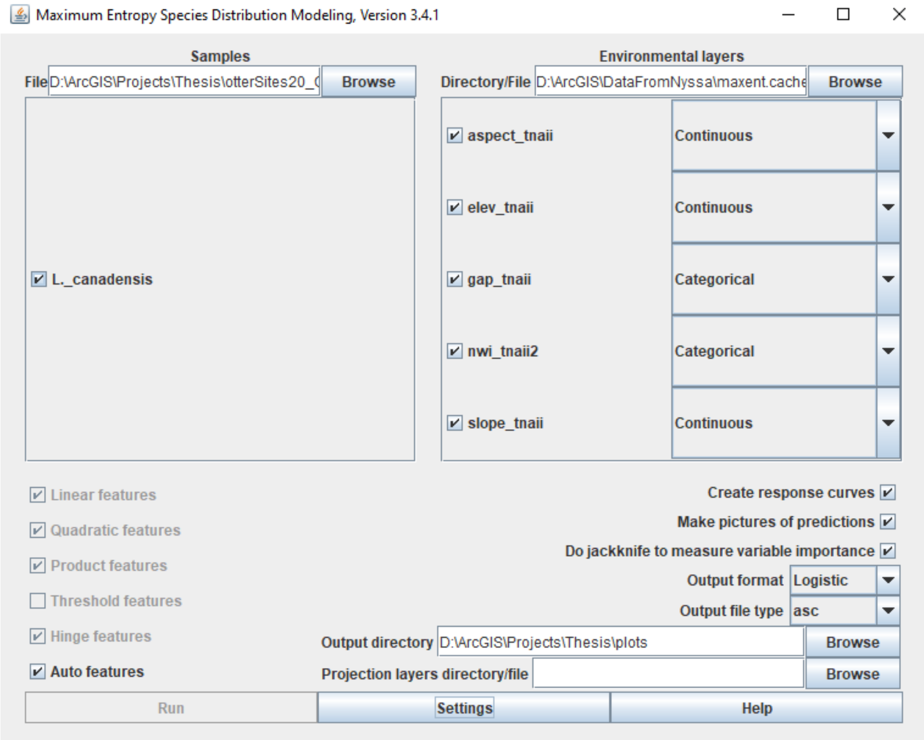
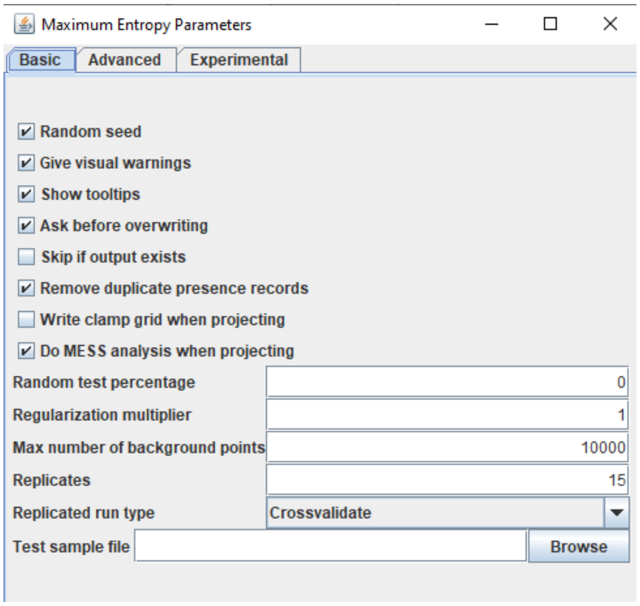
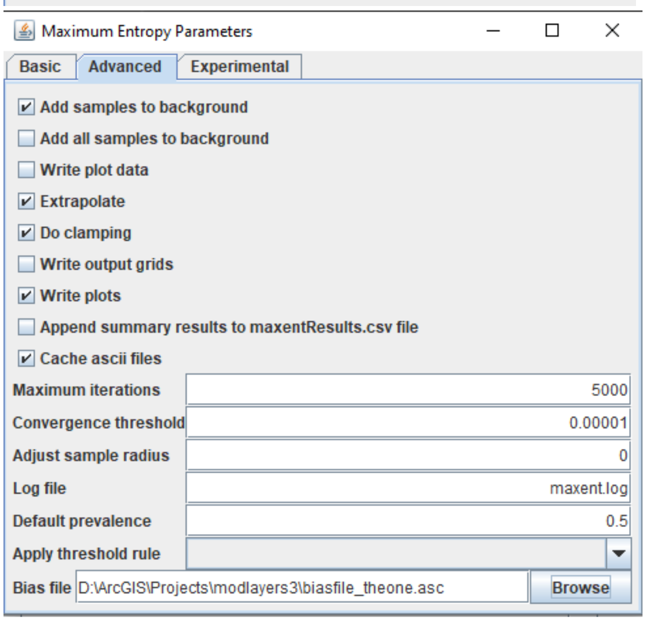
APPENDIX A

MAXENT INPUT FOR EAST TENNESSEE

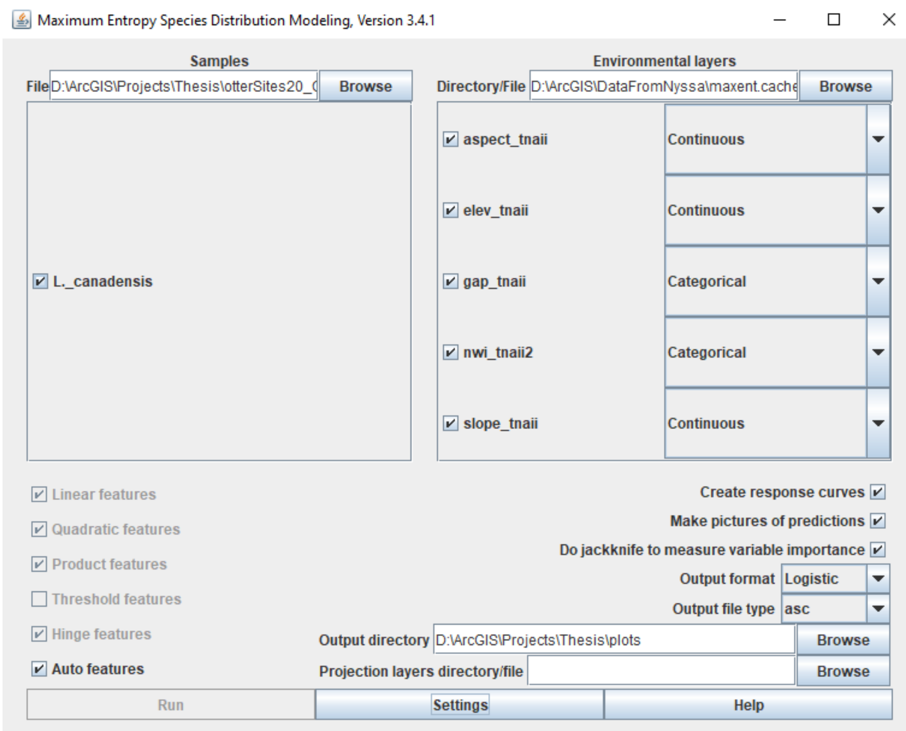
The following is the Maxent Input for Determining River Otter Habitat Suitability in East Tennessee using Cross-Validation.

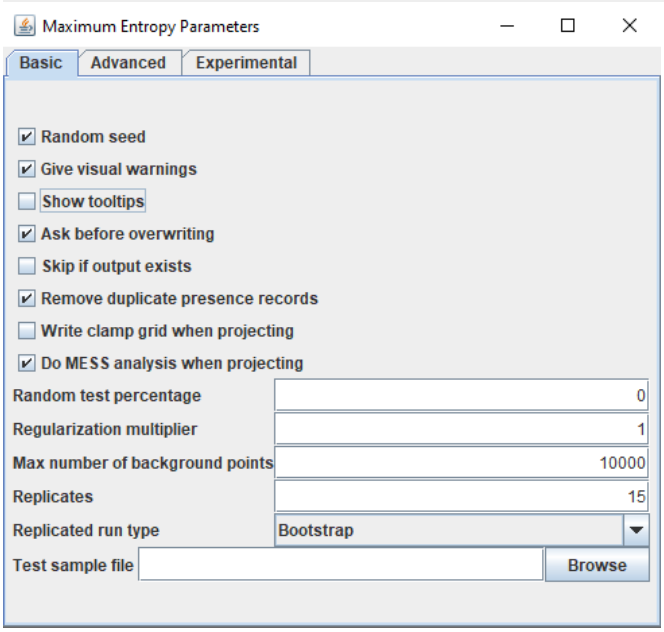


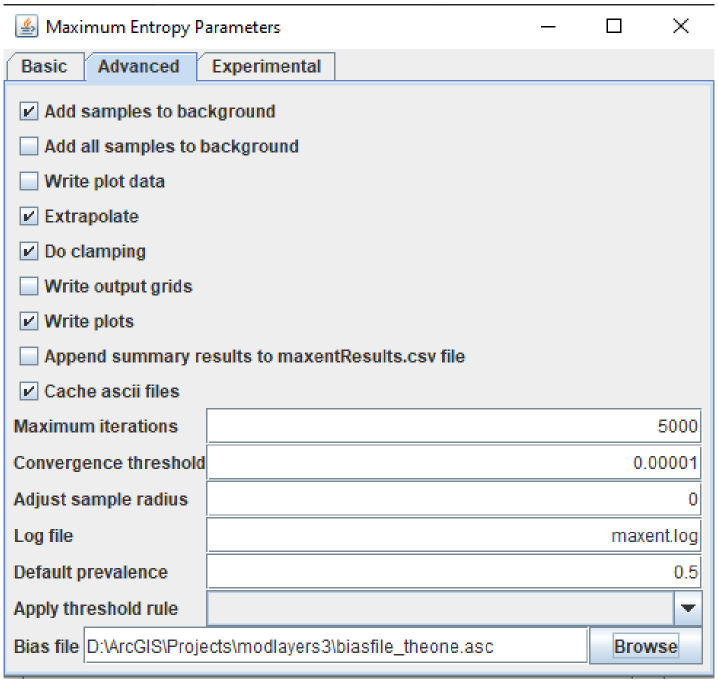

Maximum Entropy Parameters
Basic
Advanced
Experimental
Random seed
Give visual warnings
Show tooltips
Ask before overwriting
Skip if output exists
Remove duplicate presence records
Write clamp grid when projecting
Do MESS analysis when projecting
Random test percentage
0
Regularization multiplier
1
Max number of background points
10000
Replicates
15
Replicated run type
Crossvalidate
Test sample file
Browse


Maximum Entropy Parameters
Basic
Advanced
Experimental
Add samples to background
Add all samples to background
Write plot data
Extrapolate
Do clamping
Write output grids
Write plots
Append summary results to maxentResults.csv file
Cache ascii files
Maximum iterations
5000
Convergence threshold
0.00001
Adjust sample radius
0
Log file
maxent.log
Default prevalence
0.5
Apply threshold rule
Bias file
D:\ArcGIS\Projects\modlayers3\biasfile_theone.asc
Browse

The following is the Maxent Input for Determining River Otter Habitat Suitability in East Tennessee using Bootstrapping.



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Advanced
Experimental
Add samples to background
Add all samples to background
Write plot data
Extrapolate
Do clamping
Write output grids
Write plots
Append summary results to maxentResults.csv file
Cache ascii files
Maximum iterations
5000
Convergence threshold
0.00001
Adjust sample radius
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Log file
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Default prevalence
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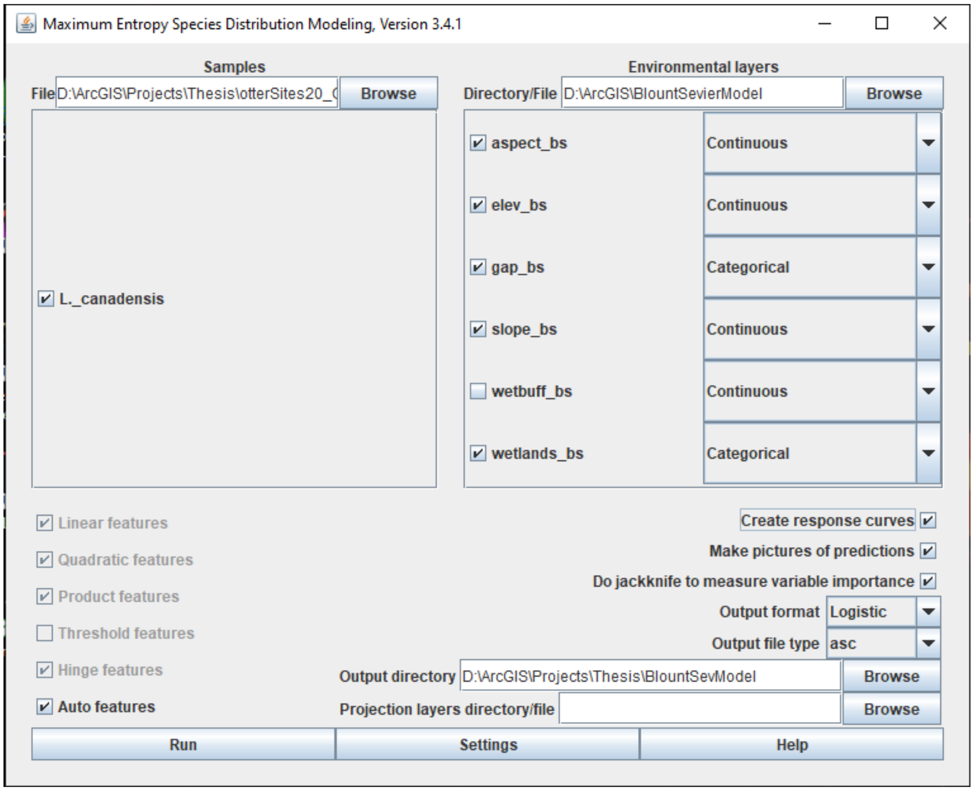
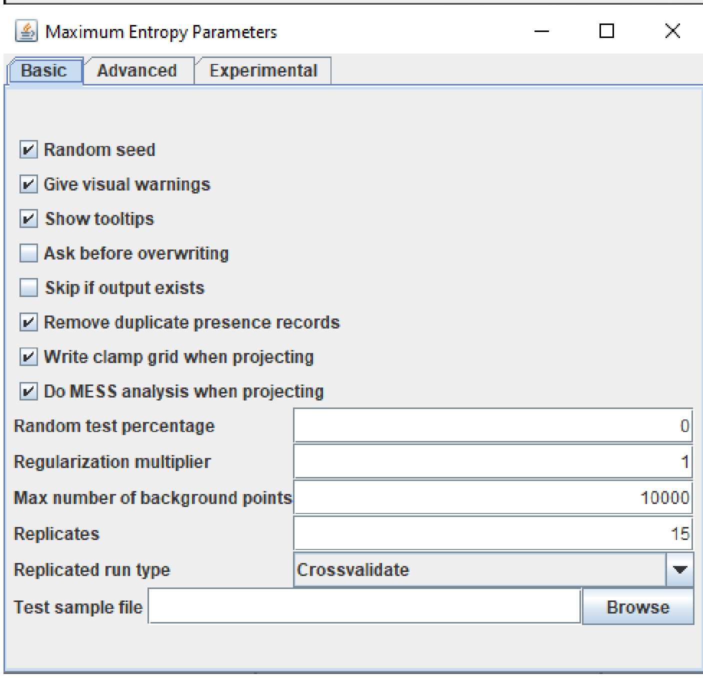
Apply threshold rule
Bias file
D:\ArcGIS\Projects\modlayers3\biasfile_theone.asc
Browse

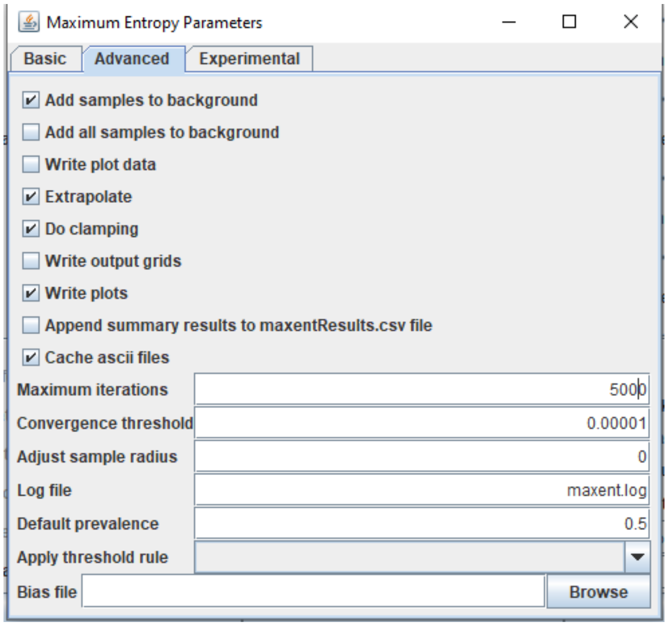
APPENDIX B

MAXENT INPUT FOR BLOUNT & SEVIER COUNTIES

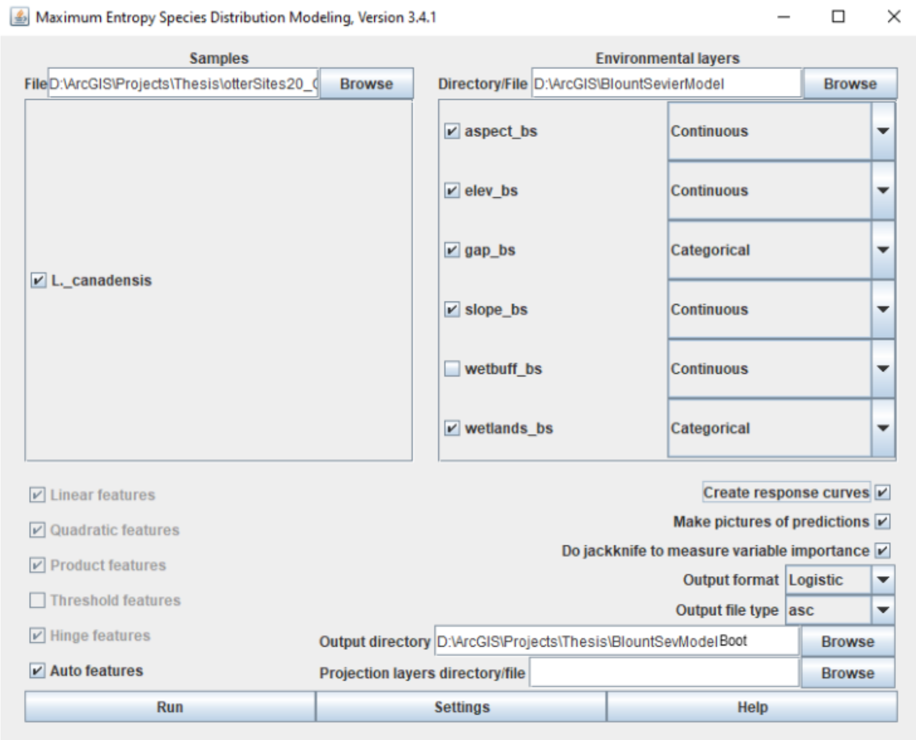
The following is the Maxent Input for Determining River Otter Habitat Suitability in Blount & Sevier Counties of Tennessee using Cross-Validation.

