Distribution, Relative Abundance, and Habitat Association of Tallapoosa Bass *Micropterus tallapoosae* in the Tallapoosa River Drainage, Alabama.

by

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Abstract

The diversity of freshwater fishes and black bass *Micropterus* spp. in the United States are concentrated in the southeastern region. Dams, anthropogenic land use, fragmentation, invasive species and other factors are contributing to decreasing distributions and increasing imperilment of native fishes in this region. Some black bass, such as the Tallapoosa Bass *Micropterus tallapoosae*, have recently been elevated to species status but their distribution and imperilment status are unknown. The goal of this study was to determine the distribution of Tallapoosa Bass and examine the land use, habitat, and abiotic variables that contribute to the occurrence and relative abundance of Tallapoosa Bass.

Fifty-eight creeks were sampled from May 2019-June 2020 using canoe and backpack electrofishing across six sub-basins. Results indicated that Tallapoosa Bass are well-distributed throughout the Piedmont region, and both average detection and occurrence probability were high. Tallapoosa Bass presence was positively related to the relative abundance of rocky substrate and watersheds that contained a majority percent of hydrologic soil group B (MPSB), which is a measure of runoff potential. Abundance was positively related to rocky substrate, MPSB, the amount of disturbance in the watershed, pool, and gradient; it was negatively related to watershed area. There was good variation in habitat characteristics across the range of Tallapoosa Bass streams sampled during this study. The Little Tallapoosa River Basin above Lake Wedowee seems to have the best assemblage of good streams and habitat characteristics of all the areas examined during this study. Some streams in other areas were also typified by ideal characteristics for Tallapoosa Bass habitat. Streams with small watersheds, high rock scores, and medium to high gradients should be prioritized for protection. Several specific streams across the sub-basin with quality populations based on genetic results, CPUE, and quality habitat characteristics are suggested for protection and conservation. Urban land use impacts, a more extensive temperature study, investigating the effects of flow on movement, migration dynamics, spawning characteristics, influence of shoal and specific rocky substrates, influence of various mesohabitats, interactions with native Alabama Bass, diet, and influence of vegetative cover are suggested as areas of further research for Tallapoosa Bass.

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List of Abbreviations

TW	Tallapoosa River Basin above Lake Wedowee
LTW	Little Tallapoosa River Basin above Lake Wedowee
W	Tributaries of Lake Wedowee
WM	Tallapoosa River Basin between Lake Wedowee and Lake Martin
MYT	Tributaries of Lake Martin, Yates Reservoir, and Thurlow Reservoir
BT	Tallapoosa River Basin below Thurlow Dam
ADCNR	Alabama Department of Conservation and Natural Resources
GADNR	Georgia Department of Natural Resources
NBBI	National Black Bass Initiative
IBI	Index of Biotic Integrity
LWD	Large Woody Debris
MSW	Mean Stream Width
CPUE	Catch Per Unit of Effort
TL	Total Length
NHD	National Hydrography Dataset
SARP	Southeast Aquatic Resource Partnership
NRCS	Natural Resource Conservation Service
USDA	United States Department of Agriculture
USGS	United States Geological Survey
SSURGO	Soil Survey Geographic Database
STATSGO2	Digital General Soil Map of the United States
VIF	Variance Inflation Factor

MPSB	Majority Percent Hydrologic Soil Group B
DI	Disturbance Index
QAICc	Quasi-likelihood Akaike’s Information Criteria for small sample size
AICc	Akaike’s Information Criteria for small sample size
SE	Standard Error
SD	Standard Deviation

I. Introduction

The United States is home to an impressive array of diversity among freshwater species, ranking number 7 in fish diversity worldwide, but 37% of fish species in the U.S. were endangered as of 1997 (Master et al. 1998). Imperilment of freshwater fishes in North America is increasing through time. The American Fisheries Society's Endangered Species Committee publishes periodic assessments of North American imperiled fishes, and the most recent assessment found that 39% of all the described freshwater fish species on the continent were imperiled as of 2008 (Jelks et al. 2008). Since the previous assessment (Williams et al. 1989), status improved for only 6% of fish and the number of imperiled fish species increased by 92%, including newly described or discovered species. Many new species continue to be discovered, and with the threatened state of many freshwater ecosystems and fishes (Master et al. 1998; Arthington et al. 2016), many of these new species could already be imperiled or in danger of becoming imperiled. Thus, it is even more important to determine the distribution, abundance, and status of freshwater fish species to identify the species and/or populations in greatest need of conservation and protection.

Dams and other barriers constitute one of the largest and most pervasive threats to fish biodiversity worldwide. Dams have impacted over half of the world’s large river systems (Nilsson 2005), fragmenting populations and affecting dispersal and migration of fish species (Martinez et al. 1994; Gehrke et al. 2002; Stanfield et al. 2006). They convert flowing water into lentic habitat and alter downstream flow regimes (Poff et al. 2007). This is especially impactful to fluvial species that cannot tolerate impoundment and those that have evolved to use seasonal flow patterns as cues to perform important life history behaviors such as spawning (Bunn and Arthington 2002; Potoka et al. 2016). Dams also alter sediment transport by accumulating upstream sediment and causing reaches immediately downstream of dams to become coarser, which affects the spawning capabilities and habitat preferences of various fish species (Ligon et al. 1995; Brandt 2000; Poff and Hart 2002). Furthermore, dams alter temperature regimes through hypolimnetic and epilimnetic releases, which can substantially alter growth, survival, spawn timing and other temperature-dependent life-history processes (Quinn et al. 1997; Clarkson and Childs 2000; Lessard and Hayes 2003; Steel and Lange 2007).

Introduction of non-native species is one of the leading causes of decline in native fishes and can impact native species in a variety of ways including predation, competition, habitat degradation, disease transmission, and genetic introgression (Gozlan et al. 2010). Genetic introgression is an extremely pernicious method of invasion that is very difficult to mitigate. Hybridization among native fishes creates numerous challenges for fisheries such as identifying hybrids and pure individuals, extent of hybridization or introgression, and developing management strategies for populations affected by hybridization (Rhymer and Simberloff 1996; Allendorf et al. 2001). Hybrid zones can be difficult to determine, and morphological similarities can make hybrid identification difficult without the aid of genetic analysis (Neff and Smith 1979; Dowling and Childs 1992; Schribner et al. 2001). Genetic introgression can reduce already declining populations and result in native fish populations to be rushed into protection (Costedoat et al. 2005; Mandeville et al. 2017). Genetic introgression often leads to reduced genetic purity and fitness of native species and unique genetic lineages, and results in loss of some genetic stocks (Rhymer and Simberloff 1996; Shepard et al. 2005; Muhlfield et al.

2009). Unfortunately, genetic introgression is difficult to eradicate or suppress without extreme measures or expensive processes (Hubbs et al. 1978; Campbell et al. 2002; Sato et al. 2010).

Converting landscapes from natural to urban and agricultural land often results in biodiversity losses in aquatic systems and stream communities. Streams are a product of upstream influences and changes in watershed or riparian land use can have major effects throughout stream ecosystems (Wang et al. 1997). Even though anthropogenic land uses may result in altered natural processes, it can be mediated by certain land features. For example, soil type, topography, and other features of natural terrain influence where agriculture and urban development occur (Allan 2004; Hein et al. 2011). Thus, it is important when examining the influence of land-use factors on fish distributions to also account for natural variation in geology and geography. Natural factors tend to be more important when anthropogenic influences are minor (Wang et al. 2003, Allan 2004).

Urbanization substantially affects runoff, which alters hydrologic regimes, destabilizes streams, and increases delivery of sediment, toxic material, and excessive nutrients (Wang et al. 1997; Paul and Meyer 2001; Moerke and Lamberti 2006). Sedimentation from urbanization alters substrate composition, increases turbidity, and generally homogenizes fish communities into tolerant groups (Paul and Meyer 2001; Walters et al. 2003; Walters et al. 2005). Changes in fish community structure is inevitable in urban systems, as habitat and water quality degrade and as rarer endemic species decline. Urbanization is distinct among anthropogenic land-use disturbances in that it can affect fish communities quickly, even at low coverages. Some studies found significant loss of species, diversity, and biotic integrity in urban land cover as low as

15% of the basin, and over a time frame as short as 10 years (Wang et al. 1997; Paul and Meyer 2001; Walters et al. 2005). However, high-density urban cover can have a disproportionate effect on the streams (Walters et al. 2005). Urbanization degrades habitat, but in some river systems urban land use affected water quality and biotic integrity before impacting habitat quality (Wang et al. 1997; Walters et al. 2005; Moerke and Lamberti 2006).

Agricultural land use can also have significant effects on stream communities and fish distributions through both habitat degradation and water-quality alteration. Heavy agricultural land use increases runoff, sediment and nutrient delivery, and destabilizes flow and temperature regimes (Allan et al. 1997; Wang et al. 1997; Allan 2004; Moerke and Lamberti 2006). The amount of agriculture that can occur in a watershed before negatively affecting fish communities varies widely among systems, with reported ranges of 20-50% across studies (Wang et al 1997; Moerke and Lamberti 2006; Burcher et al. 2008; Utz et al 2010). The effects of agricultural development on species distribution vary depending on type of agriculture, intensity, location in the watershed, topography, riparian type and width, and stream morphology (Wang et al. 1997; Moerke and Lamberti 2006; Yuan et al. 2009; Utz at al. 2010; Smiley et al. 2011). However, agricultural land use tends to increase sedimentation and nutrients, resulting in assemblages of tolerant species better able to adapt to degraded conditions than the previous assemblage (Berkman et al. 1986; Sutherland et al. 2002; Infante and Allan 2010). Some streams draining catchments with agricultural use have elevated concentrations of suspended sediment and turbidity levels, especially those with no riparian buffer (Wang et al. 1997; Zimmerman et al. 2003; Moerke and Lamberti 2006; Piggot et al. 2012), but other studies have found no difference between streams with or without a buffer (Smiley et al. 2011; Fischer et al. 2010).