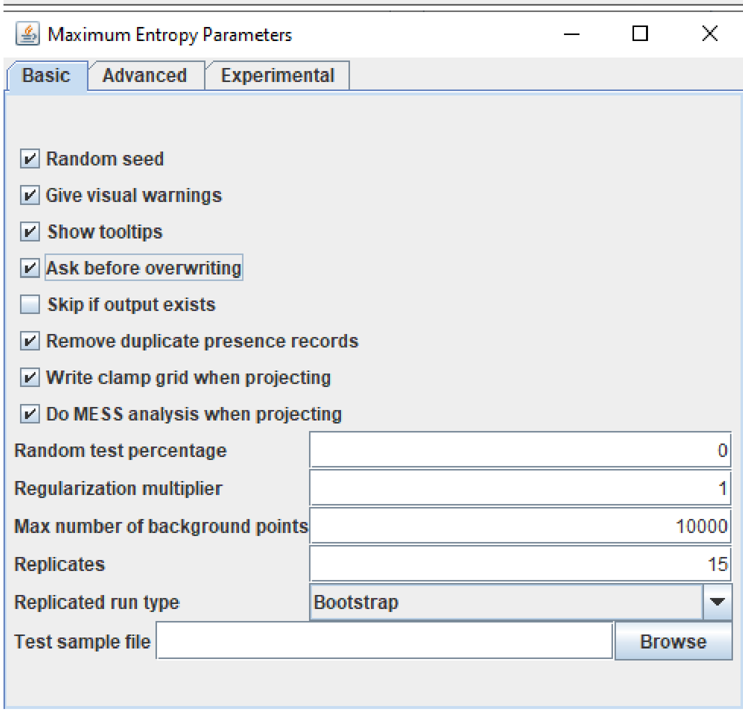


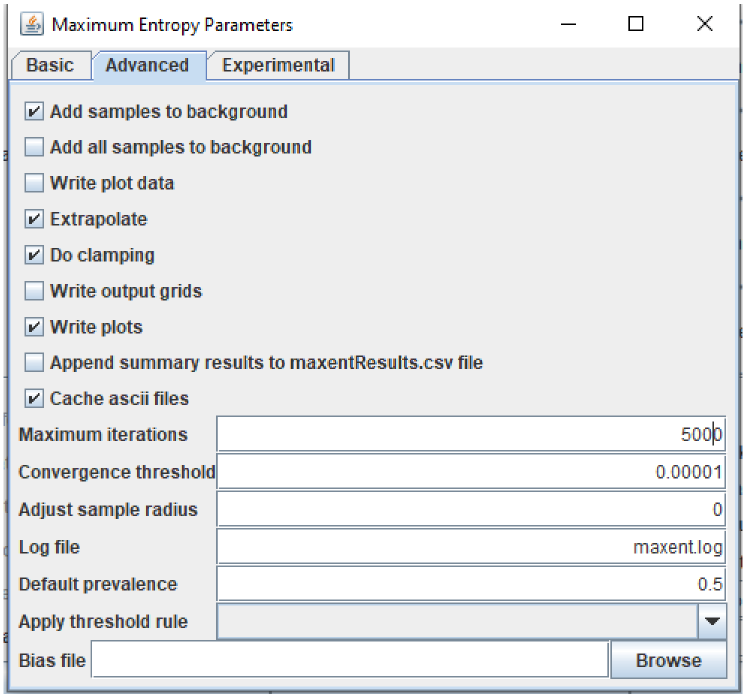



Maximum Entropy Parameters
Basic
Advanced
Experimental
Add samples to background
Add all samples to background
Write plot data
Extrapolate
Do clamping
Write output grids
Write plots
Append summary results to maxentResults.csv file
Cache ascii files
Maximum iterations
5000
Convergence threshold
0.00001
Adjust sample radius
0
Log file
maxent.log
Default prevalence
0.5
Apply threshold rule
Bias file
Browse

The following is the Maxent Input for Determining River Otter Habitat Suitability in Blount & Sevier Counties of Tennessee using Bootstrapping.



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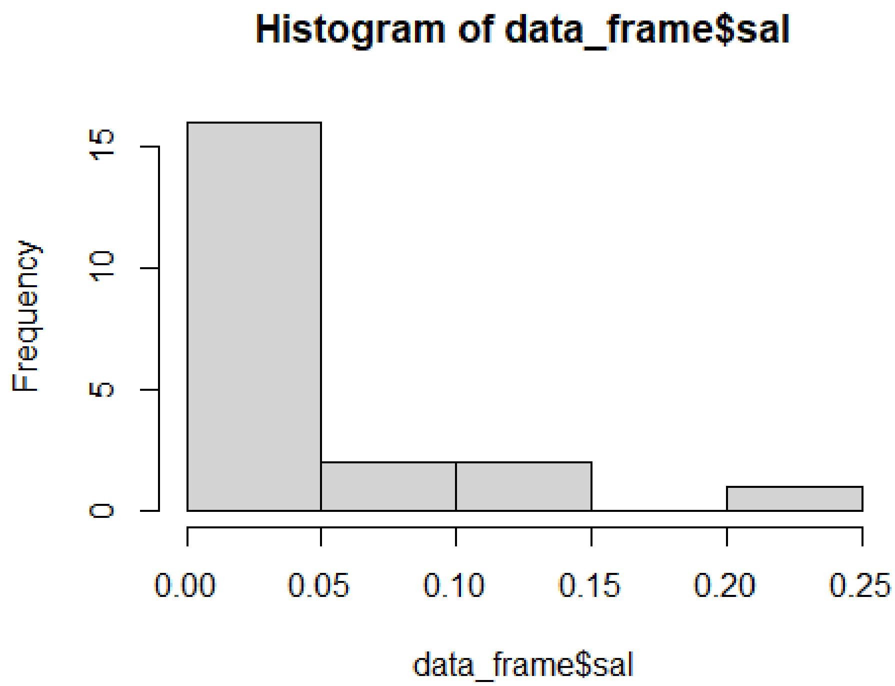
Advanced
Experimental
Add samples to background
Add all samples to background
Write plot data
Extrapolate
Do clamping
Write output grids
Write plots
Append summary results to maxentResults.csv file
Cache ascii files
Maximum iterations
5000
Convergence threshold
0.00001
Adjust sample radius
0
Log file
maxent.log
Default prevalence
0.5
Apply threshold rule
Bias file
Browse

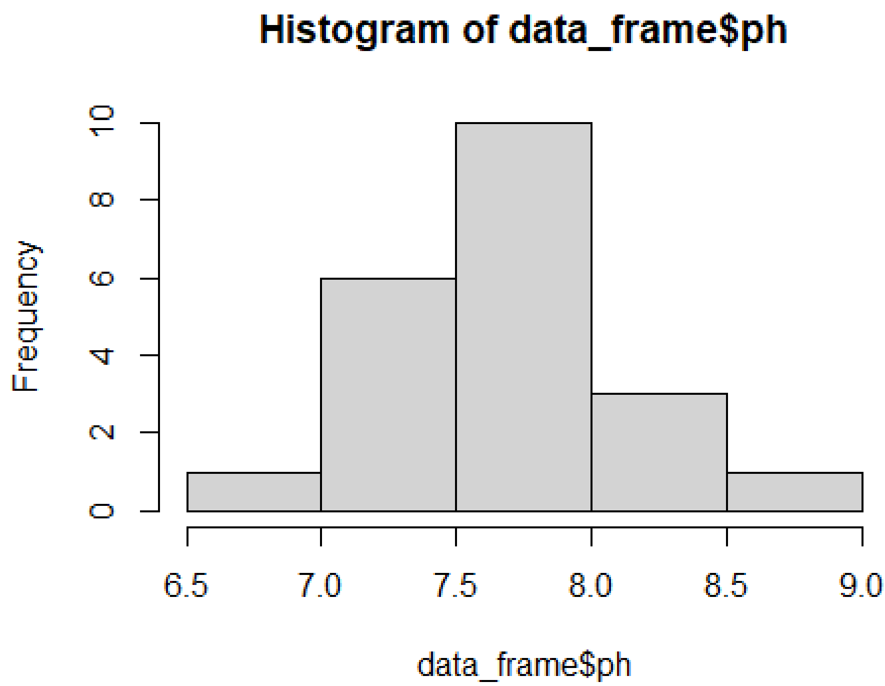
APPENDIX C

GRUBBS’ TEST FOR OUTLIERS FOR WATER QUALITY METRICS AND FIXED WATER QUALITY MEASURES OF CENTRAL TENDENCY

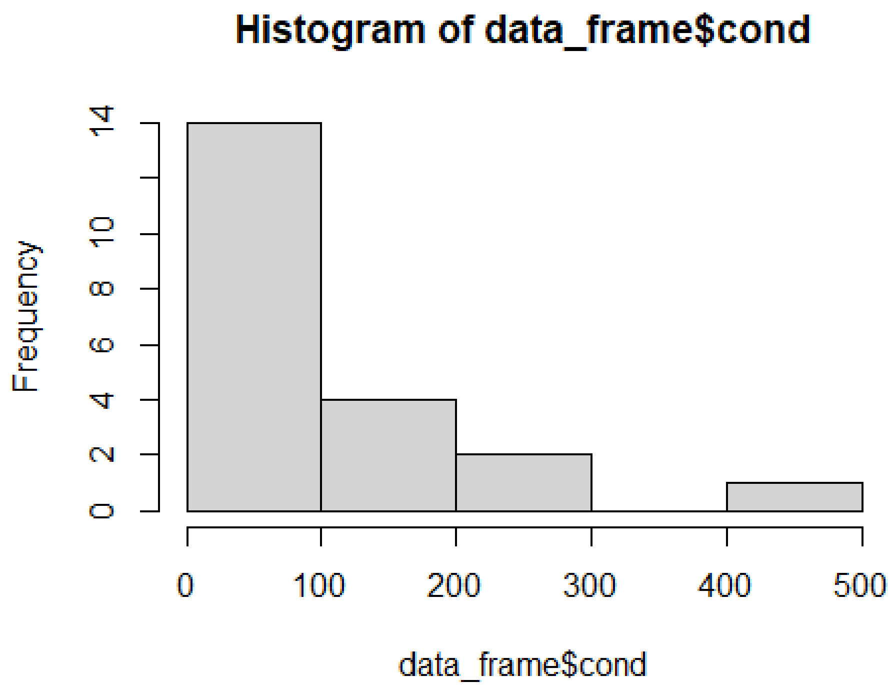
The following histograms, created using R 4.0.0 software, indicate the frequency (number of sites) of water quality metrics amongst the 21 river otter occurrence sites.



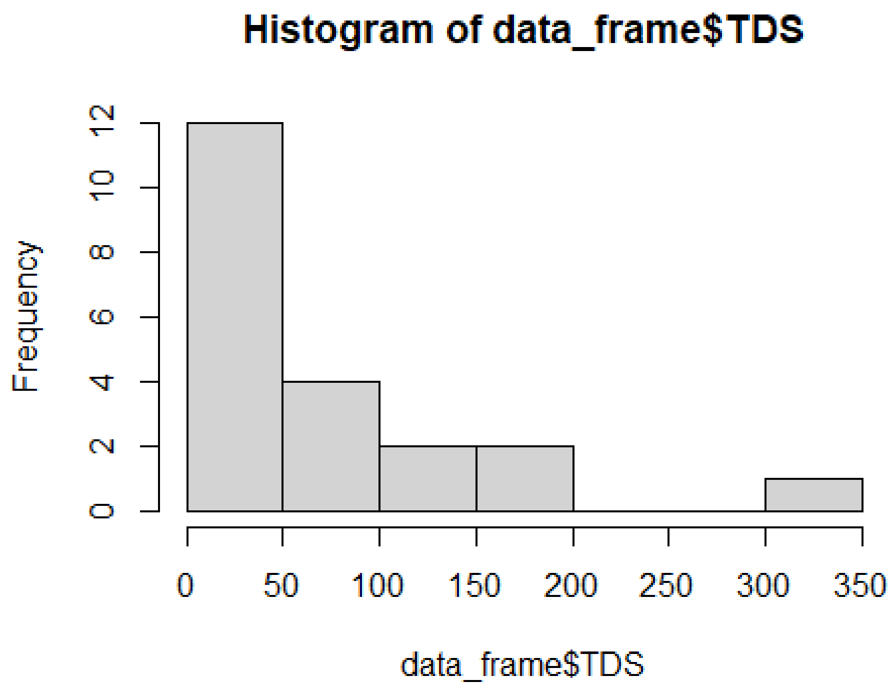
Frequency of salinity measurements at each of the 21 river otter occurrence sites. X-axis is the measurement range in parts per trillion. Y-axis is the number of sites at which the corresponding measurement range occurred.



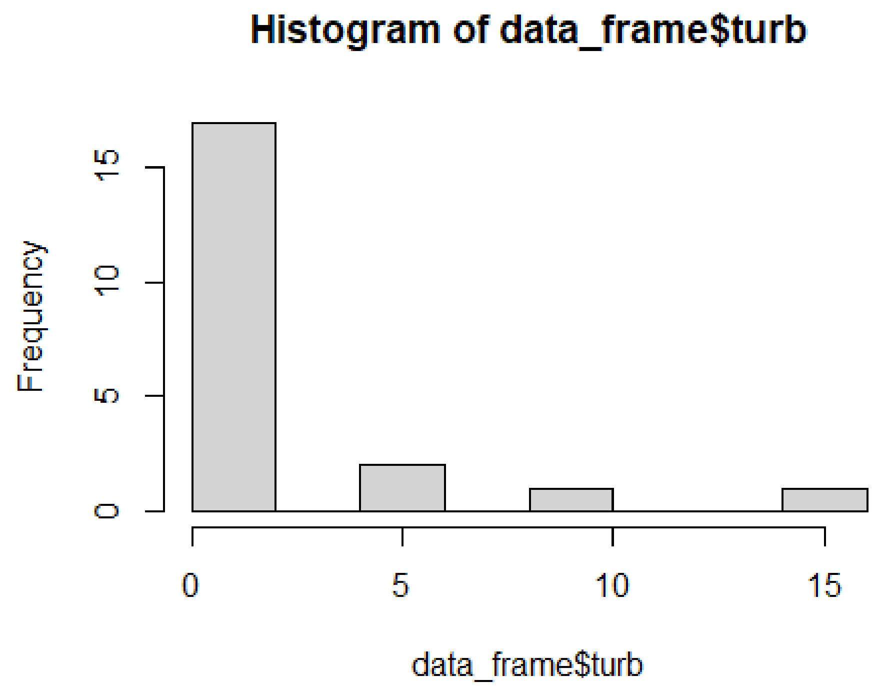
Frequency of pH measurements at each of the 21 river otter occurrence sites. X-axis is the range of pH values. Y-axis is the number of sites at which the corresponding measurement range occurred.



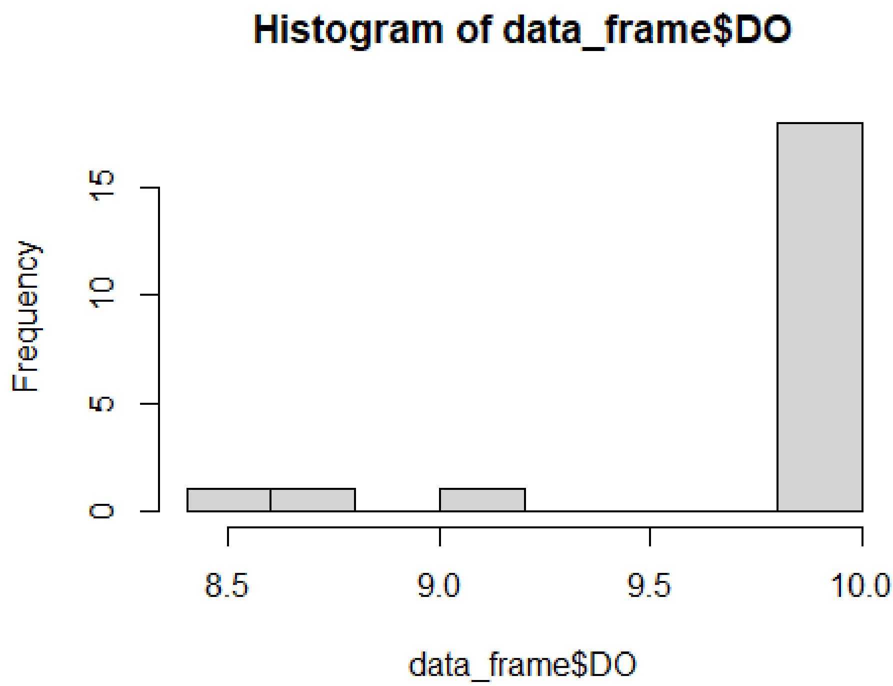
Frequency of conductivity measurements at each of the 21 river otter occurrence sites. X-axis is the measurement range in microsiemens. Y-axis is the number of sites at which the corresponding measurement range occurred.