Spatial scale of studies is also important when determining species distributions, as smaller scales can be constrained by factors occurring at larger scales (Frissell et al. 1986). Site or reach-scale factors are often important to fisheries managers, but many recent studies have shown that landscape characteristics and alterations are also extremely influential on fish communities and distributions (Wang et al. 1997; Walters et al. 2003; Walters et al. 2005; Moerke and Lamberti 2006; Infante and Allan 2010). In a relatively undegraded set of streams in the upper Midwest, Wang et al. (2003) found that local reach-scale factors best explained the presence/absence, abundance, and community characteristics of fishes. Watershed-scale characteristics were still important, partly for their influence on reach habitat, but were less important in determining fish distributions overall. Interactions among four spatial scales (catchment, network riparian, reach riparian, instream habitat) were some of the most important factors in determining fish assemblages, abundance, and presence/absence of specific species in Wisconsin and northern Michigan streams (Wang et al. 2006). Instream and local factors better explained fish assemblages in less disturbed catchments, whereas catchment-scale factors were more important in more heavily disturbed systems. In the Elk River, Tennessee, local factors such as substrate availability and species-specific substrate affinities, along with distance from an upstream hypolimnetic-release dam, were the primary factors in determining darter distributions (Potoka et al. 2016), In contrast, land use/land cover was the most important variable influencing salmonid distributions in Lake Ontario tributaries (Stanfield et al. 2006). Salmonid densities were best explained by site-level factors, but catchment size, geology, and stream slope still played an important role. Natural ecosystems have a set equilibrium across spatial scales, and large-scale changes in catchment conditions and upstream land use can have a trickle-down effect on local conditions. Therefore, when addressing factors that affect fish distributions, watershed and catchment-wide factors must also be considered along with local-scale factors.

Research on fish distribution is lacking in the southeastern U.S., which contains a diversity of species and endemics that is unmatched by other areas of the U.S. (Warren et al. 2000; Jenkins et al. 2015). Over 1,800 aquatic species can be found within the 70 major river basins in this region and over 500 of these species are endemic to the southeastern states alone, some to individual watersheds (Birdsong et al. 2015). However, this region is experiencing rapid declines in native fish. The Nature Conservancy identified 87 watershed "hotspots" with at least 10 or more "at risk" species of freshwater fish and mussels, and 75 of these occur in the 14 southeastern states alone (Master et al. 1998). Furthermore, 34% of fish species and 90% of mussels in peril throughout the U.S. are found in the southeast (Birdsong et al. 2015). Causes behind these declines involve processes that are affecting many across the world such as dams, anthropogenic land use, hydrologic alteration, habitat destruction, fragmentation, and non-native invasive species (Warren et al. 2000; Birdsong et al. 2015).

Diversity of black bass *Micropterus* spp. follows the national pattern, with most of the black basses occurring in the southeastern U.S. All 14 species and subspecies of black bass described as of 2013 are found in this area, and 9 are endemic (Baker et al. 2013; Birdsong et al. 2015; Taylor et al. 2019). Several of these species are newly described, and many provisional and undescribed forms exist. Most of them have small ranges and are in need of conservation efforts to prevent extinction or further imperilment (Birdsong et al. 2015; Freeman et al. 2015; Taylor et al. 2019).

The conservation of native black basses received little consideration from most fisheries professionals until the formation of the Native Black Bass Initiative (NBBI), originally a keystone initiative under the National Fish and Wildlife Foundation (Birdsong et al. 2015). Initially, this plan identified three main species in four areas as the primary focus: Redeye Bass *Micropterus* sp. cf. *cataractae* (Bartram's Bass) in the Savannah River basin, Shoal Bass *Micropterus cataractae* in the Chattahoochee River in Alabama and Georgia as well as the Chipola River in Florida, and the Guadalupe Bass *Micropterus treculli* in Texas. However, the goal was to expand this plan over time to fund research for all endemic black bass species with conservation needs. The NBBI identified conservation needs for the initial focus requiring about $23 million over 10 years. Most of this money has still not been realized, but the NBBI supplied a framework for state agencies such as Alabama Department of Conservation and Natural Resources (ADCNR) and private power companies such as Georgia Power to provide some funds for black bass conservation work. This initiative has resulted in a large increase in research on the rare black bass species; for example, more than 13 studies on Shoal Bass have been published since the implementation of the NBBI plan; only six published papers on this species existed over the 50 years prior to the NBBI.

Endemic black basses in the southeastern U.S. likely have different ecology and biology than more cosmopolitan species like Smallmouth Bass *Micropterus dolomieu* (Sammons et al. 2019), but some similarities surely exist. All of these species evolved in lotic systems and many of them are lotic-obligate; thus, they likely face similar threats to their persistence as other fluvial fishes (Birdsong et al. 2015). However, few distribution and abundance studies have been conducted on these species. Conversely, Smallmouth Bass distribution has been examined in several areas of its range and these studies may provide a template for other black basses. Smallmouth Bass are more likely to be found in streams with high amounts of rocky substrates in the streams and watersheds with large proportions of rock in the soils (Lyons 1991; Brewer et al. 2007; Brewer and Orth 2015). As rocky soils/substrates decrease and sedimentation from anthropogenic land use increases, Smallmouth Bass are less likely to occur (Paragamian 1991; Brewer and Rabeni 2011). Furthermore, Smallmouth Bass in Missouri are less likely to be present in watersheds containing soil types with low permeability and high runoff potential (Brewer et al. 2007).

Both reach-scale and watershed-scale variables were important in determining Smallmouth Bass distribution, but watershed variables were more important (Brewer et al. 2007; Brewer 2013; Hessenauer et al. 2019). For Smallmouth Bass, local variables influenced abundance more than distribution (Brewer et al. 2007). Channel units (such as pool) were still significant in determining Smallmouth Bass presence, but watershed land use was still the dominant variable (Brewer 2013). Smallmouth Bass were more likely to occur in forested streams with limited anthropogenic change, and land use significantly affected Smallmouth Bass probability of presence even if the percentage of pools in streams was ideal (Brewer and Rabeni 2011; Brewer 2013). Some Missouri streams affected by agricultural land use still had good Smallmouth Bass populations, with no significant difference found between those streams and the forested streams (Brewer and

Rabeni 2011). Streams with good natural conditions (best substrates, ideal gradient) were more resilient to anthropogenic change.

Distance from impoundments, free-flowing fragment length, and discharge may be important to Shoal Bass distributions (Taylor et al. 2018a) but are not usually mentioned in Smallmouth Bass studies. Northern strain Smallmouth Bass can live in lakes and reservoirs and are more of a habitat generalist (Brewer and Orth 2015), but Shoal Bass are a river obligate species and require streams with adequate flow regimes (Sammons et al. 2015). Shoal Bass have been shown to have other unique traits that are distinct from other black basses, such as long spawning migrations (Sammons 2015). Factors affecting distribution and abundance of stream-dwelling bass can be both similar and very distinct across species, but previous studies provide potential factors that may be considered in distribution studies on other endemic black basses.

One endemic black bass in great need of study is the Redeye Bass *Micropterus coosae* clade. The Redeye Bass was originally described by Hubbs and Bailey (1940) from specimens from the Mobile Basin in Alabama, the upper Chattahoochee River in Alabama and Georgia, and the upper Savannah River in Georgia-South Carolina. The original native range of Redeye Bass included the upper Savannah and Altamaha drainages on the Atlantic slope, and the upper Chattahoochee River and Mobile Basin (Tallapoosa, Coosa, Cahaba and Black Warrior rivers) on the Gulf Slope (Boschung and Mayden 2004; Leitner and Earley 2015; Taylor et al. 2019). Recently, Redeye Bass in the Mobile and Chattahoochee drainages were proposed to be five species, each now occurring in a single drainage (Baker at al. 2013). There is ample evidence that the two Atlantic slope populations likewise constitute distinct species (Freeman et al. 2015).

Thus, the Redeye Bass complex is an example of cryptic biodiversity, where multiple species can be hard to distinguish morphologically and tend to be incorrectly grouped as nominal species (Freeman et al. 2015). A significant consequence of these new species descriptions is large range decline, as one species thought to inhabit multiple rivers in a large area is now considered to be as many as seven species occupying primarily individual rivers (Baker et al. 2013; Freeman et al. 2015). Smaller ranges can increase conservation risk because the loss of a single population has a disproportionate effect on species vitality (Angermeier 1995; Warren et al. 1997; Warren et al. 2000; Reynolds et al. 2005; Jelks et al. 2008; Alofs et al. 2014). Furthermore, the Redeye Bass group was already significantly understudied, and now that multiple species have been described and proposed, most of them have never been studied as a single species and current distribution and status are unknown.

One such bass is the Tallapoosa Bass *Micropterus tallapoosae*, found throughout the Tallapoosa River Basin above the Fall Line (Baker et al. 2013). Dams are one of the threats facing Tallapoosa Bass that could significantly impact their distribution, as they inhabit small to medium upland streams, are rarely found in large rivers, and are widely considered to be largely intolerant of impoundment (Mettee et al. 1996; Leitner and Earley 2015). Warrior Bass *Micropterus warriorensis* from the Black Warrior River Basin and Redeye Bass from the Coosa River Basin quickly disappeared from reservoirs soon after impoundment (Boschung and Mayden 2004). The Bartram's Bass variety from the Savannah drainage is different in that they live and thrive in reservoirs and can grow larger than the rest of the Redeye Bass clade (Koppelman and Garrett 2002; Boschung and Mayden 2004; Leitner and Earley 2015). Shoal Bass, another fluvial specialist with a small range, have been impacted severely by dams and have declined due to fragmentation, migration blockage, restriction of genetic connectivity, and inundated habitats due to impoundment (Williams and Burgess 1999; Dakin et al. 2015; Sammons and Earley 2015; Sammons et al. 2015; Taylor et al. 2018a). The Tallapoosa River has been fragmented by four dams, which has isolated many populations of Tallapoosa Bass, but the effects of this are unknown. Movement, habitat use, and growth of Tallapoosa Bass were not negatively affected by the altered flow regime of Harris Dam (Earley and Sammons 2015; Earley and Sammons 2018), but more research is needed to fully understand how dams may affect the movement, habitat use, and distribution of Tallapoosa Bass.

Invasive species and genetic introgression have also severely impacted some of the rare black bass species (Birdsong et al. 2015; Koppelman 2015) but have not been studied for Tallapoosa Bass. Introduced Alabama Bass *Micropterus henshalli* have severely hybridized with Bartram's Bass in the Savannah drainage (Leitner et al. 2015) and have replaced Bartram's Bass in some reservoirs (Bangs et al. 2018). Shoal Bass have hybridized with non-native congeners across its range; including Smallmouth Bass, Spotted Bass *Micropterus punctulatus*, and Alabama Bass (Alvarez et al. 2015; Dakin et al. 2015; Tringali et al. 2015; Taylor et al. 2018b). Pure Guadalupe Bass were nearly extirpated from much of their range due to hybridization from introduced Smallmouth Bass; recovery was only achieved through extensive and expensive restoration efforts such as removal of non-natives, restocking of pure Guadalupe Bass, and habitat restoration (Birdsong et al. 2015; Fleming et al. 2015; Garrett et al. 2015). Extensive hybridization of Chattahoochee Bass *Micropterus chattahoochae* with non-native congeners has been documented throughout its range (B. Bowen, GADNR, unpublished data), but no extensive genetic dataset exists for other species in the Redeye Bass group. More samples are needed to gain a baseline genetic structure for the Tallapoosa Bass and determine the genetic integrity of these fish across their range.

Little is known about the effects of land-use changes on most of these endemic, fluvial specialist black bass, including Tallapoosa Bass. Recreational areas in a Texas state park have caused riparian degradation and bank erosion in Guadalupe Bass streams, but efforts are currently ongoing to restore the habitat (Garrett et al. 2015). Instream habitat degradation and increased water withdrawals are possible reasons for Shoal Bass decline in Alabama tributaries of the Chattahoochee River (Stormer and Maceina 2008, 2009), and data suggest that anthropogenic land use contributed to assemblage shifts in some of the same tributaries (Johnston and Maceina 2009). Saalfeld et al. (2012) found that streams in the Tallapoosa Basin with a high percentage of agricultural land use had lower Index of Biotic Integrity (IBI) scores and a shift towards omnivorous and tolerant assemblages. The agricultural streams had significantly higher nutrient loads and suspended solids, most likely from the traffic and manure of grazing cattle, poultry house manure spread on fields, and lack of protected riparian zones. However, little is known about the effects that anthropogenic land use may have on the distribution and abundance of Tallapoosa Bass.

In general, rocky substrates and vegetative cover are important to species of the Redeye Bass group, but the precise relationships are unknown (Leitner and Earley 2015). Earley and Sammons (2015) and Knight (2011) both found that radio-tagged Tallapoosa Bass commonly used rocky substrates, but little other work has been done on this species.

Past studies have demonstrated that drainage-scale modeling efforts can provide insight into factors that predict fish distributions, identify constraints, and determine what spatial scales should be targeted for restoration or best management practices (Stanfield et al. 2006; Wang et al. 2006; Brewer et al. 2007; Potoka et al. 2016; Taylor et al. 2018a). Basic knowledge on the current distribution and habitat use of Tallapoosa Bass is a prerequisite before any extensive conservation or restoration efforts can begin. The goal of this study is to determine the current distribution of Tallapoosa Bass within the Tallapoosa River drainage in Alabama. The objectives are to: 1) ascertain the land use, habitat, abiotic variables, and interactions that contribute to their presence and abundance; and 2) construct exploratory descriptive models to explain their distribution and abundance patterns. Data from this study will be used in the future to guide compilation of a Redeye Bass complex management plan for Alabama, which will prioritize populations for conservation, restoration, and further study.

II. Methods

II.1. Study area

This study will focus on the Tallapoosa River drainage within Alabama (Figure 1). The Tallapoosa River originates in northwestern Georgia and flows southwesterly across east-central Alabama for 421 km before joining the Coosa River, forming the Alabama River (Earley and Sammons 2015, 2018). Most of the Tallapoosa River drainage lies primarily in the Piedmont Upland physiographic region, which has a complex geology developed on igneous and metamorphosed sedimentary rock (Boschung and Mayden 2004). The Fall Line is a transitional region between the Coastal Plain and the other upland regions characterized by a sudden drop in elevation, with a commensurate increase in gradient creating rapids and waterfalls (Mullholland and Lenat 1992; Boschung and Mayden 2004). Below the Fall Line, the Tallapoosa River flows through the Alluvial-deltaic plain in the Coastal Plain physiographic region; whereas its lower tributaries are in the Fall Line Hills and Black Prairie districts of this region (Boschung and Mayden 2004). The Piedmont portion of the Tallapoosa River and its tributaries are characterized by a physically stable channel, with a mix of low-gradient habitats with sand and silt substrate and high-gradient shoal habitats dominated by boulder and bedrock substrate (Earley and Sammons 2015, 2018). The lower sections of the Tallapoosa River and its tributaries in the Coastal Plain typically have unstable channels and are of moderate to low gradients with sandier substrates and gravel riffles near the Fall Line Hills district and chalk substrates near the Black Prairie district (Boschung and Mayden 2004). The Tallapoosa River has four impoundments (Figure 1). The uppermost is R. L. Harris Reservoir, just below the Tallapoosa River and Little Tallapoosa River confluence. Further downstream a series of dams (Martin, Yates, and Thurlow) encompass most of the lower Piedmont and Fall Line regions.

II.2. Site Selection

Sixty Tallapoosa River tributaries were selected for sampling (Table 1). The Tallapoosa River mainstem was not sampled because the distribution of the species there has been well documented (Sammons et al. 2013; Earley 2012). Potential study sites were selected based on collection data from Baker et al. (2013), angler reports, and visual assessment of stream size and basin characteristics. Streams were grouped spatially by sub-basins or barriers such as large impoundments (Table 1). The sub-basins were defined as the Tallapoosa River Basin above Lake Wedowee (TW), the Little Tallapoosa

River Basin above Lake Wedowee (LTW), Tributaries of Lake Wedowee (W), the Tallapoosa River Basin between Lake Wedowee and Lake Martin (WM), Tributaries of Lake Martin, Yates Reservoir, and Thurlow Reservoir (MYT), and the Tallapoosa River Basin below Thurlow Dam (BT; Table 1, Figure 1). A subset of streams in each basin were then selected for the study with consultation of ADCNR biologists. Streams were selected to encompass a range of land uses and habitat types across the entire expected distribution of Tallapoosa Bass. Streams now flowing into reservoirs were included to assess how impoundment intolerance might affect abundance and distribution of Tallapoosa Bass in these streams.

II.3. Sampling design and data collection

Sampling was conducted May-August 2019 and May-June 2020. Initial stream sites consisted of a section of stream between two bridges. These stream sections were selected to encompass a range of distances from the mainstem Tallapoosa River, with some streams being sampled close to the mouth and others up near the headwaters. Sampling locations on each stream were primarily determined by the number of available access points, with streams that contained few access points being decided first and streams with several access points being adjusted accordingly to attempt to capture as much longitudinal variation as possible across the Tallapoosa River drainage. Within each section, three to eight transects were sampled, depending on the length of the stream section and the gear used. Final stream sites were defined as the length of stream it took to sample the three to eight transects and were bounded by the start of the first transect and end of the last transect. Most stream sites contained five to six transects. The number of transects was chosen to encompass as much habitat variation as possible while being able to finish the sample in one day. Due to the difficulty of measuring longitudinal distance on streams while sampling, transects were timed. Mean stream width (MSW) was determined by measuring five to seven random widths within the first 50 m of the study site. Timed transect length for that site was then determined by multiplying MSW by 90 seconds then dividing by 60 to obtain transect length in minutes. Transects were separated by a minimum of 10 MSW (typically longer) to ensure that previously sampled bass were not recaptured.