Frequency of total dissolved solutes measurements at each of the 21 river otter occurrence sites. X-axis is the measurement range in parts per million. Y-axis is the number of sites at which the corresponding measurement range occurred.



Frequency of turbidity measurements at each of the 21 river otter occurrence sites. X-axis is the measurement range in Jackson turbidity units. Y-axis is the number of sites at which the corresponding measurement range occurred.



Frequency of dissolved oxygen measurements at each of the 21 river otter occurrence sites. X-axis is the measurement range in parts per million. Y-axis is the number of sites the corresponding measurement range occurred at.

Frequency of stream width measurements at each of the 21 river otter occurrence sites. X-axis is the measurement range in meters. Y-axis is the number of sites the corresponding measurement range occurred at.

The following is the code associated with conducting the Grubbs' Test for Outliers, conducted in R 4.0.0 software. Three versions of this test were run: (1) to test for one maximum outlier, in which the null hypothesis is "there are no outliers in the dataset" and the alternative hypothesis is "the maximum value is an outlier;" (2) to test for two opposite outliers, in which the null hypothesis is "there are no outliers in the dataset" and the alternative hypothesis is "the maximum and minimum values are outliers;" (3) to test for two outliers in the same tail, in which the null hypothesis is "there are no outliers in the dataset" and the alternative hypothesis is "the two values are outliers in the same tail." A p-value less than 0.5 indicates significance.

```
print("Salinity")

## [1] "Salinity"

grubbs.test(data_frame$sal, type=10, opposite=FALSE, two.sided=FALSE)

##
##  Grubbs test for one outlier
##
## data:  data_frame$sal
## G = 3.4014, U = 0.3926, p-value = 0.0003283
## alternative hypothesis: highest value 0.24 is an outlier

grubbs.test(data_frame$sal, type=11, opposite=FALSE, two.sided=FALSE)

##
##  Grubbs test for two opposite outliers
##
## data:  data_frame$sal
## G = 4.13824, U = 0.37569, p-value = 0.2711
## alternative hypothesis: 0.01 and 0.24 are outliers

grubbs.test(data_frame$sal, type=20, opposite=FALSE, two.sided=FALSE)

##
##  Grubbs test for two outliers
##
## data:  data_frame$sal
## U = 0.25915, p-value < 2.2e-16
## alternative hypothesis: highest values 0.13 , 0.24 are outliers

summary(data_frame$sal) #summary is used for basic stats

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.01000 0.02000 0.03000 0.05095 0.05000 0.24000
```

```r
print("pH levels")

## [1] "pH levels"

grubbs.test(data_frame$ph, type=10, opposite=FALSE, two.sided=FALSE)

##
##  Grubbs test for one outlier
##
## data:  data_frame$ph
## G = 2.46290, U = 0.68154, p-value = 0.08087
## alternative hypothesis: highest value 8.76 is an outlier

grubbs.test(data_frame$ph, type=11, opposite=FALSE, two.sided=FALSE)

##
##  Grubbs test for two opposite outliers
##
## data:  data_frame$ph
## G = 4.58408, U = 0.47143, p-value = 0.04239
## alternative hypothesis: 6.85 and 8.76 are outliers

grubbs.test(data_frame$ph, type=20, opposite=FALSE, two.sided=FALSE)

##
##  Grubbs test for two outliers
##
## data:  data_frame$ph
## U = 0.5839, p-value = 0.1768
## alternative hypothesis: highest values 8.25 , 8.76 are outliers

summary(data_frame$ph)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   6.850   7.470   7.800   7.734   7.900   8.760

print("Conductivity")

## [1] "Conductivity"

grubbs.test(data_frame$cond, type=10, opposite=FALSE, two.sided=FALSE)

##
##  Grubbs test for one outlier
##
## data:  data_frame$cond
## G = 3.3292, U = 0.4181, p-value = 0.000608
## alternative hypothesis: highest value 475 is an outlier

grubbs.test(data_frame$cond, type=11, opposite=FALSE, two.sided=FALSE)
```

```
##
##  Grubbs test for two opposite outliers
##
## data:  data_frame$cond
## G = 4.12412, U = 0.39731, p-value = 0.2854
## alternative hypothesis: 16 and 475 are outliers
```

```r
grubbs.test(data_frame$cond, type=20, opposite=FALSE, two.sided=FALSE)
```

```
##
##  Grubbs test for two outliers
##
## data:  data_frame$cond
## U = 0.27571, p-value < 2.2e-16
## alternative hypothesis: highest values 269 , 475 are outliers
```

```r
summary(data_frame$cond)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    16.0    37.8    54.0   104.5   103.8   475.0
```

```r
print("Total Dissolved Solids")
```

```
## [1] "Total Dissolved Solids"
```

```r
grubbs.test(data_frame$TDS, type=10, opposite=FALSE, two.sided=FALSE)
```

```
##
##  Grubbs test for one outlier
##
## data:  data_frame$TDS
## G = 3.36496, U = 0.40554, p-value = 0.000451
## alternative hypothesis: highest value 340 is an outlier
```

```r
grubbs.test(data_frame$TDS, type=11, opposite=FALSE, two.sided=FALSE)
```

```
##
##  Grubbs test for two opposite outliers
##
## data:  data_frame$TDS
## G = 4.15977, U = 0.38488, p-value = 0.2506
## alternative hypothesis: 11.3 and 340 are outliers
```

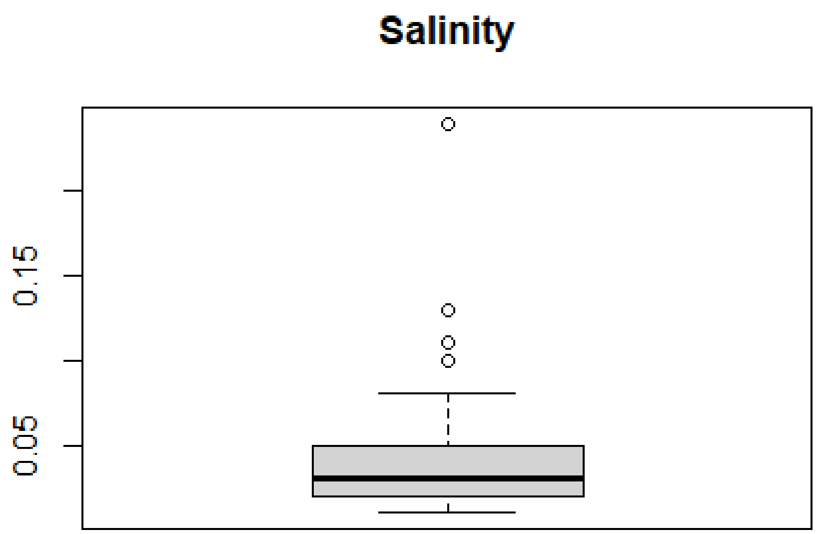
```r
grubbs.test(data_frame$TDS, type=20, opposite=FALSE, two.sided=FALSE)
```

```
##
##  Grubbs test for two outliers
##
## data:  data_frame$TDS
## U = 0.27554, p-value < 2.2e-16
## alternative hypothesis: highest values 185 , 340 are outliers
```

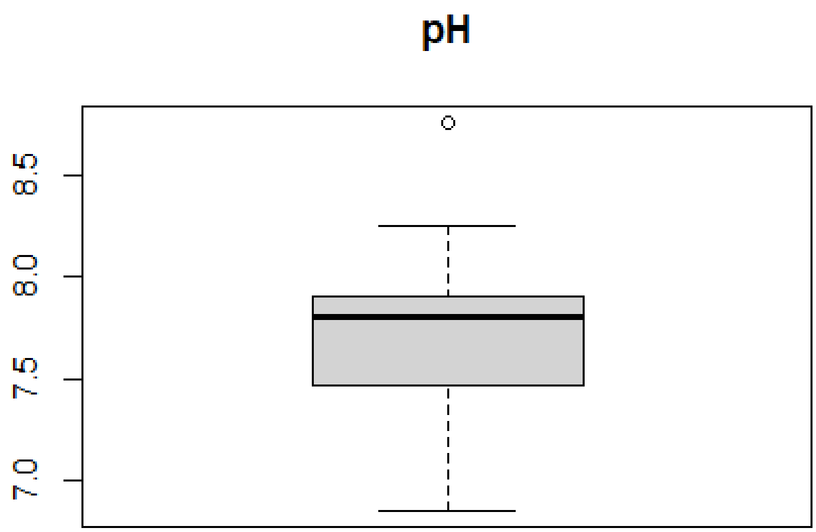
```
summary(data_frame$TDS)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    11.3    27.7    42.8    74.1    74.2   340.0

print("Turbidity")

## [1] "Turbidity"

grubbs.test(data_frame$turb, type=10, opposite=FALSE, two.sided=FALSE)

##
##  Grubbs test for one outlier
##
## data:  data_frame$turb
## G = 3.29941, U = 0.42848, p-value = 0.0007735
## alternative hypothesis: highest value 15 is an outlier

grubbs.test(data_frame$turb, type=11, opposite=FALSE, two.sided=FALSE)

##
##  Grubbs test for two opposite outliers
##
## data:  data_frame$turb
## G = 3.7251, U = 0.4249, p-value = 1
## alternative hypothesis: 0 and 15 are outliers

grubbs.test(data_frame$turb, type=20, opposite=FALSE, two.sided=FALSE)

##
##  Grubbs test for two outliers
##
## data:  data_frame$turb
## U = 0.16847, p-value < 2.2e-16
## alternative hypothesis: highest values 10 , 15 are outliers

summary(data_frame$turb)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   0.000   0.000   1.714   0.000  15.000

print("Dissolved Oxygen")

## [1] "Dissolved Oxygen"

grubbs.test(data_frame$DO, type=10, opposite=FALSE, two.sided=FALSE)

##
##  Grubbs test for one outlier
##
## data:  data_frame$DO
```

```
## G = 3.12262, U = 0.48808, p-value = 0.002793
## alternative hypothesis: lowest value 8.4 is an outlier

grubbs.test(data_frame$DO, type=11, opposite=FALSE, two.sided=FALSE)

##
##  Grubbs test for two opposite outliers
##
## data:  data_frame$DO
## G = 3.50904, U = 0.48529, p-value = 1
## alternative hypothesis: 8.4 and 10 are outliers

grubbs.test(data_frame$DO, type=20, opposite=FALSE, two.sided=FALSE)

##
##  Grubbs test for two outliers
##
## data:  data_frame$DO
## U = 0.18455, p-value < 2.2e-16
## alternative hypothesis: lowest values 8.4 , 8.8 are outliers

summary(data_frame$DO)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   8.400  10.000  10.000   9.824  10.000  10.000
```

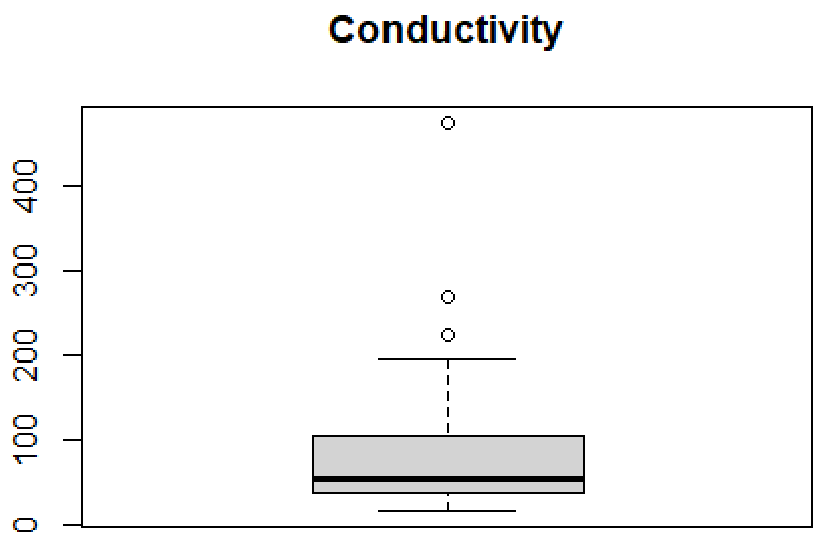
The following boxplots, created using R 4.0.0 software, illustrate water quality measurements amongst the 21 river otter occurrence sites.



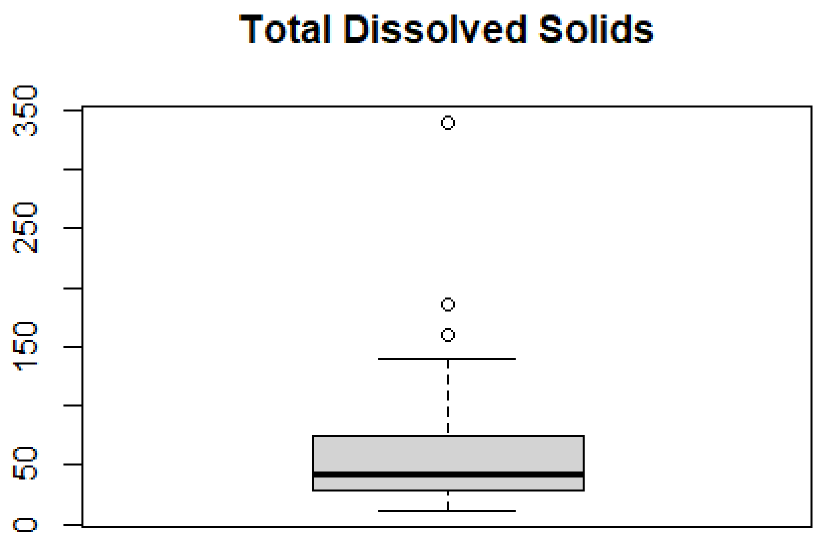
Measurements for salinity amongst the 21 river otter occurrence sites. Y-axis is measurement of salinity in parts per trillion. The gray box indicates the interquartile range (IQR); the top of the gray box indicates the 75th percentile (Q_3); the bottom of the gray box indicates the 25th percentile (Q_1); the bold black line in the middle of the gray box indicates the median (Q_2); the vertical line extending from the top of the gray box indicates the minimum value in the data excluding outliers (Q_1-1.5 IQR); the vertical line extending from the bottom of the gray box indicates the minimum value in the data excluding outliers (Q_3+1.5 IQR); the circles indicate outliers.



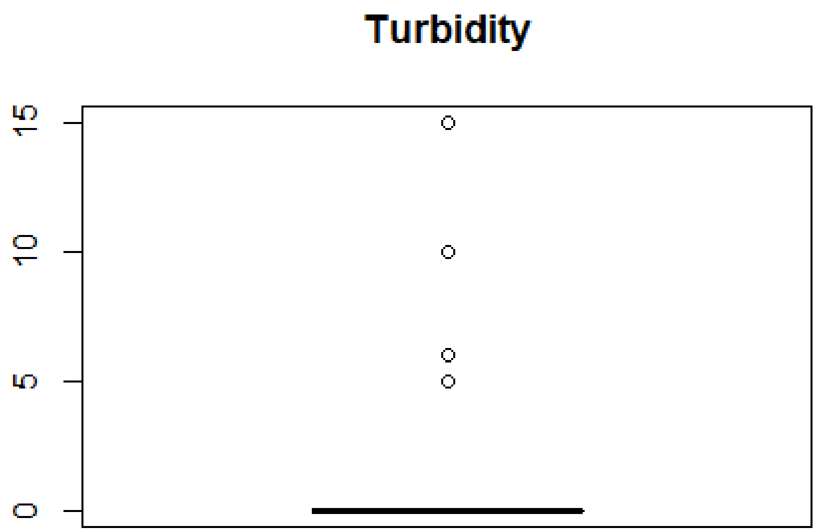
Measurements for pH amongst the 21 river otter occurrence sites. Y-axis is measurement of pH. The gray box indicates the interquartile range (IQR); the top of the gray box indicates the 75th percentile (Q_3); the bottom of the gray box indicates the 25th percentile (Q_1); the bold black line in the middle of the gray box indicates the median (Q_2); the vertical line extending from the top of the gray box indicates the minimum value in the data excluding outliers (Q_1-1.5 IQR); the vertical line extending from the bottom of the gray box indicates the minimum value in the data excluding outliers (Q_3+1.5 IQR); the circles indicate outliers.