Prior to sampling, conductivity, temperature, dissolved oxygen, and turbidity were measured at the beginning of each transect. GPS coordinates were recorded at the beginning and end of each transect. The primary sampling gear used for this project was a DC electrofishing unit and a hand-held anode operated out of a 4.6-m aluminum canoe (Sammons et al. 1999). The DC unit was powered by a 2000-Watt Honda generator. The anode was a 3 m pole with a 35 cm ring with mesh attached to make a net. The anode was connected via a 7.6-m cord that had floats attached. Transects were sampled going downstream, alternating left and right banks to target all habitat; all stunned black bass were collected. Sections of transects that were shallow enough were sampled using the canoe as a barge; most transects were sampled using this method. During sampling, estimates of percent mesohabitat types (pool, run, riffle, shoal) were visually assessed for each transect. Bank stability, bank vegetative protection, large woody debris (LWD), and rocky substrate were visually assessed and assigned a score for each transect. Bank stability and bank vegetative protection were scored according to the Georgia Stream Team protocol (GADNR Stream Team 2005); these scores ranged from 0 to 10 and were scored independently for the right and left riverbank. Rocky substrate and LWD were scored according to a new protocol based on the Georgia Stream Team protocol (Tables 2, 3); these scores ranged from 1 to 10 and were scored once for the entire transect. Maximum depth was estimated by taking measurements in several deep pools within each transect with a handheld SpeedTech Depthmate Portable Sounder or by using a meter stick in shallower pools. All habitat data collected at the transect level was averaged for each stream site and summarized by sub-basin and across the Tallapoosa River drainage (Table 4). At the end of each transect, black bass were identified, measured for total length (TL, mm), and weighed (g). Fin clips were taken from all black bass for a concurrent genetic analysis. Species IDs were updated with genetic results for more accurate analysis of pure Tallapoosa Bass (Matthew Lewis, unpublished data). Total effort in seconds was recorded via a stopwatch at the end of every transect and averaged for each site. The datasheet for recording information is located in Appendix IX.1 and the sampling protocol is in Appendix IX.2. Coordinates for each canoe site and range of transect lengths are in Appendix IX.3.

Streams of MSW >8 m were generally considered canoe streams unless the water was too shallow to allow for canoe sampling. Streams that were smaller, wadeable, and not suited for canoe shocking were sampled using one (≤6 m MSW) or two (>6 m MSW) Smith Root LR-24 backpack units. Backpack streams were sampled over a standard distance of 40 MSW, which was measured in a similar manner as described above. A minimum of 35 MSW has been shown to adequately sample available habitat with acceptable standard deviations (Lyons 1992; Simonson and Lyons 1995; GADNR Stream Team 2005). Sites with very small MSW (2-3 m) were increased to 150 m transect lengths to cover more habitat. The same general sampling protocol was used for habitat, water quality, and fish collection as described above. Backpack streams were sampled going upstream, and transect distance was measured using a laser rangefinder. Three to five transects were sampled, depending on the MSW and the amount of water available as sampling continued upstream. Wider streams contained fewer transects due to the transects being longer, as all sampling was conducted over a single day for each study site. Total effort in seconds for each transect was recorded from the output on the back of the shocking unit and averaged for each site. Coordinates for each backpack site and range of transect lengths are in Appendix IX.4.

II.4. Additional data collection

ArcMap 10.6.1 (ESRI) was used to calculate segment and watershed data that was not collected in the field. Stream order, stream gradient, transect gradient, and distance from the original mainstem Tallapoosa River were obtained from the USGS National Hydrography Dataset (NHD; using NHDPlusHR) for each stream segment sampled (Table 5). Here, stream segment is defined as the stretch of stream between two tributary confluences (Frissell et al. 1986). When multiple segments comprised a sample site or transect, NHD segment data was averaged across segments using a weighted average for each transect and site based on the length of each segment. Site-averaged values are summarized in Table 5. Watershed area, dominant geology, and dominant hydrologic soil group was calculated for the area of the watershed that drained into the bottom point of the sampling site. For sites that encompassed multiple stream orders, the stream order of the segment flowing through the bottom of the site was used as the site stream order. Geology and soil data were obtained from the USDA NRCS Geospatial Data Gateway. Soil data was housed in the STATSGO2 dataset for the state of Alabama using the template provided by the SSURGO dataset (USDA NRCS 2012; Table 5) and supporting geology data came from Dicken et al. (2007). Soil data was classified into hydrologic soil groups A, B, C, or D as defined by the USDA, which measure soil permeability and runoff potential (USDA NRCS 1997). Dams were counted as the number of dams in the network in which the stream site resides until that network's confluence with the Tallapoosa River. Information on dams came from the Southeast Aquatic Barrier Prioritization Tool from the Southeast Aquatic Resources Partnership (SARP) website (Table 5).

ArcMap was used to calculate floodplain land use along the sampling site of both canoe and backpack streams, and total watershed land use above the reach (Table 5). The 100-year floodplain was used because it serves as a better proxy for water quality than does an arbitrary riparian buffer (Kat Hoenke, SARP, personal communication). Land cover data was downloaded from the CropNASS dataset from the USDA; CropNASS provides better estimates of agricultural land use (Kat Hoenke, SARP, personal communication). Land use was divided into proportions of forested/natural, agriculture/cropland, and urban/developed and land use proportions were converted into a disturbance index (DI) that was a simplified version of the landscape development index of Brown and Vivas (2005). Coefficients can range from 1 to 10 with higher numbers representing increased disturbance. When Brown and Vivas (2005) had multiple categories that covered the categories in my dataset, these values were averaged, and the average value was applied to each respective land category (Mouser et al. 2019; Miller and Brewer 2021). For example, Brown and Vivas (2005) had the categories woodland pasture (2.02), pasture without livestock (2.77), low intensity pasture (3.41), and high intensity pasture (3.74); these were averaged to the value 2.99 and applied to all ag/pasture categories in my dataset.

II.5. Data analysis

Once all the field data and computer data were entered and organized, several variable reduction techniques were implemented. All variables were checked for correlations using Pearson's correlation coefficient and all variables with $r > 0.6$ were removed from the dataset (Dormann et al. 2013; Guisan et al. 2017; Miller and Brewer 2020). Variables in the dataset were also checked for a variance inflation factor (VIF) and all variables with a VIF score >3 were also removed from the dataset (Guisan et al. 2017; Rahel and Jackson 2007; Thompson et al. 2017). Many of the variables in Tables 4 and 5 did not pass the correlation or VIF threshold and thus were not included in the models. I then picked the ones that seemed to be the most biologically relevant or kept occurring in preliminary explorations of the data (Guisan et al. 2017).

Temperature was converted to a categorical variable representing warm or cool streams since the temperatures for the transects were all point measurements obtained in one day and did not accurately portray daily temperatures. Streams were considered warm if the site-averaged value was greater than one standard deviation below the monthly mean for all the sites, and cool if less than one standard deviation below the monthly mean. soil group B was the dominant soil group for the Tallapoosa Basin and was chosen as the representative soil category and calculated as a percent. Percent soil group B was then converted to a categorical variable since there were no values between 40 and 70%, thus rendering it a non-continuous variable. The variable was then described as majority percent soil group B (MPSB), with majority defined as >50%. Thus, values of

70% and greater were placed in the Yes category for MPSB and the values of 40% and lower were placed in the No category.

Average CPUE (fish/hr) for the site was calculated using a weighted average based on the proportion of total effort for each transect. Average CPUE was then compared across the six sub-basins and an ANOVA was used to test for significant differences in catch rates. A Tukey's post-hoc test was then used to calculate the specific pair-wise differences. Additionally, sites were pooled into month categories and frequency of CPUE per month was calculated. Transects in September that coincided with a June site were excluded from this part of the analysis. Since early season months May and June were not suspected to be different, sites were further pooled into Early (May/June) and Late (July/August) categories and tested with an ANOVA to test for significant differences in seasonal catch rates. Due to suspected low power because of the small sample size (58) split between the six sub-basins and seasonal categories, a significance level 0.1 was used.

II.6. Occupancy model

For the presence/absence data I used a single-season, single-species site-occupancy model to assess the relationships for Tallapoosa Bass in relation to both detection and occurrence using the format described by MacKenzie et al. (2002). The site-occupancy model is a hierarchical model that simultaneously models detection probability and occurrence probability in two binomial generalized linear models with a Bernoulli distribution (binomial with a trial size of 1). A species can occupy a site but may go undetected (Bailey et al. 2014; MacKenzie and Royle 2005; MacKenzie et al. 2006). The site-occupancy model enables the researcher to estimate probability of occurrence while accounting for incomplete detection (MacKenzie et al 2002). Covariates such as habitat variables are often added to the model if it is expected that probability of occurrence and detection may be a function of site characteristics (MacKenzie et al. 2002; Albanese et al. 2007; Peoples and Frimpong 2015). The occurrence sub-model is estimating the latent state variable z (the true state of occupancy) based on occurrence probability "psi" (Ψ) at site i, designated by: $z_i \sim \text{Bernoulli}(\Psi_i)$, where z_i is the true state of occupancy at site i. The detection sub-model is estimating the detection probability conditional on the true presence (z), designated by: $y_{ij}|z_i \sim \text{Bernoulli}(z_i * p_{ij})$, where y_{ij} refers to each detection at site i and survey j, p_{ij} is detection probability at site i and survey j, and the vertical bar references the conditional relationship of detection to presence (Kéry and Royle 2016). The basis of the design involves surveying each site multiple times and developing an encounter history (1 if detected, 0 if not). In using these encounter histories, the model is able to simultaneously estimate occupancy probability (Ψ) and detection probability (p) (MacKenzie and Royle 2005; Kéry and Royle 2016; Gerber et al. 2020). If a site is only surveyed once and results in a 0, it is hard to know if the site was truly unoccupied or if the species was simply undetected. Using an encounter history of 1s and 0s enables the model to more accurately estimate detection probability. Each sub-model is independent but informs the other.

Typically, surveying a site multiple times involves repeat visits over time (MacKenzie et al. 2006). The spatially separated sampling transects from this study were used as the repeat surveys that are needed to account for species detection probability (Albanese et al. 2007; Hagler et al. 2011; Anderson et al. 2012; Kéry and Royle 2016;

Potoka et al. 2016). My study was designed to sample as many sites as possible during the sampling season, in essence sacrificing some quality for quantity. Due to the logistical constraints of this sampling method, sites could not feasibly be visited multiple times and so a space-for-time approach was implemented (Albanese et al. 2007; Hagler et al. 2011; Anderson et al. 2012; Kéry and Royle 2016; Potoka et al. 2016). Each sampling transect was considered a separate survey, and detection was defined as the probability of detecting Tallapoosa Bass in a survey given that it is present at the site. Using this method, the detection probability is composed of two products: 1) the availability of the species at the transect given its availability at the site; and 2) the probability of detecting the species given that it is available for detection (Kendall and White 2009; Guillera-Arroita et al. 2011; Kéry and Royle 2016). The concept of using spatially separated surveys in place of temporally replicated surveys is a technique that has been used before and is a valid technique. Since spatially replicated transects can introduce dependency (Kendall and White 2009), I introduced a "trap" factor similar to Mollenhauer et al. (2018). All initial surveys were assigned a category of 0. If a Tallapoosa Bass was detected on the first survey, all subsequent surveys were assigned a 1, 0 if otherwise. The category 1 means that I was more likely to detect Tallapoosa Bass on all subsequent surveys.

Occupancy modelling has four basic assumptions: 1) the state of occupancy is closed during the sampling season and does not change over the season, 2) the probability of occupancy does not change between sites or is modelled with covariates, 3) the probability of detection is constant across all sites and surveys or is modelled with covariates, and 4) detections between surveys are independent. All sampling during this project occurred over a 4-month period in the spring and summer and I assumed that no seasonal change in occupancy would occur over that relatively short time. The second and third assumptions were met using covariates hypothesized to explain differences in both detection and occupancy probabilities (MacKenzie et al. 2002; MacKenzie et al. 2006). The fourth assumption was met by introducing a "trap" factor similar to Mollenhauer et al. (2018).

The variable and model selection process on the detection side of the model were started while holding occurrence constant. I used data from both sites where bass were detected and sites where bass were not detected to better allow for relating detection probability to the covariates (MacKenzie et al. 2006). I limited the number of transects per site to six to avoid major imbalances in the dataset since very few sites had seven or eight transects. All detection covariates were measured at the transect level. For potential detection covariates, I selected variables that made it through the initial screening process that were deemed most likely to impact the detection of Tallapoosa Bass. Interactions were considered in initial data exploration, but none were statistically significant and were not retained for model selection to help reduce model complexity. Continuous covariates that were right-skewed were natural log-transformed to improve linearity. Categorical variables were dummy coded to allow for direct correlations with continuous covariates. All variables were then reassessed for collinearity post-transformation and all variables with an $r < 0.6$ were retained. All continuous variables were then standardized to a mean of 0 and standard deviation of 1 using the package MuMIn (Barton 2018) in the statistical software R to help improve model convergence and allow for direct comparison of effect sizes. I fit the models using the package "unmarked" in R (Fiske and

Chandler 2011). The most complex detection sub-model was then used in an all-subsets analysis using the dredge function from the R package MuMIn. This was used in an exploratory sense due to lack of previous knowledge on Tallapoosa Bass, but careful and considerable *a priori* biological consideration was put into the variable selection beforehand.

I then went through a similar process on the occurrence sub-model. I went through the variable and model selection process while holding the detection side constant. Site-level covariates that were measured at the transect level were averaged over the sampling transects. Other variables were measured at the watershed scale. I selected potential variables that made it through the initial screening process that were most likely to affect Tallapoosa Bass occupancy. Interactions and quadratic terms were considered but removed after initial exploratory analysis due to lack of significance and to avoid over-complicating the model and reduce degrees of freedom. Continuous covariates that were right-skewed were natural log-transformed to improve linearity. Categorical variables were dummy coded to allow for direct correlations with continuous covariates. All occurrence covariates were then reassessed for correlations and variables less than 0.6 were retained. All continuous variables were standardized to a mean of 0 and standard deviation of 1 using the package MuMIn.

Once the most complex occurrence sub-model was built, I went through an all-subsets analysis using the dredge function from the MuMIn package. Variables for the all-subsets received considerable and careful *a priori* consideration, and this approach is considered to be mostly exploratory. The occurrence sub-model (detection still held constant) was assessed for goodness-of-fit using the MacKenzie and Bailey (2004) test for occupancy models (n=1000 simulations) from the R package AICcmodavg (Mazerolle 2020). The test indicated some overdispersion ($\hat{c} = 1.44$). To account for this, I used the quasi-Akaike information criterion corrected for small sample size (QAICc) to rank the candidate models within the all-subsets analysis (Burnham and Anderson 2002; MacKenzie and Bailey 2004).

Once my top occurrence sub-models were identified, I added my best detection sub-model to all top occurrence sub-models to create top full models. The global full model indicated some mild overdispersion ($\hat{c} = 1.15$), so QAICc was used to rank the top full models. The SE of the coefficients for the best full model were adjusted for overdispersion by multiplying the variance-covariance matrix by $\sqrt{\hat{c}}$ from the global model (MacKenzie and Bailey 2004). I approximated 95% confidence intervals for coefficients and probabilities of the best full model using the formula: coefficient ± 1.96*SE. I used the predict function in R for the best full model to create plots that show the relationship between detection and occurrence probabilities and their respective continuous covariates. Occupancy model code is given in Appendix IX.5.

II.7. Relative abundance model

Preliminary analysis for the relative abundance data indicated that my counts were both overdispersed and zero-inflated. I used a zero-inflated negative binomial model with a log-link function using the package glmmTMB (Magnusson et al. 2020) in R. Negative binomial models are useful for when count data are overdispersed (Kéry and Royle 2016; Brooks et al. 2017). I used the quadratic parameterization of the negative binomial (nbinom2 in glmmTMB) as it provided better fit (7 ΔAICc units, ΔAICc weight = 0.97) over the linear parameterization (nbinom1 in glmmTMB). I modeled counts at the transect level to assess both within and between site relative abundance. I picked variables that made it through the initial screening process that seemed the most likely to affect Tallapoosa Bass abundance. Interactions and quadratic terms that did not appear to be significant or important in preliminary analyses were not retained for the global model to avoid over-complicating the model and reduce degrees of freedom. I kept in effort and gear type to account for those processes and to keep the effort analysis consistent between the occupancy and relative abundance models. Watershed level covariates that applied to the site were repeated for each transect within the site. Continuous covariates that were right-skewed were natural log-transformed to improve linearity. Categorical variables were dummy coded to allow for direct correlations with continuous covariates. All covariates were then reassessed for correlations and variables less than 0.6 were retained. All continuous variables were standardized to a mean of 0 and standard deviation of 1 using the package MuMIn. I also included random effects of stream and subbasin in the model to partition the variance and account for nestedness. The zero-inflation part of the model helps to model the probability of extra zeros (Kéry and Royle 2016; Brooks et al. 2017). The variables that were significant in the occurrence sub-model of the occupancy model were used for the zero-inflation sub-model.

While withholding the zero-inflation sub-model initially due to convergence problems, I conducted an all-subsets analysis using the full model described above with random effects. Careful and extensive *a priori* consideration was given to the variable set prior to the all-subsets analysis. I used the dredge function from the MuMIn package and ranked all models via AICc. According to Burnham and Anderson (2002), if a large number of models are closely related, then picking one best model is not ideal and model-averaging can help reduce selection bias in model coefficients, including in all-subsets analysis. Many of the examples given by Burnham and Anderson (2002) considered seven or more candidate models, so if my model set contained seven or more equivalent models then I averaged the coefficients from the top models using the MuMIn package to obtain my final coefficients. Model code is given in Appendix IX.6.

II.8. Variable comparisons

Variables that were significant in the models or of particular interest to Tallapoosa Bass ecology were compared for good Tallapoosa Bass sites and poor Tallapoosa Bass sites using either mean values or percent frequency. Sites where at least three Tallapoosa Bass collected during my study were considered to be good sites, whereas sites where less than three Tallapoosa Bass were collected were considered poor sites. This cutoff value was chosen because sites where three or more Tallapoosa Bass were collected rarely had a rock score lower than five, which seemed like a possible threshold for rocky substrate based on visual inspection of the data. In order to show greater contrast for certain variables, comparisons were also made for sites with and without Tallapoosa Bass.

III. Results

III.1. Field and GIS collection

In total, 49 of the 60 selected sites were successfully sampled from May-September 2019. A further nine samples were taken in May-June 2020 to fill in data gaps identified after the 2019 field season and finish one uncompleted site. Two of these samples occurred on previously sampled streams but on the other side of an impoundment, whereas six more occurred on streams that had a high amount of developed disturbance in the watersheds because most streams from the 2019 sampling had low developed land cover. Furthermore, data analysis and field observations indicated that counts declined towards the end of the summer of 2019, perhaps due to low water levels. Therefore, six streams were resampled in 2020 to assess the potential for seasonal variations in relative abundance of Tallapoosa Bass affecting the results. Resamples of those six streams were conducted in the spring of 2020 on streams that had previously been sampled in late summer of 2019 that yielded very few or no Tallapoosa Bass, yet had habitat characteristics that suggested they should harbor good populations. In addition, two of the coastal plains streams with the best habitat were resampled to confirm Tallapoosa Bass absence status. If the resample did not significantly change the results (much greater counts, or absence to presence), then the resample was not used in the analysis. Only two streams were changed by the resample: only three Tallapoosa Bass were collected in Lockhelooge Creek in 2019 but 13 were collected in 2020, and no Tallapoosa Bass were collected in Kemp Creek in 2019 but one was collected in 2020, changing its status from absent to present. Two sites were discarded from model analysis due to one or fewer completed transects (Harold Creek and Wallahatchee Creek, Table 1). This resulted in 47 sites from 2019, nine new sites from 2020, and two replacement resamples from 2020 being retained for model analysis, for a total of 58 sites.