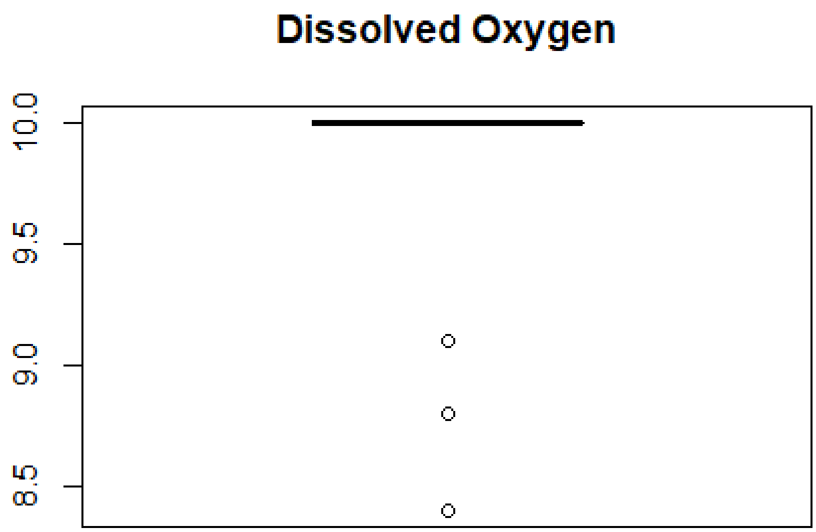
Measurements for conductivity amongst the 21 river otter occurrence sites. Y-axis is measurement of conductivity in microsiemens. The gray box indicates the interquartile range (IQR); the top of the gray box indicates the 75th percentile (Q_3); the bottom of the gray box indicates the 25th percentile (Q_1); the bold black line in the middle of the gray box indicates the median (Q_2); the vertical line extending from the top of the gray box indicates the minimum value in the data excluding outliers (Q_1-1.5 IQR); the vertical line extending from the bottom of the gray box indicates the minimum value in the data excluding outliers (Q_3+1.5 IQR); the circles indicate outliers.



Measurements for total dissolved solutes amongst the 21 river otter occurrence sites. Y-axis is measurement of total dissolved solutes in parts per million. The gray box indicates the interquartile range (IQR); the top of the gray box indicates the 75th percentile (Q_3); the bottom of the gray box indicates the 25th percentile (Q_1); the bold black line in the middle of the gray box indicates the median (Q_2); the vertical line extending from the top of the gray box indicates the minimum value in the data excluding outliers (Q_1-1.5 IQR); the vertical line extending from the bottom of the gray box indicates the minimum value in the data excluding outliers (Q_3+1.5 IQR); the circles indicate outliers.



Measurements for turbidity amongst the 21 river otter occurrence sites. Y-axis is measurement of turbidity in Jackson turbidity units. The bold black line in the middle of the gray box indicates the median (Q_2); the circles indicate outliers.



Measurements for dissolved oxygen amongst the 21 river otter occurrence sites. Y-axis is measurement of dissolved oxygen in parts per million. The bold black line in the middle of the gray box indicates the median (Q_2); the circles indicate outliers.

Water quality measurements and calculations for 21 river otter occurrence sites utilized in the present study. Salinity is measured in parts per trillion (ppt); conductivity is measured in microsiemens (µS); total dissolved solutes and dissolved oxygen are measured in parts per million (ppm); turbidity is measured in Jackson turbidity units (JTLJ); stream width is measured in meters (m). Outliers existed where the highlighted boxes are; they were removed to calculated mean, median, mode and standard deviation (std. dev.) for each metric.

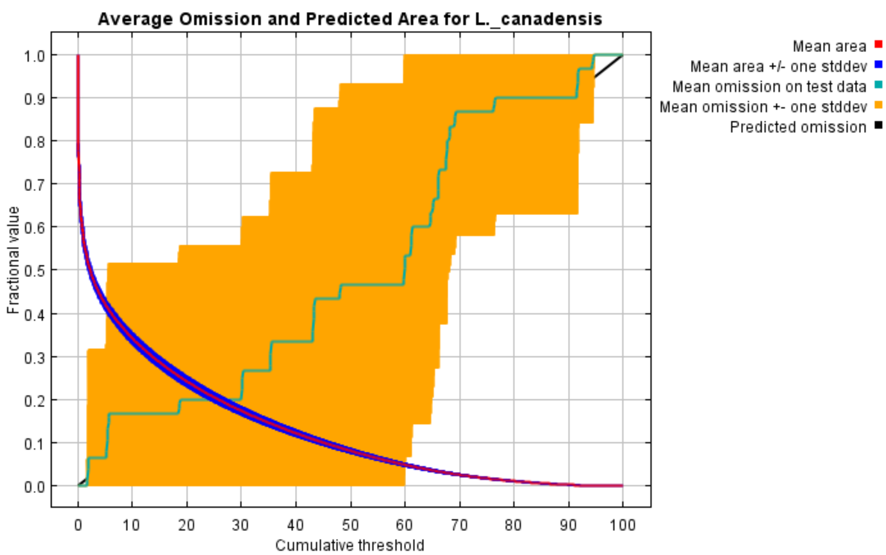
Site	Salinity (ppt)	pH	Conductivity (µS)	Total Dissolved Solutes (ppm)	Turbidity (JTLJ)	Dissolved Oxygen (ppm)	Stream Width (m)
1	0.02	7.84	28.8	20	0	10	15
2	0.1	7.98	195.9	139	0	10	4
4	0.11	7.9	224	160			5
6	0.02	7.49	44.4	31.4	0	10	6
8	0.04	7.7	91.7	60.3	0	10	1
9	0.03		46.6	42.8	0	10	6
10	0.13				0	10	15
12	0.01	7.83	29.2	20.2	0	10	2
20	0.01	7.36	16.7	11.7	0	10	3
22	0.03	7.9	54	38.3	6	10	n/a
23	0.01	7.45	16	11.3	0	10	4
24	0.08	8.25	183	130		9.1	10
25	0.04	7.79	81	57.6	0	10	1
26	0.03	7.8	66.8	44.2	0	10	2
29	0.02	8.15	42	29	0	10	15
31	0.01	7.2	48.7	34.5	0	10	10
34		8.09			0		2
39	0.05	7.58	103.8	74.2	0	10	5
40	0.02	7.22	37.8	27.7	0	10	1
41	0.05	7.47	102.3	72.8	5	10	2
42	0.02	7.8	37.1	26.2	0	10	8
Mean	0.0415	7.726316	76.30526316	54.273684	0.57894737	9.952631579	5.85
Median	0.03	7.8	48.7	38.3	0	10	4.5
Mode	0.02	7.9	#N/A	#N/A	0	10	2
Std. Dev.	0.0348246	0.293512	59.95749787	42.555992	1.6956846	0.20096719	4.671991

APPENDIX D

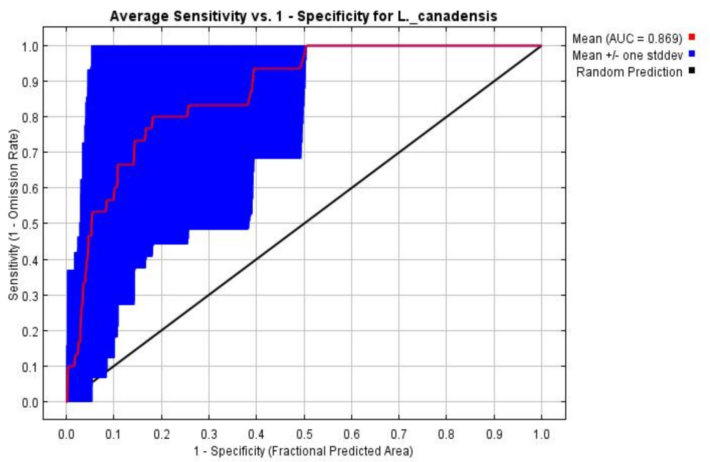
MAXENT OUTPUT FOR EAST TENNESSEE

The following is the Maxent Output for Determining River Otter Habitat Suitability in East Tennessee using Cross-Validation (Phillips et al. 2010).

The following graph indicates how testing and training omission and predicted area (of suitable habitat for river otter) varies with the choice of cumulative threshold. The red line indicates the mean area; blue indicates the standard deviation of mean area; green indicates mean omission as determined by test data input into Maxent; orange indicates the standard deviation of the mean omission; black indicated predicted omission. Y-axis is the fractional value of each variable represented. X-axis is the cumulative threshold within which it falls. Although the black line is covered by the orange here, it runs at a 45-degree angle (+,+) from (0,0). The green and black line being close indicates omission rate and predicted omission rate were good matches.

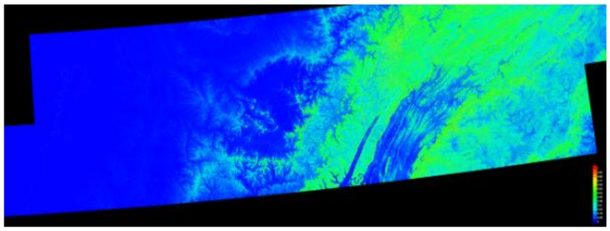


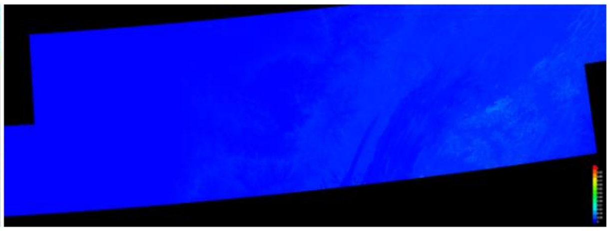
The following graph indicates the receiver operating curve for the data. Red indicates the man; blue indicates standard deviation of the mean; black indicates a random prediction. The area under the curve (AUC) is also provided, indicated the performance of the model. The closer to 1 the AUC is, the better the model performed. This logistic graph indicates receiver operating characteristic curve averaged on replicate runs. The x-axis, specificity, is defined using specificity (fractional predicted area), which is the proportion of absences correctly predicted, rather than true commission. The y-axis indicates sensitivity of the model, defined by sensitivity (omission rate), which is the proportion of presences correctly predicted (Phillips 2010).



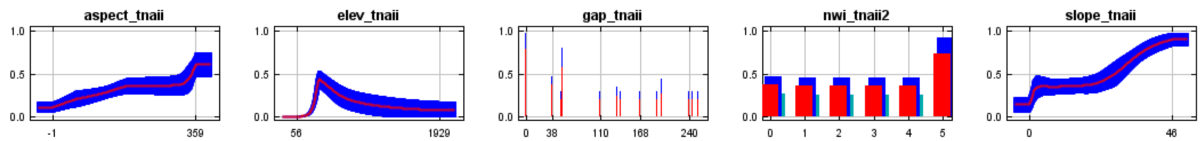
Pictures of the model

The following two pictures show the point-wise mean and standard deviation of the 15 output grids. Other available summary grids are min, max and median.





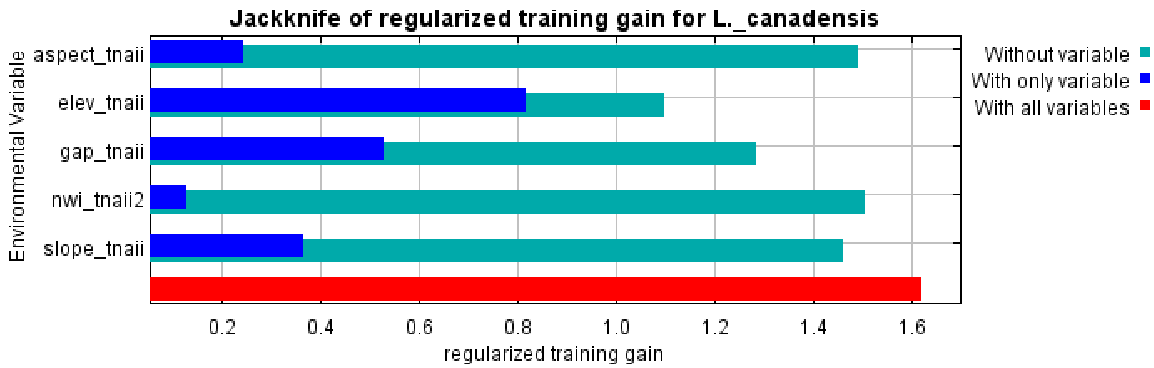
The following charts indicate response curves of the how the model/prediction depends on the variables input elev_tnaii = elevation; gap_tnaii = land cover; aspect_tnaii = aspect; slope_tnaii = slope; nwi_tnaii2 = riparian habitat). Y-axis is the predicted probability of suitable conditions where all other variables are set to their own average value over the set of presence localities (Phillips 2010). Red indicates the correlation, while blue indicates the standard deviation of that correlation.



Variable	Percent contribution	Permutation importance
elev_tnaii	50.3	71.3
gap_tnaii	21.7	10.6
aspect_tnaii	10.2	9.1
slope_tnaii	9.3	6.8
nwi_tnaii2	8.5	2.1

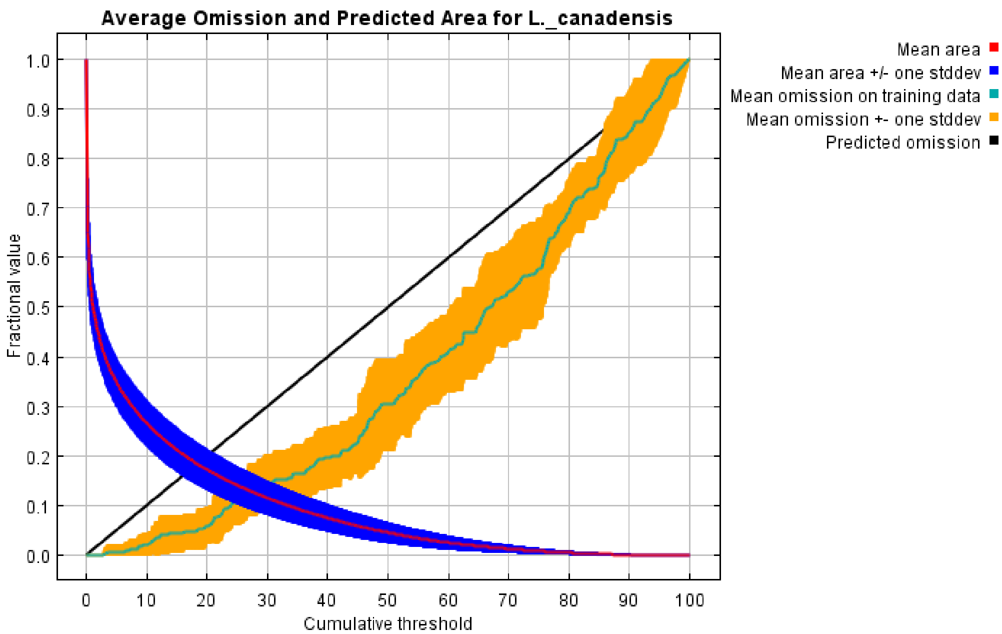
The table above indicates percent contribution, determined by the order variables were input in to Maxent code, and permutation importance, unbiased measure dependent on the final Maxent model to define environmental variables correlated to river otter presence (elev_tnaii = elevation; gap_tnaii = land cover; aspect_tnaii = aspect; slope_tnaii = slope; nwi_tnaii2 = riparian habitat). The permutation importance is the better estimate of variable correlation to river otter presence, as it is not defined by the user's order of input and the path used to obtain it (Phillips 2010).

The following charts indicate the jackknife response the how the model/prediction depends on the variables input elev_tnaii = elevation; gap_tnaii = land cover; aspect_tnaii = aspect; slope_tnaii = slope; nwi_tnaii2 = riparian habitat). Y-axis is the environmental variable. The x-axis is the regularized training gain, test gain, and AUC, respectively. Green indicates the gain/AUC without the specified variable included; blue indicates the gain/AUC with only the specified variable included; red indicates the gain/AUC with all variables included.

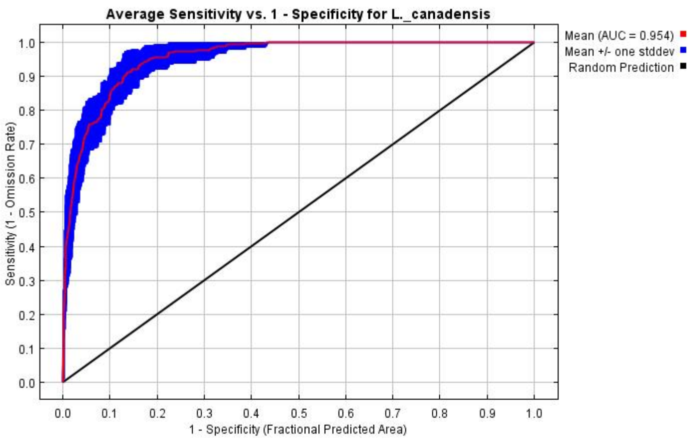


The following is the Maxent Output for Determining River Otter Habitat Suitability in East Tennessee using Bootstrapping (Phillips et al. 2010).

The following graph indicates how testing and training omission and predicted area (of suitable habitat for river otter) varies with the choice of cumulative threshold. The red line indicates the mean rea; blue indicates the standard deviation of mean area; green indicates mean omission as determined by test data input into Maxent; orange indicates the standard deviation of the mean omission; black indicated predicted omission. Y-axis is the fractional value of each variable represented. X-axis is the cumulative threshold within which it falls. The green and black lines are a somewhat close, indicating omission rate and predicted omission rate were fair matches.