Tallapoosa Bass were found at 40 of the 58 distinct sites used for model analysis. Overall, the total number of Tallapoosa Bass sampled over the 58 sites was 452 (Table 6), and Tallapoosa Bass were by far the most commonly captured bass. The size range of Tallapoosa Bass spanned 50 mm to 300 mm TL, and the most common size range was 150 – 230 mm TL (Figure 2). A total of 710 black bass was collected, including hybrids

(Table 6). Tallapoosa Bass were fairly well-distributed across the five Piedmont sub-basins, with the 75 to 127 collected in each sub-basin, except for the TW sub-basin where only 28 bass were collected in 10 sites (Table 6). The LTW sub-basin had the second highest total count, but only had five sites total. Catch rates were highly variable across the sub-basins and a few sub-basins had significant differences. The LTW sub-basin also had the highest mean CPUE and highest median CPUE (Table 6, Figure 3), and significantly differed from the TW and BT sub-basins; its mean CPUE was also more than twice as high as the other sub-basins. The W and WM sub-basins also significantly differed from the BT sub-basin (Table 6). The outlier in the BT sub-basin (Figure 3) was the only site in the sub-region where Tallapoosa Bass were found and was immediately below Thurlow Dam close to the Fall Line. The four outliers for the WM and MYT sub-basins were four of the highest catch totals throughout the entire Tallapoosa River drainage. The highest outliers for the WM and MYT sub-basins were small second order streams in highly urbanized areas (Rocky Branch Creek = 63.25% developed in the watershed, Town Creek = 61.02% developed in the watershed). The LTW sub-basin is the only area to not have sites with no Tallapoosa Bass collected.

Additionally, CPUE for Tallapoosa Bass varied seasonally (Figure 4). The best months for higher CPUEs were May and June, while there was a large drop-off from June to July. Also, May and June were the only months to have sampling sites with greater than 20 CPUE and July only had one site with greater than 10 CPUE (Figure 5). The mean CPUE for the Early season sites was 8.26 and the mean for the Late season sites was 1.71 and there was a significant difference ($P = 0.002$) at the 0.1 significance level. Coastal Plains sites (where no Tallapoosa Bass were found except for one site) were fairly evenly distributed across months, with one site sampled in May, three sites each in June and July, and two in August. Thus, they likely had little effect on the seasonal pattern observations.

The LTW sub-basin, which had the some of the highest counts and highest mean CPUE, also had the highest average rock score (Table 4). It also had consistently lower LWD scores compared to the other sub-basins and average percent pool was roughly half that of the other sub-basins. The highest LWD scores were in the MYT and BT subbasins, the two most southern sub-basins in the Tallapoosa River drainage (Table 4). Shoal was the most variable of the mesohabitats, and while run did not seem to differ much among sub-basins. The LTW sub-basin had the tightest range for temperature and contained the highest DO values. Riffle mesohabitat was also highly variable among sub-basins (Table 4). The more southern sub-basins contained the deepest depths. Mean bank stability and vegetative cover scores ≤ 5 across all sub-basins and the Tallapoosa Basin in general (Table 4). Although samples were conducted on second to sixth order streams, the majority of sites were located on third and fourth order streams (Figure 5).

Moving from north to south in the Tallapoosa River drainage progressing from the TW to BT sub-basins, the percent agricultural land in the floodplain tended to decrease and the percent natural/forested in the floodplain tended to increase in terms of mean values (Table 5). Development was low in the floodplain across the Tallapoosa River drainage, with exception of one creek in the W sub-basin. At the watershed scale, there was little agricultural or developed land in the Tallapoosa River drainage. Agricultural land use did not top 40%, and most means were below 15%. Developed land use was generally very low, and most means were below 10% (Table 5). Natural/forested was the dominant land cover. There were a few exceptions, most notably in the WM, MYT, and BT sub-basins, where all three had a site that was over 60% developed. The disturbance index metrics mirror the trends observed in the percent land use, with most floodplains and watersheds characterized by low to medium index values, and the highest index values occurring in the regions with the highest developed land use (Table 5).

Mean watershed area was noticeably smaller in the three upper sub-basins than in those further down in the Tallapoosa River drainage (Table 5). The largest watersheds tended to be in the lowest sub-basins. For the MYT sub-basin, 50% of the values were between 28.58 km^2 and 181.89 km^2, while for the BT sub-basin 50% of the values were between 15.09 km^2 and 152.36 km^2. However, the 3rd quartile of watershed area for the other sub-basins was around 45-78 km^2. There was a good range of distance to mainstem in each of the sub-basins, except for the LTW sub-basin which had a tight range, and all distances were close (Table 5).

The soil category with the most representation in the sub-basins was soil group B (Table 5). The majority of the Tallapoosa River drainage above the Fall Line had soil group B. The entire LTW sub-basin contained 100% soil group B, and none of the other Piedmont sub-basins had less than 70% soil group B. The BT sub-region varied quite a bit between soil groups A and C, but none of the sub-basins had large amounts of hydrologic soil group D (Table 5).

III.2. Model results: occupancy

Initial variables selected for detection after screening for correlations and VIF were LWD, turbidity, max depth, seconds of effort, and gear type. LWD had initially been excluded due to high correlations with other variables in contention for the occupancy sub-model but was re-included here since it was not correlated with other detection covariates. Since the detection and occurrence sub-models are each modeling a different process, correlated variables cannot occur within each process but can be shared between the processes. For detection, LWD was selected based on the intricacy of electrofishing around woody structures; turbidity was selected based on how it obscures vision; depth was selected due to shocking becoming less effective at greater depths; seconds was selected as a measure of effort; and gear type was selected to investigate how detection differs between gears. Max depth and seconds of effort were natural log-transformed to reduce skewness. All variables passed the 0.6 correlation threshold and were retained (Table 7).

Since all five variables were retained, all were included in the most complex detection model (Table 8). I hypothesized that detection would increase with increasing effort, decrease with increasing turbidity, decrease with increasing depth, decrease with increasing LWD, and that canoe gear detection was higher than backpack gear. There was a total of 32 possible candidate models in the all-subsets analysis, and the best model retained all five of the variables. This was reduced to the two variables of greatest effect (depth and gear type) and effort, with the trap factor to account for independence added in independently once model selection had occurred. This reduction was done to reduce the degrees of freedom taken up by the detection side of the model to leave more room for the occurrence sub-model.

For the occurrence sub-model, the final variable list after screening for correlations and VIF included rock score, watershed area, DI for the watershed, site gradient, site-average percent pool, site-average max depth, temperature category, dams in the stream network, MPSB, and sampling year. Watershed area, DI for the watershed, site gradient, site-average percent pool, and site-average max depth were natural log-transformed to reduce skewness. All variables except depth passed the correlation threshold (Table 9) and were included in the most complex occurrence sub-model (Table 8). I hypothesized that occurrence probability would increase with increasing rock score, increase with increasing percent pool, increase with increasing site gradient, decrease with increasing DI, decrease with increasing dams, be better in Yes for MPSB, be better in cool streams, and no difference between years. For the all-subsets analysis, there were a total of 512 candidate models for the occurrence sub-model. Four models were within two ΔQAICc units and these were the only models retained.

The top four occurrence sub-models were then added to the top detection model. Three models still remained within two ΔQAICc units, and the model explaining the most variation with the fewest number of variables was picked as the final model (Table 10). The global occupancy model did show some overdispersion ($\hat{c} = 1.15$), but also indicated adequate fit (Chi-square = 129.36; $P = 0.147$). The final model chosen (Table 10), also showed some overdispersion ($\hat{c} = 1.17$) and adequate goodness-of-fit (Chi-square = 133.53; $P = 0.104$). The chosen top model had a ΔQAICc score of 0.19 compared to the top-ranked model and differed by only one parameter (Table 10). The log-likelihood of the top two models was hardly different (only differs by 1.8) suggesting the additional parameter in the other model is potentially uninformative and does not contribute meaningful support even though it lowers the QAIC (Arnold 2010; Burnham and Anderson 2002).

In the final global model, the detection sub-model contained depth, gear type, effort, and the trap factor (Table 11). Effort and gear type were not significant at the 0.05 level, but gear type was close at $P = 0.061$. The P-value for gear type was initially 0.053 but inflating the standard errors to account for over-dispersion also inflated the P-values. Detection probability decreased as depth increased and increased with effort (Table 11; Figures 6,7). Detections for both variables were higher in the canoe samples for gear type than backpack samples (Figures 15,16). Detection probability was negatively associated with trap factor 0 (sites where Tallapoosa Bass were not detected on the first survey and unlikely to be detected on subsequent surveys) with trap factor 1 as the reference. Average detection probability at mean levels of depth and effort was 0.75, with canoe as the reference for gear type and 1 as the reference for trap factor (Table 11).