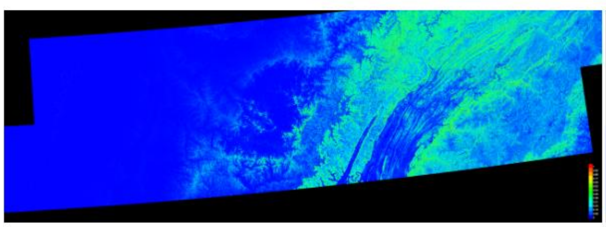


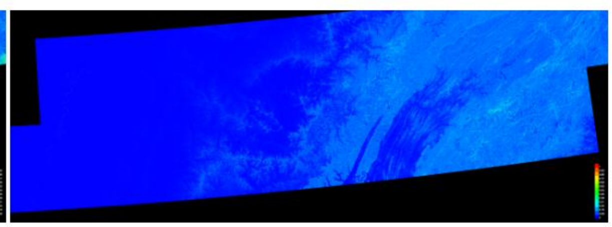
The following graph indicates the receiver operating curve for the data. Red indicates the man; blue indicates standard deviation of the mean; black indicates a random prediction. The area under the curve (AUC) is also provided, indicated the performance of the model. The closer to 1 the AUC is, the better the model performed. This logistic graph indicates receiver operating characteristic curve averaged on replicate runs. The x-axis, specificity, is defined using specificity (fractional predicted area), which is the proportion of absences correctly predicted, rather than true commission. The y-axis indicates sensitivity of the model, defined by sensitivity (omission rate), which is the proportion of presences correctly predicted (Phillips 2010).



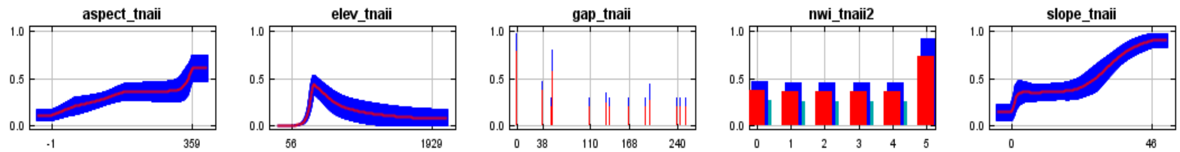
Pictures of the model

The following two pictures show the point-wise mean and standard deviation of the 15 output grids. Other available summary grids are min, max and median.





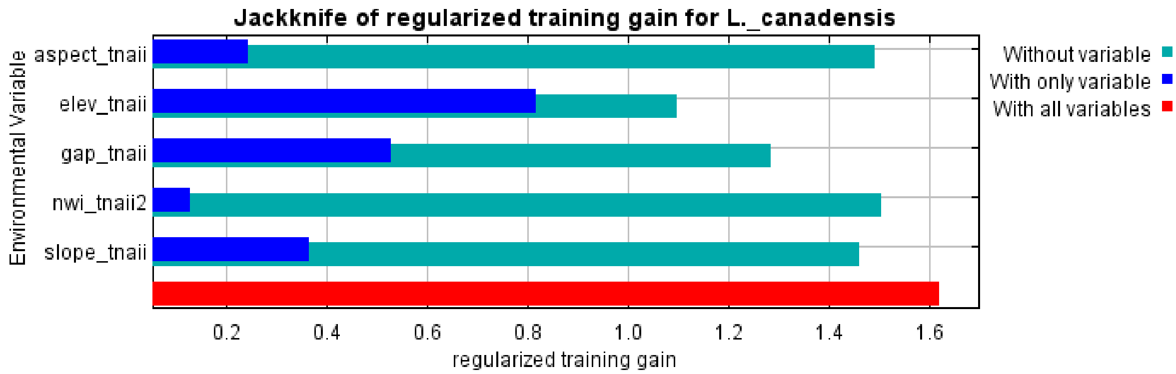
The following charts indicate the response curves of how the model/prediction depends on the variables input elev_tnaii = elevation; gap_tnaii = land cover; aspect_tnaii = aspect; slope_tnaii = slope; nwi_tnaii2 = riparian habitat). Y-axis is the predicted probability of suitable conditions where all other variables are set to their own average value over the set of presence localities (Phillips 2010). Red indicates the correlation, while blue indicates the standard deviation of that correlation.



Variable	Percent contribution	Permutation importance
elev_tnaii	50.3	71.3
gap_tnaii	21.7	10.6
aspect_tnaii	10.2	9.1
slope_tnaii	9.3	6.8
nwi_tnaii2	8.5	2.1

The table above indicates percent contribution, determined by the order variables were input in to Maxent code, and permutation importance, unbiased measure dependent on the final Maxent model to define environmental variables correlated to river otter presence (elev_tnaii = elevation; gap_tnaii = land cover; aspect_tnaii = aspect; slope_tnaii = slope; nwi_tnaii2 = riparian habitat). The permutation importance is the better estimate of variable correlation to river otter presence, as it is not defined by the user's order of input and the path used to obtain it (Phillips 2010).

The following charts indicate the jackknife response the how the model/prediction depends on the variables input elev_tnaii = elevation; gap_tnaii = land cover; aspect_tnaii = aspect; slope_tnaii = slope; nwi_tnaii2 = riparian habitat). Y-axis is the environmental variable. The x-axis is the regularized training gain, test gain, and AUC, respectively. Green indicates the gain/AUC without the specified variable included; blue indicates the gain/AUC with only the specified variable included; red indicates the gain/AUC with all variables included.

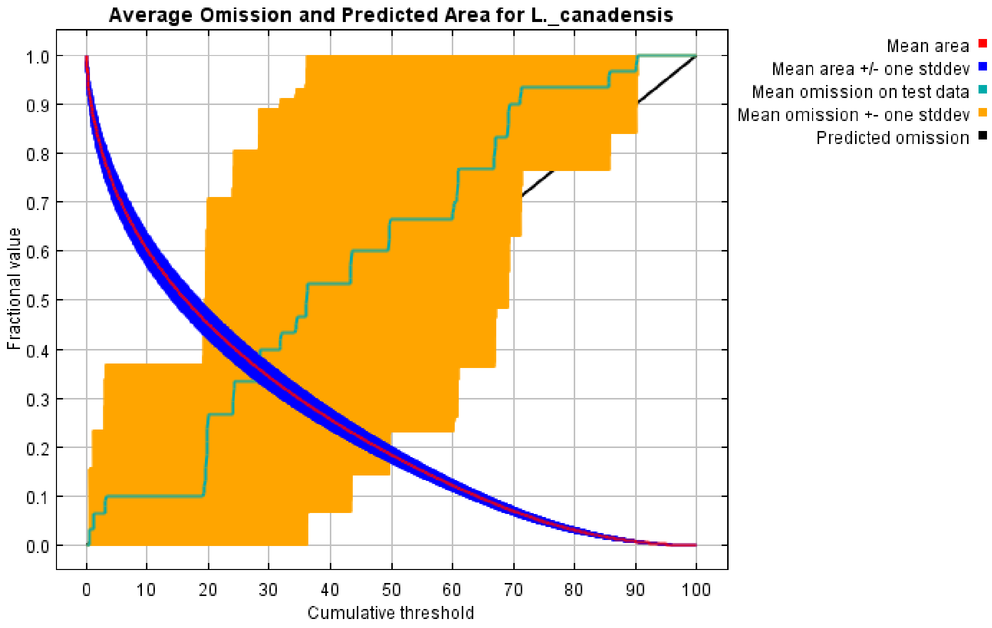


APPENDIX E

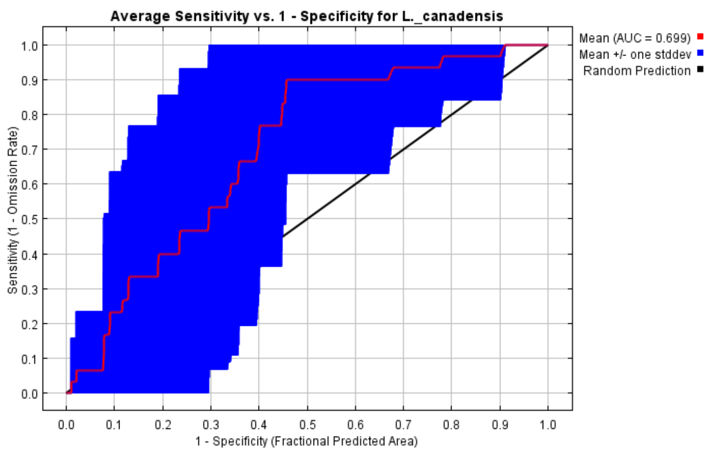
MAXENT OUTPUT FOR BLOUNT & SEVIER COUNTIES

The following is the Maxent Output for Determining River Otter Habitat Suitability in Blount & Sevier Counties of Tennessee using Cross-Validation (Phillips et al. 2010).

The following graph indicates how testing and training omission and predicted area (of suitable habitat for river otter) varies with the choice of cumulative threshold. The red line indicates the mean rea; blue indicates the standard deviation of mean area; green indicates mean omission as determined by test data input into Maxent; orange indicates the standard deviation of the mean omission; black indicated predicted omission. Y-axis is the fractional value of each variable represented. X-axis is the cumulative threshold within which it falls. Although the black line is covered by the orange here, it runs at a 45-degree angle (+,+) from (0,0). The green and black line being close indicates omission rate and predicted omission rate were good matches.

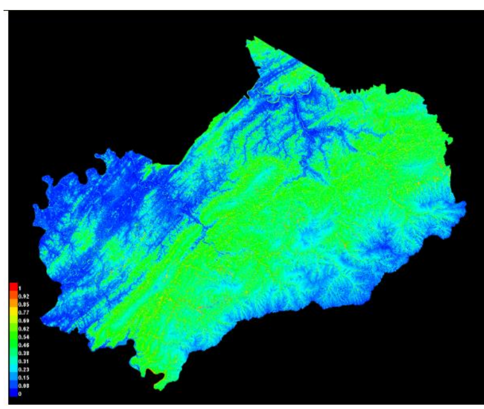


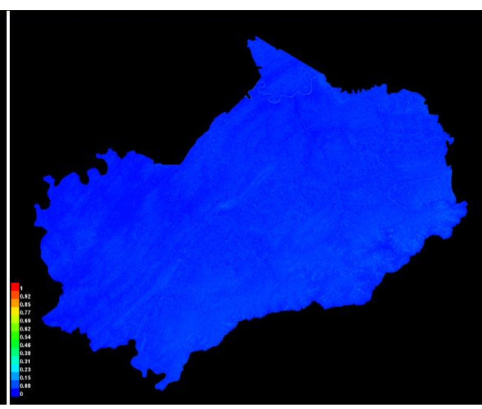
The following graph indicates the receiver operating curve for the data. Red indicates the man; blue indicates standard deviation of the mean; black indicates a random prediction. The area under the curve (AUC) is also provided, indicated the performance of the model. The closer to 1 the AUC is, the better the model performed. This logistic graph indicates receiver operating characteristic curve averaged on replicate runs. The x-axis, specificity, is defined using specificity (fractional predicted area), which is the proportion of absences correctly predicted, rather than true commission. The y-axis indicates sensitivity of the model, defined by sensitivity (omission rate), which is the proportion of presences correctly predicted (Phillips 2010).

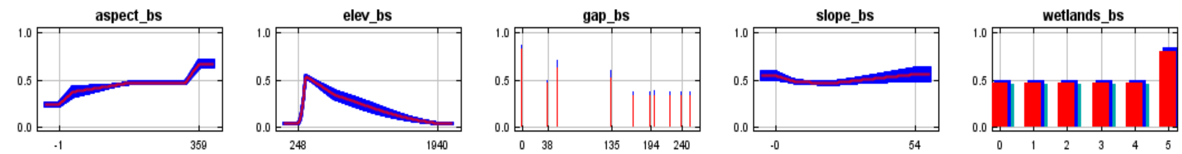


Pictures of the model

The following two pictures show the point-wise mean and standard deviation of the 15 output grids. Other available summary grids are min, max and median.



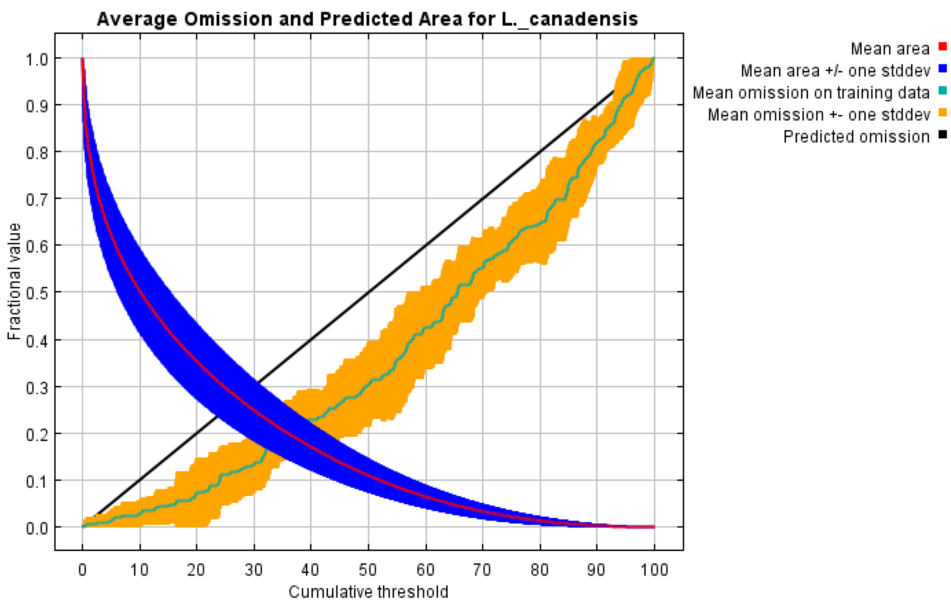




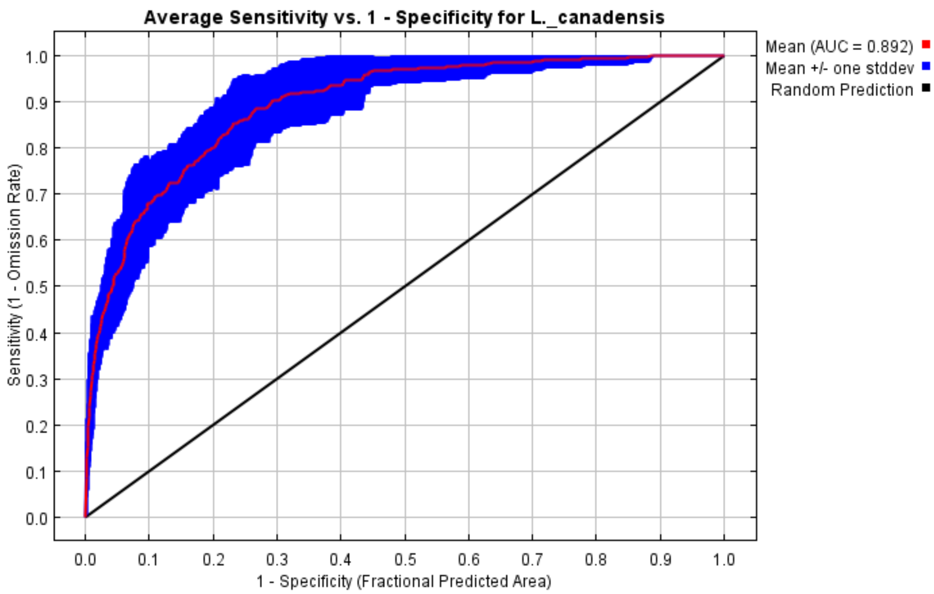
The above charts indicate the response curves of how the model/prediction depends on the variables input elev_tnaii = elevation; gap_tnaii = land cover; aspect_tnaii = aspect; slope_tnaii = slope; nwi_tnaii2 = riparian habitat). Y-axis is the predicted probability of suitable conditions where all other variables are set to their own average value over the set of presence localities (Phillips 2010). Red indicates the correlation, while blue indicates the standard deviation of that correlation

The following is the Maxent Output for Determining River Otter Habitat Suitability in Blount & Sevier Counties of Tennessee using Bootstrapping (Phillips et al. 2010).

The following graph indicates how testing and training omission and predicted area (of suitable habitat for river otter) varies with the choice of cumulative threshold. The red line indicates the mean rea; blue indicates the standard deviation of mean area; green indicates mean omission as determined by test data input into Maxent; orange indicates the standard deviation of the mean omission; black indicated predicted omission. Y-axis is the fractional value of each variable represented. X-axis is the cumulative threshold within which it falls. The green and black line being relatively close indicates omission rate and predicted omission rate were fair matches.