For the occurrence sub-model, the variables retained in the final model were rock score and MSPB, and both variables were significant (Table 11). Occurrence probability increased with rock score (Table 11, Figure 8). The occurrence probabilities for rock score were higher in the Yes category for MPSB than in the No category (Figure 8). Occupancy probability was negatively associated with the No category for MPSB with Yes as the reference (Table 11). Average occurrence probability at mean levels of rock and in the Yes category for MPSB was 0.88. The naïve average occurrence probability (all occupied sites/total number of sites; 40/58) was 0.69.

III.3. Model results: relative abundance

For the relative abundance model, the final list after screening for correlations and VIF included rock score, MPSB, temperature category, sampling year, watershed area, transect gradient, DI for the watershed, transect percent pool, transect max depth, gear type, and seconds of effort. Watershed area, transect gradient, DI for the watershed, transect percent pool, transect max depth, and seconds of effort were all log-transformed to help with linearity. Most variables passed the 0.6 correlation threshold, but gear type was removed due to high (0.74) correlation with watershed area (Table 12). The remaining variables were retained for model analysis (Table 13), and a quadratic term for transect gradient was added. I hypothesized that counts would increase with increasing seconds, be higher in cool streams, be higher for Yes category for MPSB, decrease with increasing watershed area, increase with increasing depth, decrease with DI for the watershed, increase with increasing percent pool, increase with increasing rock score, increase and then decrease for transect gradient, and that there was no year effect. Since rock score and MSPB were the most important variables in the occurrence sub-model, I included those variables in the zero-inflation sub-model to help account for the extra zeros (Kéry and Royle 2016; Brooks et al. 2017).

From the all-subsets analysis, there were a total of 2048 candidate models. Only 13 models were within two ΔAICc units of each other. Four models included the quadratic term but not the linear term for gradient and were discarded, leaving 9 models. Once those models were pulled from the all-subsets analysis, I re-inserted the zero-inflation component and reranked the models. Only 7 models were still within two ΔAICc units and were retained for the final average (Table 14). The significant variables in the averaged model were rock score, DI for the watershed, MPSB, and seconds of effort (Table 15). Tallapoosa Bass relative abundance increased with rock score, disturbance index, percent pool, transect gradient, the quadratic term for gradient, warm streams with cool as the reference, Yes for MPSB with No as the reference, and effort.

Relative abundance decreased with watershed area, depth, and year 2020 with 2019 as the reference (Table 15).

III.4. Variable comparison

Variables that were significant in the models or of particular interest to Tallapoosa Bass ecology were compared for good Tallapoosa Bass sites (≥3 bass) and poor Tallapoosa Bass sites (<3 bass). For percent soil group B, the mean value for good sites was about 93%, while it was about 71% for poor sites (Figure 9). The contrast was even greater between sites with and without Tallapoosa Bass, with sites containing bass having a mean value of 94% and sites without bass having a mean value of 56% (Figure 9). Rock scores for good Tallapoosa Bass sites were skewed to the right and approximately 75% of the sites had scores of six or higher (Figure 10). Approximately 90% of poor Tallapoosa Bass sites had rock scores <6. Good Tallapoosa Bass sites had more sites with smaller watershed areas, whereas poor Tallapoosa Bass sites tended to have larger areas (Figure 11). Eighty-three percent of good Tallapoosa Bass sites had watershed areas <80 km^2, whereas only 65% of poor Tallapoosa Bass sites had watershed areas <80 km^2. Good Tallapoosa Bass sites had more sites with DI values at the watershed scale between one and two (roughly 80%) compared to poor Tallapoosa Bass sites (roughly 60%), and the only site with a DI value greater than six was a poor Tallapoosa Bass site (Figure 12). Good Tallapoosa Bass sites had more medium and high gradients than poor Tallapoosa Bass Sites (Figure 13). Forty-seven percent of good Tallapoosa Bass sites had gradients ≥5 m/km, whereas 82% of poor Tallapoosa Bass sites had gradients <5 m/km. Percent pool looked very similar between good sites and poor sites, as 67% of good and poor sites had a percent pool less than 20% (Figure 14). About 33% of good Tallapoosa sites were between 20 and 40% pool, whereas about 14% of poor Tallapoosa Bass site were between 20 and 40% pool.

IV. Discussion

Tallapoosa Bass appear to be widespread throughout the Tallapoosa River drainage, collected at 40 of 58 sites. Tallapoosa Bass were found in all six sub-basins (albeit only 1 of 9 sites in the BT sub-basin) and for the most part were well-distributed among the Piedmont sub-basins in terms of overall numbers. Furthermore, length ranges of Tallapoosa Bass suggested robust populations with plenty of old fish. Most Tallapoosa Bass collected were in the 150-230 mm size range. Boschung and Mayden (2004) stated that Redeye Bass are typically 230-400 mm in total length, but that could potentially include hybrids with native Alabama Bass, as a concurrent genetic study has found many instances of fish that phenotypically resembled Redeye Bass but were hybrids (Matthew Lewis, Auburn University, unpublished data). The 150-230 mm size range that dominated this study likely includes several different age classes (Mike Holley, ADCNR, unpublished data). Redeye Bass in general are slow-growing fish compared to other black basses, especially after age 4 (Catchings 1978; Etnier and Starnes 1993).

Mean detection of Tallapoosa Bass was 0.75 across all sites at mean levels of depth and effort and while using canoe gear and after detecting bass on the first survey, close to the level of 0.8 considered by Mackenzie and Royle (2005) as the threshold of high detection. My detection sub-model for occupancy suggested that detection decreased with max depth and increased after detecting bass on the first survey. Electrofishing gear is less effective in deeper habitats (Fisher and Brown 1993; Peterson et al. 2004; Rabeni et al. 2009), and this was observed in this study for both gears. The model also indicated that if Tallapoosa Bass were collected during the first survey, they were very likely to be collected on all subsequent surveys. When designing the study, I tried to ensure that the transects were as spatially independent as possible, but sampling surveys on streams will generally be somewhat related, especially when separated by only a few hundred meters, as was done in this study. Essentially the model infers that Tallapoosa Bass are more likely to occupy large sections of the streams they inhabit (i.e., the several kilometers of stream we sampled) and not just localized areas (i.e., only one transect). This suggests that Tallapoosa Bass are likely more of a generalist than other fluvial specialists such as Shoal Bass, which are predominantly associated with boulder/bedrock substrate and shoal habitat (Goclowski 2013; Cottrell 2018; Ingram et al 2019). Certain habitats may be more ideal for Tallapoosa Bass, but they were detected across a variety of habitats in this study.

Surprisingly, Tallapoosa Bass detection was similar between gears. Based on field observations, the canoe gear seemed far more effective; further, barge shocking (comparable to the canoe setup) was more efficient than backpack electrofishing in wadeable warmwater streams (Rabeni et al. 2009). However, gear type in my study was essentially standardized to stream size, with 1-2 backpacks used in smaller streams and the canoe gear used in larger systems. Therefore, each gear may have adequately sampled each system. Average detection probability dropped from 0.75 to 0.60 if backpack was the reference for gear type in the model instead of canoe. If Tallapoosa Bass were not collected on the first survey (meaning less likely to detect bass on subsequent surveys), the average detection probabilities for canoe and backpack gear were 0.59 and 0.42, respectively. This demonstrates that average detection probability for canoe gear when bass were not likely to be detected on subsequent surveys was approximately equal to average detection probability for backpack gear when bass were more likely to be detected on subsequent surveys. Thus, canoe gear is clearly better for detecting Tallapoosa Bass than backpack gear, even though the two gears were not statistically different in the model.

There were two sub-basins that stood out in terms of CPUE, total bass, and habitat variables. The first is the TW region, which had the lowest total number of bass and lowest median, median, and range of CPUE's of the Piedmont sub-basins despite having 10 sites. Furthermore, the TW had 4 of the 18 sites where no Tallapoosa Bass were collected. In contrast, the adjacent LTW sub-basin had the second highest catch total and the highest median and mean CPUE, even though it had the fewest number of sites (5). Mean CPUE was higher for the LTW sub-basin than the TW and BT sub-basins, suggesting that Tallapoosa Bass may be more abundant in the LTW sub-basin compared to the other two. The mean rock score for the LTW sub-basin was highest among all sub-basins, but conversely TW had the second highest mean rock score.

Both Tallapoosa Bass occupancy and counts from the relative abundance model increased with rock score, suggesting rocky substrate is an important habitat feature for Tallapoosa Bass. The distribution of mean rock scores clearly demonstrated that good Tallapoosa Bass sites (≥3 bass) usually had rock scores greater than 6, whereas poor sites rarely had rock scores that high. Rocky substrate has been noted to be important for or associated with several other black bass species, including Smallmouth Bass (Brewer et al. 2007; Brewer and Orth 2015), Alabama Bass (Rider and Maceina 2015), and Shoal Bass (Goclowski et al. 2013, Ingram et al. 2019). Rocky substrate has also been associated with the Redeye Bass clade in the past, including Tallapoosa Bass and

Chattahoochee Bass (Knight 2011; Earley and Sammons 2015; Katechis 2015; Leitner and Earley 2015). The rock score protocol used was designed to increase with the amount of rocky substrate in the stream as well as the size and complexity of it (i.e., more boulders and bedrock). Thus, Tallapoosa Bass presence and relative abundance was associated with large amounts of rock as well as larger and more complex rocky substrate. This association with larger rocky substrate has been described for the Redeye Bass clade and Tallapoosa Bass before (Earley and Sammons 2015; Leitner and Earley 2015), as well as Shoal Bass (Cottrell 2018; Ingram et al. 2019). However, Chattahoochee Bass, another member of the Redeye Bass clade, were found in streams that contained a greater proportion of gravel and cobble substrates than boulder and bedrock (Katechis 2015). More rocky substrate and larger rocky substrate appears to increase the likelihood that stream will be occupied by Tallapoosa Bass. For every 1 SD increase in rock score, Tallapoosa bass were 4.18 times as likely to occupy the site (95% CI; 1.20-14.73) if the site had a majority percent of soil group B (i.e., the Piedmont region). At the transect level, more rocky substrate and larger rocky substrate made it more likely that the transect contained large numbers of Tallapoosa Bass. For every 1 SD increase in rock score, 1.36 times as many Tallapoosa Bass were collected (95% CI; 1.08-1.73) in a transect at mean levels of continuous covariates and in sites that had a majority percent of soil group B, were warm streams, and sampled in the year 2019. It seems likely that counts would exhibit this pattern at the site level as well. Thus, streams with complex and abundant rocky substrate should be prioritized for conservation actions in any future Tallapoosa Bass management plan.