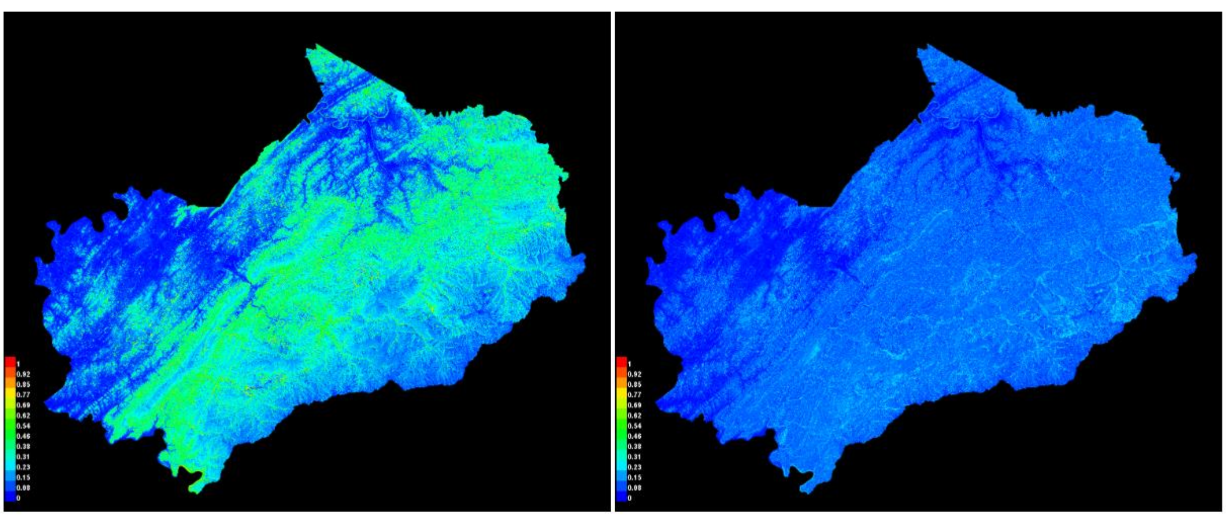


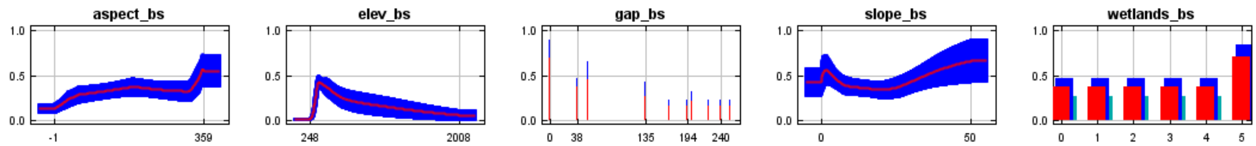
The following graph indicates the receiver operating curve for the data. Red indicates the man; blue indicates standard deviation of the mean; black indicates a random prediction. The area under the curve (AUC) is also provided, indicated the performance of the model. The closer to 1 the AUC is, the better the model performed. This logistic graph indicates receiver operating characteristic curve averaged on replicate runs. The x-axis, specificity, is defined using specificity (fractional predicted area), which is the proportion of absences correctly predicted, rather than true commission. The y-axis indicates sensitivity of the model, defined by sensitivity (omission rate), which is the proportion of presences correctly predicted (Phillips 2010).



Pictures of the model

The following two pictures show the point-wise mean and standard deviation of the 15 output grids. Other available summary grids are min, max and median.



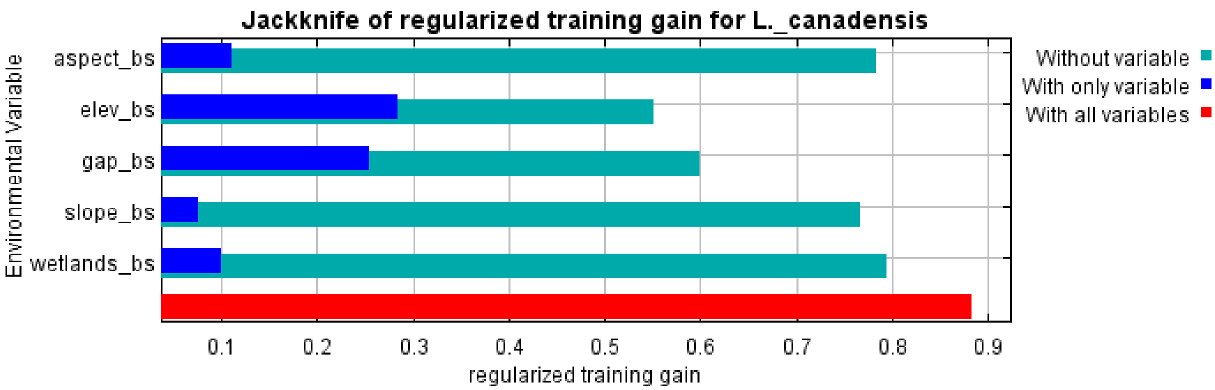


The charts above indicate the response curves of how the model/prediction depends on the variables input elev_tnaii = elevation; gap_tnaii = land cover; aspect_tnaii = aspect; slope_tnaii = slope; nwi_tnaii2 = riparian habitat). Y-axis is the predicted probability of suitable conditions where all other variables are set to their own average value over the set of presence localities (Phillips 2010). Red indicates the correlation, while blue indicates the standard deviation of that correlation.

Variable	Percent contribution	Permutation importance
elev_bs	34.2	37.4
gap_bs	29.1	17.9
wetlands_bs	13.5	4.3
aspect_bs	12.4	23.6
slope_bs	10.8	16.8

The table above indicates percent contribution, determined by the order variables were input in to Maxent code, and permutation importance, unbiased measure dependent on the final Maxent model to define environmental variables correlated to river otter presence (elev_tnaii = elevation; gap_tnaii = land cover; aspect_tnaii = aspect; slope_tnaii = slope; nwi_tnaii2 = riparian habitat). The permutation importance is the better estimate of variable correlation to river otter presence, as it is not defined by the user's order of input and the path used to obtain it (Phillips 2010).

The following charts indicate the jackknife response the how the model/prediction depends on the variables input elev_tnaii = elevation; gap_tnaii = land cover; aspect_tnaii = aspect; slope_tnaii = slope; nwi_tnaii2 = riparian habitat). Y-axis is the environmental variable. The x-axis is the regularized training gain, test gain, and AUC, respectively. Green indicates the gain/AUC without the specified variable included; blue indicates the gain/AUC with only the specified variable included; red indicates the gain/AUC with all variables included.



APPENDIX F

HUC12 EXPLORATORY REGRESSION

The following is the output results of exploratory regression, conducted using ArcGIS Pro 2.4, to determine land cover type correlation to river otter presence within each Hydrologic Unit Code 12 (HUC 12) in east Tennessee. 15 land cover types from GAP NLCD are used. Multiple models were run to determine the best combination of land cover types to best predict river otter presence. "+" indicates positive correlation with river otter presence; "-" represents negative correlation with river otter presence. The only relevant number to the analyses included in this project is the AIC. (MIXFORPR = Mixed Forest; SHRSCRPR = Shrub/Scrub; HAYPASTPR = Hay/Pasture; HERBPR = Herbaceous; OPENWATERPR = Open Water; DECIDFORPR = Deciduous Forest; DEVLOWPR = Developed Low Intensity; EMHERBWETPR = Emergent Herbaceous Wetland; CULTCROPPR = Cultivated Crop; BARRENPR = Barren Land; EVERFORPR = Evergreen Forest; WOODWETLANDSPR = Woody Wetlands; DEVOPENPR = Developed Open Space; DEVMEDPR = Developed Medium Intensity; DEVHIGHPR = Developed High Intensity).

```
******************************************************************************
Choose 1 of 15 Summary
   Highest Adjusted R-Squared Results
AdjR2   AICc   JB K(BP)  VIF   SA   Model
 0.04 348.40 0.00  0.00 1.00 0.00  +MIXFORPR***
 0.01 363.83 0.00  0.06 1.00 0.00  -HAYPASTPR**
 0.01 364.73 0.00  0.07 1.00 0.00  +EVERFORPR*
     Passing Models
AdjR2 AICc JB K(BP) VIF SA   Model
******************************************************************************
Choose 2 of 15 Summary
        Highest Adjusted R-Squared Results
AdjR2   AICc   JB K(BP)  VIF   SA   Model
 0.05 345.66 0.00  0.00 1.08 0.00  +DEVOPENPR*  +MIXFORPR***
 0.04 348.06 0.00  0.00 1.01 0.00  +MIXFORPR***  -SHRSCRPR**
 0.04 348.93 0.00  0.00 1.02 0.00  +MIXFORPR***  -HERBPR**
     Passing Models
AdjR2 AICc JB K(BP) VIF SA   Model
******************************************************************************
Choose 3 of 15 Summary
             Highest Adjusted R-Squared Results
AdjR2   AICc   JB K(BP)  VIF   SA   Model
 0.07 335.03 0.00  0.00 5.68 0.00  +DEVOPENPR*  -DEVLOWPR*  +MIXFORPR***
 0.05 344.55 0.00  0.00 2.84 0.00  +DEVOPENPR*  -DEVMEDPR  +MIXFORPR***
 0.05 345.43 0.00  0.00 2.10 0.00  +DEVOPENPR*  -DEVHIGHPR  +MIXFORPR***
     Passing Models
```

AdjR2 AICc JB K(BP) VIF SA   Model
****
Choose 4 of 15 Summary
Highest Adjusted R-Squared Results
AdjR2   AICc   JB K(BP)   VIF   SA   Model
0.08 332.93 0.00 0.00 17.64 0.00 +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +MIXFORPR***
0.07 334.56 0.00 0.00 12.10 0.00 +DEVOPENPR* -DEVLOWPR* +DEVHIGHPR +MIXFORPR***
0.07 335.84 0.00 0.00 6.17 0.00 +DEVOPENPR* -DEVLOWPR* +MIXFORPR*** -HAYPASTPR
Passing Models
AdjR2 AICc JB K(BP) VIF SA   Model
****
Choose 5 of 15 Summary
Highest Adjusted R-Squared Results
AdjR2   AICc   JB K(BP)   VIF   SA   Model
0.07 334.09 0.00 0.00 17.65 0.00 +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR +MIXFORPR***
0.07 334.17 0.00 0.00 17.75 0.00 +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +MIXFORPR*** -HAYPASTPR
0.07 334.37 0.00 0.00 17.67 0.00 -OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +MIXFORPR***
Passing Models
AdjR2 AICc JB K(BP) VIF SA   Model
****
Choose 6 of 15 Summary
Highest Adjusted R-Squared Results
AdjR2   AICc   JB K(BP)   VIF   SA   Model
0.07 335.26 0.00 0.00 17.71 0.00 +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR +EVERFORPR +MIXFORPR***
0.07 335.30 0.00 0.00 17.76 0.00 +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +MIXFORPR*** -SHRSCRPR** -HAYPASTPR
0.07 335.36 0.00 0.00 17.80 0.00 -OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +MIXFORPR*** -HAYPASTPR
Passing Models
AdjR2 AICc JB K(BP) VIF SA   Model
****
Choose 7 of 15 Summary
Highest Adjusted R-Squared Results
AdjR2   AICc   JB K(BP)   VIF   SA   Model
0.08 335.92 0.00 0.00 17.80 0.00 -OPENWATERPR* +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +MIXFORPR** -SHRSCRPR** -HAYPASTPR

0.08 336.05 0.00 0.00 17.80 0.00 +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR +EVERFORPR +MIXFORPR*** -SHRSCRPR*
0.08 336.09 0.00 0.00 17.42 0.00 -OPENWATERPR*** +DEVOPENPR* -DEVLOWPR** +DEVMEDPR -DECIDFORPR** -SHRSCRPR*** -HAYPASTPR***

Passing Models

AdjR2 AICc JB K(BP) VIF SA Model

****

Choose 8 of 15 Summary

Highest Adjusted R-Squared Results

AdjR2 AICc JB K(BP) VIF SA Model
0.07 337.22 0.00 0.00 17.91 0.00 -OPENWATERPR* +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +EVERFORPR +MIXFORPR** -SHRSCRPR* -HAYPASTPR
0.07 337.51 0.00 0.00 17.82 0.00 +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR +EVERFORPR +MIXFORPR*** -SHRSCRPR +CULTCROPPR**
0.07 337.52 0.00 0.00 17.82 0.00 -OPENWATERPR* +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR +EVERFORPR +MIXFORPR*** -SHRSCRPR*

Passing Models

AdjR2 AICc JB K(BP) VIF SA Model

****

Choose 9 of 15 Summary

Highest Adjusted R-Squared Results

AdjR2 AICc JB K(BP) VIF SA Model
0.07 339.17 0.00 0.00 17.84 0.00 -OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR +EVERFORPR +MIXFORPR*** -SHRSCRPR* +CULTCROPPR*
0.07 339.24 0.00 0.00 17.94 0.00 -OPENWATERPR* +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +EVERFORPR +MIXFORPR* -SHRSCRPR* -HERBPR -HAYPASTPR
0.07 339.26 0.00 0.00 18.53 0.00 +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR* +EVERFORPR +MIXFORPR*** -SHRSCRPR +HAYPASTPR +CULTCROPPR**

Passing Models

AdjR2 AICc JB K(BP) VIF SA Model

****

Choose 10 of 15 Summary

Highest Adjusted R-Squared Results

AdjR2 AICc JB K(BP) VIF SA Model
0.07 341.19 0.00 0.00 17.85 0.00 -OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR +EVERFORPR +MIXFORPR*** -SHRSCRPR* +CULTCROPPR* -EMHERBWETPR
0.07 341.24 0.00 0.00 18.57 0.00 +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR* +EVERFORPR +MIXFORPR*** -SHRSCRPR* +HERBPR +HAYPASTPR +CULTCROPPR**

0.07 341.26 0.00 0.00 17.85 0.00 -OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* -BARRENPR +DECIDFORPR +EVERFORPR +MIXFORPR*** -SHRSCRPR* +CULTCROPPR*

Passing Models

AdjR2 AICc JB K(BP) VIF SA Model

****

Choose 11 of 15 Summary

Highest Adjusted R-Squared Results

AdjR2 AICc JB K(BP) VIF SA Model

0.07 343.29 0.00 0.00 17.86 0.00 -OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* -BARRENPR +DECIDFORPR +EVERFORPR +MIXFORPR*** -SHRSCRPR* +CULTCROPPR* -EMHERBWETPR

0.07 343.29 0.00 0.00 17.92 0.00 -OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR +EVERFORPR +MIXFORPR*** -SHRSCRPR* +CULTCROPPR* +WOODWETLANDSPR -EMHERBWETPR

0.07 343.30 0.00 0.00 17.86 0.00 -OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR +EVERFORPR +MIXFORPR** -SHRSCRPR* +HERBPR +CULTCROPPR* -EMHERBWETPR

Passing Models

AdjR2 AICc JB K(BP) VIF SA Model

****

Choose 12 of 15 Summary

Highest Adjusted R-Squared Results

AdjR2 AICc JB K(BP) VIF SA Model

0.07 345.40 0.00 0.00 18.70 0.00 +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* +DECIDFORPR* +EVERFORPR +MIXFORPR*** -SHRSCRPR* +HERBPR +HAYPASTPR +CULTCROPPR** +WOODWETLANDSPR -EMHERBWETPR

0.07 345.40 0.00 0.00 56.26 0.00 -OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* -BARRENPR +DECIDFORPR +EVERFORPR +MIXFORPR** -SHRSCRPR* -HAYPASTPR +CULTCROPPR -EMHERBWETPR

0.07 345.40 0.00 0.00 17.93 0.00 -OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* -BARRENPR +DECIDFORPR +EVERFORPR +MIXFORPR*** -SHRSCRPR* +CULTCROPPR* +WOODWETLANDSPR -EMHERBWETPR

Passing Models

AdjR2 AICc JB K(BP) VIF SA Model

****

Choose 13 of 15 Summary

Highest Adjusted R-Squared Results

AdjR2 AICc JB K(BP) VIF SA Model

0.07 347.53 0.00 0.00 18.96 0.00 +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* -BARRENPR +DECIDFORPR* +EVERFORPR +MIXFORPR*** -SHRSCRPR* +HERBPR +HAYPASTPR +CULTCROPPR** +WOODWETLANDSPR -EMHERBWETPR

0.07 347.53 0.00 0.00 24.01 0.00 -OPENWATERPR* +DEVOPENPR* -DEVLOWPR* +DEVMEDPR -DEVHIGHPR -BARRENPR +EVERFORPR +MIXFORPR* -SHRSCRPR* -HERBPR -HAYPASTPR +CULTCROPPR -EMHERBWETPR
0.07 347.53 0.00 0.00 17.95 0.00 -OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR* -BARRENPR +DECIDFORPR +EVERFORPR +MIXFORPR** -SHRSCRPR* +HERBPR +CULTCROPPR* +WOODWETLANDSPR -EMHERBWETPR

Passing Models

AdjR2 AICc JB K(BP) VIF SA Model

****

Choose 14 of 15 Summary

Highest Adjusted R-Squared Results

AdjR2 AICc JB K(BP) VIF SA Model

0.06 349.67 0.00 0.00 23.91 0.00 -OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR -DEVHIGHPR -BARRENPR +DECIDFORPR +EVERFORPR +MIXFORPR** -SHRSCRPR* +HERBPR +CULTCROPPR* +WOODWETLANDSPR -EMHERBWETPR
0.06 349.67 0.00 0.00 25.22 0.00 -OPENWATERPR** +DEVOPENPR* -DEVLOWPR* +DEVMEDPR -DEVHIGHPR -BARRENPR -DECIDFORPR +EVERFORPR +MIXFORPR -SHRSCRPR* -HERBPR -HAYPASTPR* -WOODWETLANDSPR -EMHERBWETPR
0.06 349.67 0.00 0.00 866.09 0.00 -OPENWATERPR +DEVOPENPR* -DEVLOWPR* +DEVMEDPR -DEVHIGHPR -BARRENPR +DECIDFORPR +EVERFORPR +MIXFORPR -SHRSCRPR -HERBPR -HAYPASTPR +CULTCROPPR -EMHERBWETPR

Passing Models

AdjR2 AICc JB K(BP) VIF SA Model

****

Choose 15 of 15 Summary

Highest Adjusted R-Squared Results

AdjR2 AICc JB K(BP) VIF SA Model

Passing Models

AdjR2 AICc JB K(BP) VIF SA Model

****

************* Exploratory Regression Global Summary (OTTER_PRES) *************

Percentage of Search Criteria Passed

Search Criterion	Cutoff	Trials	# Passed	% Passed
Min Adjusted R-Squared	> 0.50	32759	0	0.00
Max Coefficient p-value	< 0.05	32759	286	0.87
Max VIF Value	< 7.50	32759	17408	53.14
Min Jarque-Bera p-value	> 0.10	32759	0	0.00
Min Spatial Autocorrelation p-value	> 0.10	45	0	0.00

Table Abbreviations
AdjR2 Adjusted R-Squared
AICc Akaike's Information Criterion
JB   Jarque-Bera p-value
K(BP) Koenker (BP) Statistic p-value
VIF   Max Variance Inflation Factor
SA   Global Moran's I p-value
Model Variable sign (+/-)
Model Variable significance (* = 0.10; ** = 0.05; *** = 0.01)

APPENDIX G

HUC12 EXPLORATORY REGRESSION - TOP 7 SIGNIFICANT CATEGORIES

The following is the output results of exploratory regression, conducted using ArcGIS Pro 2.4, to determine land cover type correlation to river otter presence within each Hydrologic Unit Code 12 (HUC 12) in east Tennessee. The 7 most significant categories as determined by the analysis using all 15 GAP NLCD categories were used here. Multiple models were run to determine the best combination of land cover types to best predict river otter presence. "+" indicates positive correlation with river otter presence; "-" represents negative correlation with river otter presence. The only relevant number to the analyses included in this project is the AIC (MIXFORPR = Mixed Forest; SHRSCRPR = Shrub/Scrub; HAYPASTPR = Hay/Pasture; HERBPR = Herbaceous; OPENWATERPR = Open Water; DECIDFORPR = Deciduous Forest; DEVLOWPR = Developed Low Intensity; EMHERBWETPR = Emergent Herbaceous Wetland; CULTCROPPR = Cultivated Crop; BARRENPR = Barren Land; EVERFORPR = Evergreen Forest; WOODWETLANDSPR = Woody Wetlands; DEVOPENPR = Developed Open Space; DEVMEDPR = Developed Medium Intensity; DEVHIGHPR = Developed High Intensity).

```
******************************************************************************
Choose 1 of 7 Summary
   Highest Adjusted R-Squared Results
AdjR2   AICc   JB K(BP)  VIF   SA   Model
 0.04 348.40 0.00  0.00 1.00 0.00  +MIXFORPR***
 0.01 363.83 0.00  0.06 1.00 0.00  -HAYPASTPR**
 0.01 365.36 0.00  0.12 1.00 0.00  -HERBPR*
     Passing Models
AdjR2 AICc JB K(BP) VIF SA   Model
******************************************************************************
Choose 2 of 7 Summary
        Highest Adjusted R-Squared Results
AdjR2   AICc   JB K(BP)  VIF   SA   Model
 0.04 348.06 0.00  0.00 1.01 0.00  +MIXFORPR***  -SHRSCRPR**
 0.04 348.93 0.00  0.00 1.02 0.00  +MIXFORPR***  -HERBPR**
 0.04 350.08 0.00  0.00 1.02 0.00  -DECIDFORPR**  +MIXFORPR***
     Passing Models
AdjR2 AICc JB K(BP) VIF SA   Model
******************************************************************************
Choose 3 of 7 Summary
             Highest Adjusted R-Squared Results
AdjR2   AICc   JB K(BP)  VIF   SA   Model
 0.04 349.69 0.00  0.00 1.07 0.00  -OPENWATERPR*  +MIXFORPR***  -SHRSCRPR**
 0.04 349.80 0.00  0.00 1.47 0.00  +MIXFORPR***  -SHRSCRPR**  -HAYPASTPR
 0.04 349.80 0.00  0.00 1.34 0.00  +MIXFORPR***  -SHRSCRPR**  -HERBPR**
     Passing Models
```

AdjR2 AICc JB K(BP) VIF SA Model
****
Choose 4 of 7 Summary
Highest Adjusted R-Squared Results
AdjR2 AICc JB K(BP) VIF SA Model
0.04 351.29 0.00 0.01 1.51 0.00 -OPENWATERPR* +MIXFORPR*** -SHRSCRPR** -HAYPASTPR
0.04 351.41 0.00 0.01 2.32 0.00 -DECIDFORPR +MIXFORPR*** -SHRSCRPR** -HAYPASTPR
0.04 351.45 0.00 0.01 1.35 0.00 -OPENWATERPR* +MIXFORPR*** -SHRSCRPR** -HERBPR**
Passing Models
AdjR2 AICc JB K(BP) VIF SA Model
****
Choose 5 of 7 Summary
Highest Adjusted R-Squared Results
AdjR2 AICc JB K(BP) VIF SA Model
0.04 349.88 0.00 0.00 1.69 0.00 -OPENWATERPR*** -DEVLOWPR*** -DECIDFORPR*** -SHRSCRPR*** -HAYPASTPR**
0.04 352.56 0.00 0.01 2.55 0.00 -OPENWATERPR* -DECIDFORPR +MIXFORPR** -SHRSCRPR** -HAYPASTPR
0.04 352.61 0.00 0.01 4.47 0.00 -DEVLOWPR -DECIDFORPR +MIXFORPR -SHRSCRPR** -HAYPASTPR
Passing Models
AdjR2 AICc JB K(BP) VIF SA Model
****
Choose 6 of 7 Summary
Highest Adjusted R-Squared Results
AdjR2 AICc JB K(BP) VIF SA Model
0.04 351.01 0.00 0.01 1.69 0.00 -OPENWATERPR*** -DEVLOWPR*** -DECIDFORPR*** -SHRSCRPR** -HERBPR*** -HAYPASTPR**
0.04 351.94 0.00 0.01 6.48 0.00 -OPENWATERPR* -DEVLOWPR -DECIDFORPR -MIXFORPR -SHRSCRPR** -HAYPASTPR
0.04 354.08 0.00 0.02 4.59 0.00 -DEVLOWPR -DECIDFORPR +MIXFORPR -SHRSCRPR** -HERBPR* -HAYPASTPR
Passing Models
AdjR2 AICc JB K(BP) VIF SA Model
****
Choose 7 of 7 Summary
Highest Adjusted R-Squared Results
AdjR2 AICc JB K(BP) VIF SA Model
0.04 353.01 0.00 0.01 6.76 0.00 -OPENWATERPR* -DEVLOWPR -DECIDFORPR* -MIXFORPR -SHRSCRPR** -HERBPR* -HAYPASTPR

Passing Models

AdjR2 AICc JB K(BP) VIF SA Model

****

************* Exploratory Regression Global Summary (OTTER_PRES) *************

Percentage of Search Criteria Passed

Search Criterion	Cutoff	Trials	# Passed	% Passed
Min Adjusted R-Squared	> 0.50	127	0	0.00
Max Coefficient p-value	< 0.05	127	34	26.77
Max VIF Value	< 7.50	127	127	100.00
Min Jarque-Bera p-value	> 0.10	127	0	0.00
Min Spatial Autocorrelation p-value	> 0.10	22	0	0.00

Table Abbreviations

AdjR2 Adjusted R-Squared

AICc Akaike's Information Criterion

JB Jarque-Bera p-value

K(BP) Koenker (BP) Statistic p-value

VIF Max Variance Inflation Factor

SA Global Moran's I p-value

Model Variable sign (+/-)

Model Variable significance (* = 0.10; ** = 0.05; *** = 0.01)

APPENDIX H

ORDINARY LEAST SQUARES

Below is the output from the ordinary least squares analysis conducted using ArcGIS Pro 2.4 which analyzes the correlation of river otter presence to Hydrologic Unit Code 12 (HUC12) in east Tennessee. The dependent variable is river otter presence and the independent variables run were each land cover type, i.e. "Variable": MIXFORPR = Mixed Forest; SHRSCRPR = Shrub/Scrub; HAYPASTPR = Hay/Pasture; HERBPR = Herbaceous; OPENWATERPR = Open Water; DECIDFORPR = Deciduous Forest; DEVLOWPR = Developed Low Intensity; EMHERBWETPR = Emergent Herbaceous Wetland; CULTCROPPR = Cultivated Crop; BARRENPR = Barren Land; EVERFORPR = Evergreen Forest; WOODWETLANDSPR = Woody Wetlands; DEVOPENPR = Developed Open Space; DEVMEDPR = Developed Medium Intensity; DEVHIGHPR = Developed High Intensity. "Coefficient" is a reflection of the strength and type (+ or -) of relationship the independent variable has to otter presence. "T-statistic" is assessed by a t-test used to determine the statistical significance of the variable. "Probability" is the p-value, none of which are significant in my output. The last three columns are not relevant to my data (ESRI 2018).

Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	0.023438	808281.86388	0.000000	1.000000	NaN	NaN	NaN	--------
OPENWATERPR	-0.004700	8082.818639	-0.000001	1.000000	NaN	NaN	NaN	> 1000.0
DEVOPENPR	0.030945	8082.818639	0.000004	0.999997	NaN	NaN	NaN	> 1000.0
DEVLOWPR	-0.039429	8082.818639	-0.000005	0.999996	NaN	NaN	NaN	> 1000.0
DEVMEDPR	-0.008179	8082.818639	-0.000001	0.999999	NaN	NaN	NaN	> 1000.0
DEVHIGHPR	0.052368	8082.818639	0.000006	0.999995	NaN	NaN	NaN	> 1000.0
BARRENPR	-0.004883	8082.818639	-0.000001	1.000000	NaN	NaN	NaN	> 1000.0
DECIDFORPR	-0.000977	8082.818639	-0.000000	1.000000	NaN	NaN	NaN	> 1000.0
EVERFORPR	0.001526	8082.818639	0.000000	1.000000	NaN	NaN	NaN	> 1000.0
MIXFORPR	0.001892	8082.818639	0.000000	1.000000	NaN	NaN	NaN	> 1000.0
SHRSCRPR	-0.016541	8082.818639	-0.000002	0.999998	NaN	NaN	NaN	> 1000.0
HERBPR	-0.002625	8082.818639	-0.000000	1.000000	NaN	NaN	NaN	> 1000.0
HAYPASTPR	-0.003052	8082.818639	-0.000000	1.000000	NaN	NaN	NaN	> 1000.0
CULTCROPPR	0.000122	8082.818639	0.000000	1.000000	NaN	NaN	NaN	> 1000.0
WOODWETLANDS	-0.001831	8082.818639	-0.000000	1.000000	NaN	NaN	NaN	> 1000.0
EMHERBWETPR	-0.042908	8082.818640	-0.000005	0.999996	NaN	NaN	NaN	> 1000.0

The diagnostics below provide detailed information on model performance and significance, stationarity and model bias. Multiple R-Squared is a measure of model performance ranging from 0.0 to 1.0. Only 7% of variation is explained by the model according to the Multiple R-Squared value here. The Joint F-Statistic and the Joint Wald Statistic measure overall model statistical significance; neither of these are significant in this data, as seen in the corresponding "Prob" section. The Koenker (BP) Statistic determine if the independent variable have a consistent relationship to the dependent variable geographically and data-wise; it is significant here, as seen in the corresponding "Prob" section, indicating a consistent relationship. The Jarque-Bera statistic indicates if residuals, i.e. the observed/known dependent variable value minus the predicted/estimated values, are normally distributed; the p-value is 0.00 which is less than 0.05, indicating abnormal distribution, as seen in the corresponding "Prob" section (ESRI 2018).

OLS Diagnostics

Input Features:	eastTN_HUC12_withNCLD20	Dependent Variable:	OTTER_PRES
Number of Observations:	488	Akaike's Information Criterion (AICc) [d]:	361.817196
Multiple R-Squared [d]:	0.071720	Adjusted R-Squared [d]:	0.042220
Joint F-Statistic [e]:	2.431152	Prob(>F), (15,472) degrees of freedom:	0.001210*
Joint Wald Statistic [e]:	8.124709	Prob(>chi-squared), (15) degrees of freedom:	0.918686
Koenker (BP) Statistic [f]:	36.066614	Prob(>chi-squared), (15) degrees of freedom:	0.001729*
Jarque-Bera Statistic [g]:	116578.510914	Prob(>chi-squared), (2) degrees of freedom:	0.000000*

Notes on Interpretation

* An asterisk next to a number indicates a statistically significant p-value (p < 0.01).

[a] Coefficient: Represents the strength and type of relationship between each explanatory variable and the dependent variable.

[b] Probability and Robust Probability (Robust_Pr): Asterisk (*) indicates a coefficient is statistically significant (p < 0.01); if the Koenker (BP) Statistic [f] is statistically significant, use the Robust Probability column (Robust_Pr) to determine coefficient significance.

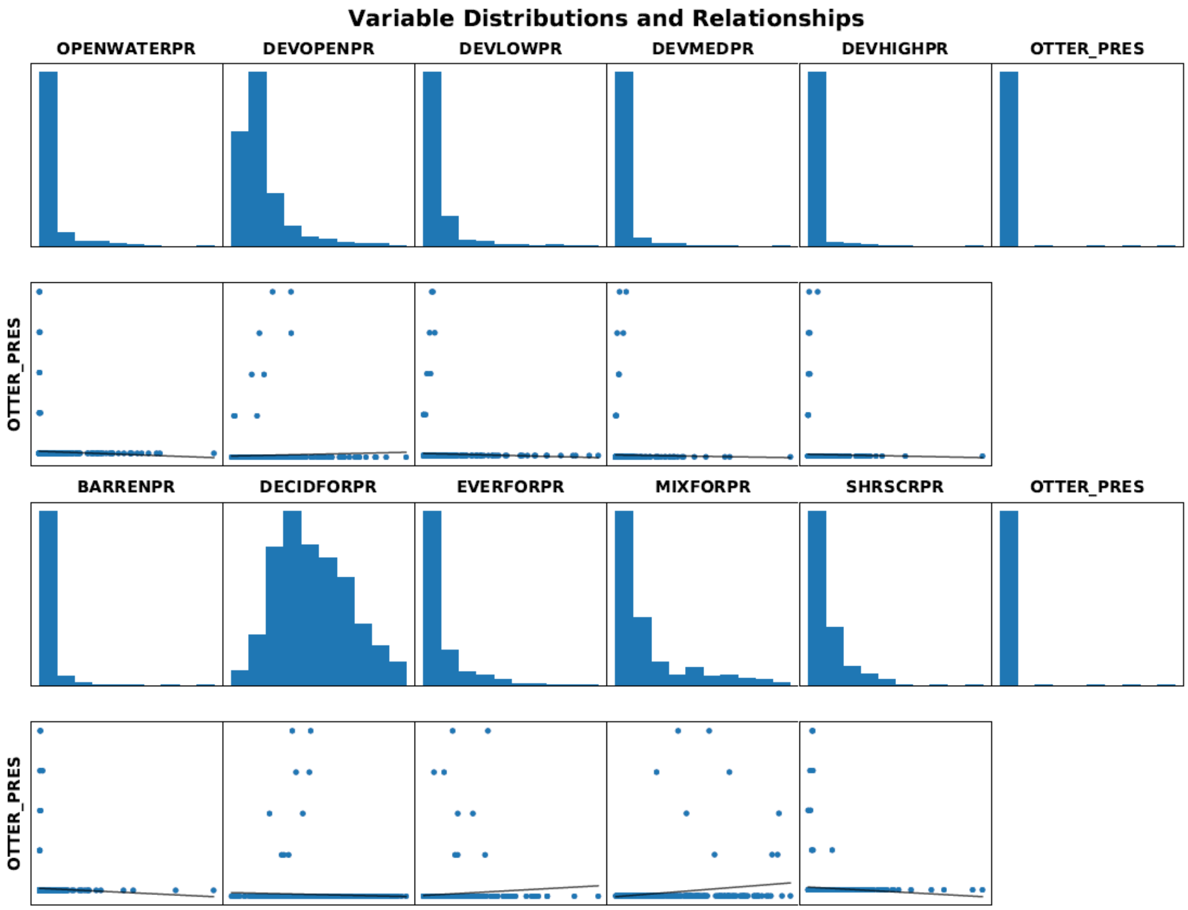
[c] Variance Inflation Factor (VIF): Large Variance Inflation Factor (VIF) values (> 7.5) indicate redundancy among explanatory variables.

[d] R-Squared and Akaike's Information Criterion (AICc): Measures of model fit/performance.

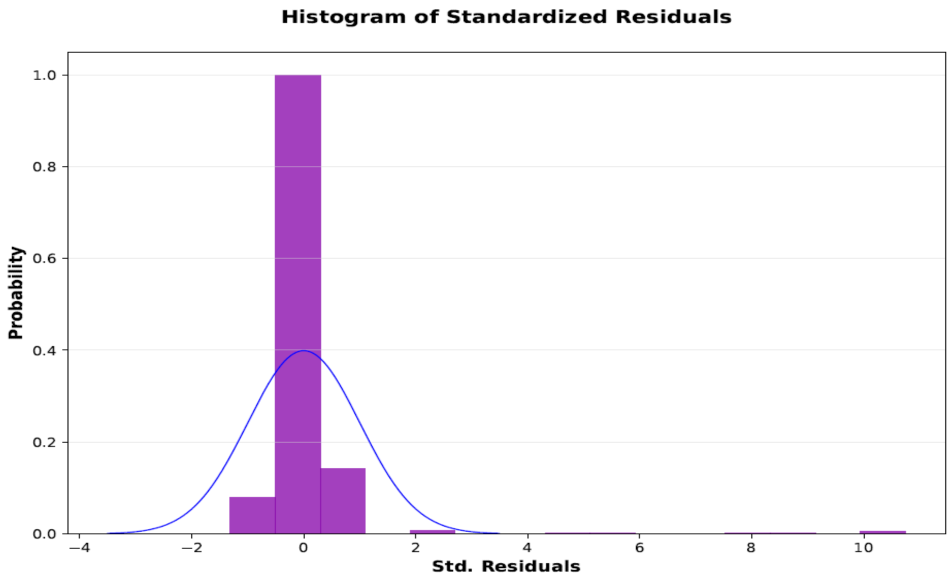
[e] Joint F and Wald Statistics: Asterisk (*) indicates overall model significance (p < 0.01); if the Koenker (BP) Statistic [f] is statistically significant, use the Wald Statistic to determine overall model significance.

[f] Koenker (BP) Statistic: When this test is statistically significant (p < 0.01), the relationships modeled are not consistent (either due to non-stationarity or heteroskedasticity). You should rely on the Robust Probabilities (Robust_Pr) to determine coefficient significance and on the Wald Statistic to determine overall model significance.

[g] Jarque-Bera Statistic: When this test is statistically significant (p < 0.01) model predictions are biased (the residuals are not normally distributed).

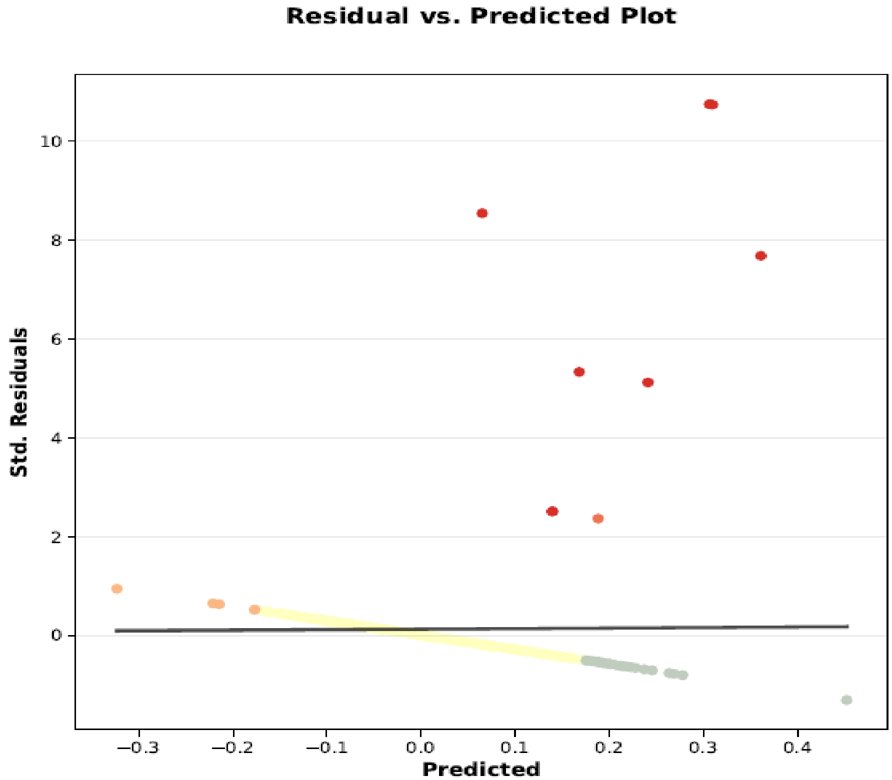


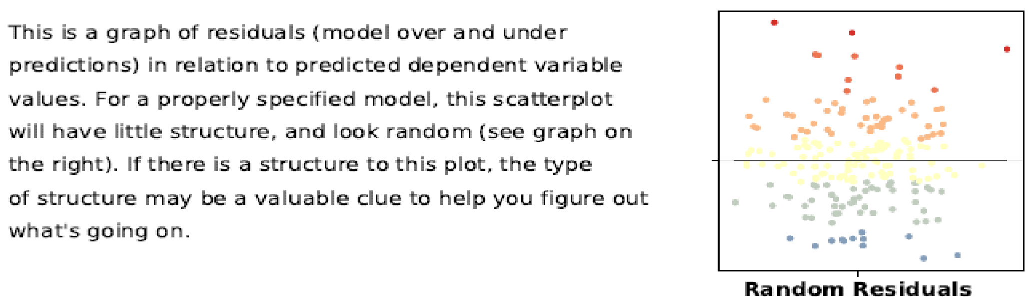
The above charts are histograms and scatterplots for each land cover type (independent variable). Histograms show the distribution, while the scatterplots show the relationship between the independent and dependent (otter presence) variables (ESRI 2018).



Ideally the histogram of your residuals would match the normal curve, indicated above in blue. If the histogram looks very different from the normal curve, you may have a biased model. If this bias is significant it will also be represented by a statistically significant Jarque-Bera p-value (*).

The above histogram indicates model overpredictions and underpredictions. The bars of the historgram are the actual distribution, while the blue line is the shape the histogram would be if the residuals were normally distributed (ESRI 2018).





The above figures are scatterplot graphs depicting the relationship between model residuals and the predicted values. The top figure represents the actual values, while the small figure represents what it would look like if randomly sampled, indicating a problem with heteroscedasticity (the variation in relation to the magnitude of the variable trying to be predicted) (ESRI 2018).

APPENDIX I

2.5-KM AVERAGE DAILY MOVEMENT EXPLORATORY REGRESSION

Exploratory Regression, conducted using ArcGIS Pro 2.4, summary of significant land cover categories based on daily movement range of river otter (2.5 km; Griess 1987; Wilson 2012) for sampled and random sites in east Tennessee. "% Significant" indicates the overall significance of the land cover type in comparison to each other type. "% Negative" and "% Positive" indicate the specific type of significance each variable played in predicting river otter presence. The only relevant number to the analyses included in this project is the AIC. (DEV_OP_PR = Developed Open; MI_FOR_PR = Mixed Forest; PA_HA_PR = Pasture/Hay; DE_FOR_PR = Deciduous Forest; OP_WA_PR = Open Water; DEV_HI_PR = Developed High Intensity; GR_LA_PR = Grassland; DEV_LO_PR = Developed Low Intensity; DEV_ME_PR = Developed Medium Intensity; SH_SC_PR = Shrub/Scrub; BA_LA_PR = Bare Land; WO_WET_PR = Woody Wetlands; EM_HER_PR = Emergent Herbaceous Wetlands; EV_FOR_PR = Evergreen Forest).

```
******************************************************************************
Choose 1 of 14 Summary
   Highest Adjusted R-Squared Results
AdjR2  AICc   JB K(BP)  VIF   SA   Model
 0.38 45.23 0.71  0.76 1.00 0.00  +MI_FOR_PR***
 0.22 55.15 0.10  0.02 1.00 0.00  -PA_HA_PR***
 0.15 58.31 0.14  0.01 1.00 0.00  +DEV_OP_PR***
     Passing Models
AdjR2 AICc JB K(BP) VIF SA   Model
******************************************************************************
Choose 2 of 14 Summary
        Highest Adjusted R-Squared Results
AdjR2  AICc   JB K(BP)  VIF   SA   Model
 0.65 24.02 0.46  0.56 1.02 0.00  +DEV_OP_PR***  +MI_FOR_PR***
 0.55 33.69 0.03  0.46 1.15 0.00  -DE_FOR_PR***  -PA_HA_PR***
 0.45 41.76 0.89  0.91 1.08 0.00  +DEV_LO_PR**  +MI_FOR_PR***
     Passing Models
AdjR2 AICc JB K(BP) VIF SA   Model
******************************************************************************
Choose 3 of 14 Summary
             Highest Adjusted R-Squared Results
AdjR2  AICc   JB K(BP)  VIF   SA   Model
 0.65 25.08 0.52  0.62 1.45 0.00  +DEV_OP_PR***  +MI_FOR_PR***  -PA_HA_PR
 0.65 25.26 0.61  0.46 1.46 0.00  +DEV_OP_PR***  +DE_FOR_PR  +MI_FOR_PR***
 0.64 26.29 0.48  0.72 1.81 0.00  +DEV_OP_PR***  -DEV_LO_PR  +MI_FOR_PR***
     Passing Models
AdjR2 AICc JB K(BP) VIF SA   Model
******************************************************************************
Choose 4 of 14 Summary
                  Highest Adjusted R-Squared Results
AdjR2  AICc   JB K(BP)  VIF   SA   Model
```

0.66 25.17 0.34 0.63 3.78 0.00 -
OP_WA_PR* +DEV_OP_PR*** +MI_FOR_PR*** +EM_HER_PR*
0.65 26.40 0.45 0.66 4.40 0.00 -
OP_WA_PR +DEV_OP_PR*** +MI_FOR_PR*** +WO_WET_PR
0.64 27.26 0.68 0.51 1.54
0.00 +DEV_OP_PR*** +DE_FOR_PR +MI_FOR_PR*** +EM_HER_PR
Passing Models
AdjR2 AICc JB K(BP) VIF SA   Model
****
Choose 5 of 14 Summary
Highest Adjusted R-Squared Results
AdjR2 AICc   JB K(BP) VIF   SA   Model
0.66 27.06 0.53 0.57 3.94 0.00 -
OP_WA_PR +DEV_OP_PR*** +DE_FOR_PR +MI_FOR_PR*** +EM_HER_PR*
0.66 27.26 0.39 0.72 4.03 0.00 -OP_WA_PR +DEV_OP_PR*** +MI_FOR_PR*** -
PA_HA_PR +EM_HER_PR*
0.66 27.67 0.29 0.76 3.87 0.00 -OP_WA_PR* +DEV_OP_PR*** -
DEV_ME_PR +MI_FOR_PR*** +EM_HER_PR*
Passing Models
AdjR2 AICc JB K(BP) VIF SA   Model
****
Choose 6 of 14 Summary
Highest Adjusted R-Squared Results
AdjR2 AICc   JB K(BP) VIF   SA   Model
0.65 29.88 0.33 0.82 4.10 0.00 -OP_WA_PR +DEV_OP_PR*** -
DEV_ME_PR +MI_FOR_PR*** -PA_HA_PR +EM_HER_PR*
0.65 29.92 0.46 0.67 4.07 0.00 -OP_WA_PR* +DEV_OP_PR*** -
DEV_ME_PR +DE_FOR_PR +MI_FOR_PR*** +EM_HER_PR*
0.65 29.96 0.35 0.24 4.16 0.00 -
OP_WA_PR +DEV_OP_PR*** +DE_FOR_PR +EV_FOR_PR +MI_FOR_PR*** +EM_HER_
PR*
Passing Models
AdjR2 AICc JB K(BP) VIF SA   Model
****
Choose 7 of 14 Summary
Highest Adjusted R-Squared Results
AdjR2 AICc   JB K(BP)   VIF   SA   Model
0.65 32.35 0.26 0.79 101.06 0.00 -OP_WA_PR* +DEV_OP_PR*** +DEV_LO_PR -
DEV_ME_PR +DEV_HI_PR +MI_FOR_PR*** +EM_HER_PR*
0.65 32.54 0.64 0.75 134.11 0.00 +DEV_OP_PR*** +DEV_LO_PR -
DEV_ME_PR* +DEV_HI_PR* +MI_FOR_PR*** -PA_HA_PR* +EM_HER_PR
0.65 32.70 0.31 0.85 12.89 0.00 -OP_WA_PR +DEV_OP_PR*** -
DEV_ME_PR +DEV_HI_PR +MI_FOR_PR*** -PA_HA_PR +EM_HER_PR
Passing Models
AdjR2 AICc JB K(BP) VIF SA   Model
****
Choose 8 of 14 Summary
Highest Adjusted R-Squared
Results

AdjR2 AICc   JB
K(BP)   VIF   SA   Model
 0.67 32.75 0.33 0.72 134.11 0.00 -OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR* +MI_FOR_PR*** -PA_HA_PR +EM_HER_PR*
 0.66 33.10 0.74 0.50 127.10 0.00 -OP_WA_PR* +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR* +DE_FOR_PR +MI_FOR_PR*** +EM_HER_PR**
 0.65 34.38 0.57 0.75 134.62 0.00 -OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR* +MI_FOR_PR*** -PA_HA_PR +WO_WET_PR
Passing Models
AdjR2 AICc JB K(BP) VIF SA   Model
****
Choose 9 of 14 Summary
Highest Adjusted R-Squared
Results
AdjR2 AICc   JB
K(BP)   VIF   SA   Model
 0.66 36.44 0.49 0.44 134.17 0.00 -OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR* +DE_FOR_PR +MI_FOR_PR** -PA_HA_PR +EM_HER_PR*
 0.66 36.46 0.49 0.24 137.71 0.00 -OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR* -EV_FOR_PR +MI_FOR_PR*** -PA_HA_PR +EM_HER_PR*
 0.66 36.49 0.31 0.76 134.62 0.00 -OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR* +MI_FOR_PR*** -PA_HA_PR -WO_WET_PR +EM_HER_PR
Passing Models
AdjR2 AICc JB K(BP) VIF SA   Model
****
Choose 10 of 14 Summary
Highest Adjusted R-Squared
Results
AdjR2 AICc   JB
K(BP)   VIF   SA   Model

 0.64 40.46 0.46 0.44 134.76 0.00 -OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR* +DE_FOR_PR +MI_FOR_PR** -PA_HA_PR -WO_WET_PR +EM_HER_PR
 0.64 40.47 0.46 0.26 138.58 0.00 -OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR* -EV_FOR_PR +MI_FOR_PR*** -PA_HA_PR -WO_WET_PR +EM_HER_PR
 0.64 40.48 0.50 0.45 138.10 0.00 -OP_WA_PR +DEV_OP_PR** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR* +DE_FOR_PR +MI_FOR_PR* +GR_LA_PR -PA_HA_PR +EM_HER_PR*
Passing Models
AdjR2 AICc JB K(BP) VIF SA   Model
****
Choose 11 of 14 Summary
Highest Adjusted R-Squared
Results
AdjR2 AICc   JB
K(BP)   VIF   SA   Model

0.63 44.80 0.47 0.46 138.50 0.00 -OP_WA_PR +DEV_OP_PR** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR +DE_FOR_PR +MI_FOR_PR* +GR_LA_PR -PA_HA_PR -WO_WET_PR +EM_HER_PR
0.63 44.80 0.45 0.29 140.00 0.00 -OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR -EV_FOR_PR +MI_FOR_PR*** -SH_SC_PR -PA_HA_PR -WO_WET_PR +EM_HER_PR
0.63 44.80 0.44 0.38 136.14 0.00 -OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR* +DEV_HI_PR +DE_FOR_PR +MI_FOR_PR* -SH_SC_PR -PA_HA_PR -WO_WET_PR +EM_HER_PR

Passing Models

AdjR2 AICc JB K(BP) VIF SA Model

****

Choose 12 of 14 Summary

Highest Adjusted R-Squared

Results

AdjR2 AICc JB
K(BP) VIF SA Model

0.62 49.46 0.45 0.32 145.33 0.00 -OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR +DEV_HI_PR -BA_LA_PR -EV_FOR_PR +MI_FOR_PR*** -SH_SC_PR -PA_HA_PR -WO_WET_PR +EM_HER_PR
0.62 49.46 0.46 0.42 148.19 0.00 -OP_WA_PR +DEV_OP_PR** +DEV_LO_PR -DEV_ME_PR +DEV_HI_PR -BA_LA_PR +DE_FOR_PR +MI_FOR_PR* +GR_LA_PR -PA_HA_PR -WO_WET_PR +EM_HER_PR
0.62 49.46 0.46 0.36 140.91 0.00 -OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR +DEV_HI_PR +DE_FOR_PR +EV_FOR_PR +MI_FOR_PR*** +SH_SC_PR +GR_LA_PR -WO_WET_PR +EM_HER_PR

Passing Models

AdjR2 AICc JB K(BP) VIF SA Model

****

Choose 13 of 14 Summary

Highest Adjusted R-Squared

Results

AdjR2 AICc JB
K(BP) VIF SA Model

0.60 54.51 0.45 0.36 708.80 0.00 +DEV_OP_PR +DEV_LO_PR* -DEV_ME_PR +DEV_HI_PR* +BA_LA_PR +DE_FOR_PR +EV_FOR_PR +MI_FOR_PR +SH_SC_PR +GR_LA_PR +PA_HA_PR +WO_WET_PR +EM_HER_PR
0.60 54.51 0.45 0.36 151.98 0.00 -OP_WA_PR +DEV_OP_PR*** +DEV_LO_PR -DEV_ME_PR +DEV_HI_PR -BA_LA_PR +DE_FOR_PR +EV_FOR_PR +MI_FOR_PR*** +SH_SC_PR +GR_LA_PR -WO_WET_PR +EM_HER_PR
0.60 54.51 0.45 0.36 154.47 0.00 -OP_WA_PR +DEV_OP_PR +DEV_LO_PR -DEV_ME_PR +DEV_HI_PR -BA_LA_PR -DE_FOR_PR*** -EV_FOR_PR -SH_SC_PR -GR_LA_PR -PA_HA_PR*** -WO_WET_PR +EM_HER_PR

Passing Models

AdjR2 AICc JB K(BP) VIF SA Model

****

Table Abbreviations
AdjR2 Adjusted R-Squared
AICc Akaike's Information Criterion
JB Jarque-Bera p-value
K(BP) Koenker (BP) Statistic p-value
VIF Max Variance Inflation Factor
SA Global Moran's I p-value
Model Variable sign (+/-)
Model Variable significance (* = 0.10; ** = 0.05; *** = 0.01)

VITA

Jordan Allen was born just outside of Atlanta, GA, to parents Gregory and Rebecca Francis. She is the first of two daughters, with a younger sister, Josie Francis. She attended Blackstock Montessori School before moving to Oak Mountain Academy for the completion of elementary, middle, and high school in Carrollton, GA. After graduation, she attended the University of Georgia, where she became interested in wildlife biology. She completed her Bachelors of Science in Forest Resources in May 2017 with a degree in Fisheries & Wildlife Sciences from the Warnell School of Forestry with honors. She married her high school sweetheart, Nathaniel Allen and moved to Chattanooga, TN, where she furthered her education at the University of Tennessee at Chattanooga. As a graduate assistant, Jordan taught introductory biology labs, in which she found a passion for education. Jordan will graduate with aa Masters of Science in Environmental Science in August 2020 before beginning higher level education instruction in the College of Natural Sciences and Mathematics at Shorter University.