The LTW sub-basin also had one of the highest mean values for percent shoal, whereas adjacent TW sub-basin had the second lowest. The other Piedmont sub-basins had larger ranges of percent shoal and higher max values than TW. Shoal was not included in the models due to its high correlation with rock score, but shoal complexes are dominated by boulder and bedrock shelf substrate (Cottrell 2018). Thus, shoal complexes represent the upper ranges of the rock score and appear to be associated with Tallapoosa Bass. During sampling, Tallapoosa Bass were often not found in the shoal complexes themselves but in the pools and runs above and below a shoal complex. Thus, they may associate with shoal complexes but may be less often found directly in them. Conversely, Knight (2011) found that Tallapoosa Bass in Hillabee Creek displayed strong affinity for shoal habitat, as 84% of telemetry locations occurred within a shoal reach and movement was predominantly confined to within shoal habitat, although sample size was small. Shoal complexes may be seasonally important to Tallapoosa Bass as spawning or nursing habitat, as has been found for Shoal Bass (Goclowski 2010; Sammons 2015; Cottrell 2018). Redeye Bass generally make spawning nests in fine rocky substrates near the head of pools close to boulders and vegetative cover (Leitner and Earley 2015). Studies have found seasonal shifts in habitat use for a variety of black bass, including Tallapoosa Bass (Todd and Rabeni 1989; Goclowski et al. 2013; Cottrell 2018; Earley and Sammons 2015; Ingram et al. 2019; Wolf et al. 2019). Similar studies would be required on these streams to both understand why, where, and how rocky substrate is used by Tallapoosa Bass.

Rock score and LWD were inversely correlated, which makes sense since rockier streams tend to have higher gradients and collect less wood. Rocky areas of streams are usually erosional areas with faster flows that usually collect less LWD than slower, more depositional areas with lower gradients and wider channels (Sedell et al. 1988; Johnson et al. 2006; Ross et al. 2019). Tallapoosa Bass have been observed using LWD as cover and do not seem avoid it (Earley and Sammons 2015), and many fish were collected in this habitat during this study. However, if rock and LWD are present at the same time, Tallapoosa Bass were more often collected near the rock and not LWD, similar to what Earley and Sammons (2015) observed for Tallapoosa Bass in the mainstem Tallapoosa River. Alabama Bass in the mainstem Tallapoosa River were also observed using a greater variety of habitats commonly associated with LWD. Streams in this study that had high CPUEs of Alabama Bass were generally larger, slower streams with high LWD scores. A similar differentiation in habitat use between co-evolved species was observed in the Flint River in Georgia, in which Largemouth Bass exhibited a greater affinity for LWD than Shoal Bass and Shoal Bass displayed a greater affinity for bedrock substrate (Goclowski et al. 2013).

Soil group B is a class of soils with moderately low runoff potential and unhindered water dispersal through the soil (USDA NRCS 1997). Soil group B is the dominant soil group for the Piedmont and Alabama Valley and Ridge regions and comprises a large section of the lower part of the Cumberland Plateau region, all of which are above the Fall Line. Soil group B is present below the Fall Line in the Coastal Plain, but the dominant soil groups in that region are soil groups A and C. Tallapoosa Bass were less likely to be found in sites that did not have a majority percent of soil group B. Tallapoosa Bass are more likely to occur and be abundant in sites with a majority percent of soil group B; Tallapoosa Bass were only found one site that did not have a majority percent of this soil group. Good Tallapoosa Bass sites had a greater mean percent soil group B than poor sites, and sites where Tallapoosa Bass were collected had more percent soil group B than sites where bass were not collected. However, having complete coverage of soil group B did not guarantee occupancy or high counts, as no Tallapoosa Bass were captured in some of these sites. This categorical variable essentially served as a proxy for physiographical regions for the Tallapoosa drainage. All sites above the Fall Line had at least 70% or more of soil group B, which corresponded to the Yes category for MPSB. None of the sites below the Fall Line in the BT sub-basin had more than 30% of soil group B, which corresponded to the No category for MPSB. Most sites in that basin were mostly soil group A, which has even lower runoff potential than group B, or soil group C, which has moderately high runoff potential and less than 50% sand. Thus, the BT sub-region is more variable in terms of runoff potential and water transmission. However, the occupancy model predicted higher occurrence probabilities with higher rock scores for sites in the No category for MPSB, meaning that rocky substrate availability may somewhat mitigate the effect of soil type. However, this is likely a rare occasion as the Coastal Plain streams below the Fall Line tend to have sandier substrates and little to no rock (Boschung and Mayden 2004).

Based on model results, the average occurrence probability for streams in the Piedmont physiographic region was 0.88. Conversely, average occurrence probability for the Coastal Plain physiographic region was 0.28, represented by occurrence probability for the No category for MPSB. This may be inflated by the one site in the Coastal Plain where Tallapoosa Bass were found. Soil groups have been found to be important for riverine Smallmouth Bass in Missouri, as streams sites with soil group D (high runoff potential) were much less likely to contain Smallmouth Bass (Brewer et al. 2007). The naïve occurrence probability for the whole drainage, which factors in both categories for MPSB, is somewhat in between the two average occurrence probabilities at 0.69. This may be more accurate for the Tallapoosa Basin as a whole since the Piedmont region understandably has a much higher probability than the Coastal Plains region. Overall model results indicate that Tallapoosa Bass are more likely to occur and be abundant in the Piedmont region, which confirms previous studies (Earley and Sammons 2015; Leitner and Earley 2015).

Watershed area or other measures of stream size are metrics that have been found to be important for the relative abundance of other black bass species such as Smallmouth Bass and are often important in structuring the general fish community (Moyle and Cech 2000; Brewer et al. 2007). Watershed area was not retained in the final occupancy model. It was not statistically significant for determining Tallapoosa Bass counts, but the coefficient was positive, indicating a decrease in counts as watershed area increases. Inspection of the data shows that higher counts generally found in smaller streams and smaller watershed areas may be important to some degree. Redeye Bass are believed to prefer small to medium Piedmont streams (Mette et al. 1996; Leitner and Earley 2015). Results of my study suggest that although Tallapoosa Bass may not need smaller watershed areas to be present, greater numbers of Tallapoosa Bass are often found in smaller watersheds. Tallapoosa Bass occur sympatrically with Alabama Bass, but they appear to be the dominant Bass in the majority of Tallapoosa River tributaries sampled during this study in terms of relative abundance. Conversely, Alabama Bass tend to be the dominant black bass in larger streams as well as reservoirs throughout the Mobile

River Basin (Rider and Maceina 2015). Alabama Bass CPUE was much higher in the mainstem Tallapoosa River than Tallapoosa Bass CPUE in all seasons (Sammons 2015b). When found in the mainstem Tallapoosa River, Tallapoosa Bass tended to be more restricted to areas with faster flow in shallow bedrock substrates, which is more similar to the habitat of smaller streams that Tallapoosa Bass seem to prefer. In this study, Alabama Bass CPUE increased with watershed area ($r = 0.61$; $P < 0.001$) and Tallapoosa Bass CPUE decreased with watershed area ($r = -0.29$; $P = 0.028$). The creeks in this study that did contain large numbers of Alabama Bass were larger creeks with watershed areas typically >100 km^2, whereas abundant Tallapoosa Bass sites were typically on creeks with watershed areas <100 km^2.

Streams that were considered good Tallapoosa Bass sites generally had smaller watersheds than did poor Tallapoosa Bass. Further, the LTW sub-basin that had the highest mean CPUE for Tallapoosa Bass also had the lowest mean and range of watershed area and smallest mean MSW in the study. The LTW also has the smallest mean MSW, another measure of stream size. Extremely high Tallapoosa Bass CPUEs often occurred in smaller streams. Distance to mainstem is crude measure of network position and was considered as a variable but did not exhibit a relationship with Tallapoosa Bass counts. Streams farther away from the mainstem are typically smaller and thus more likely to harbor greater numbers of Tallapoosa Bass. However, streams having high counts of Tallapoosa Bass in this study appeared to be located both far from and near to the Tallapoosa River mainstem. Thus, watershed area appears to be more important than network position in determining suitability for Tallapoosa Bass. Other evidence suggests that small watershed areas are important for Tallapoosa Bass relative abundance to some degree. Thus, smaller streams should be prioritized for conservation actions, including protection.

Surprisingly, the correlation between DI in the watershed and Tallapoosa Bass relative abundance was positive, indicating that Tallapoosa Bass abundance increased with disturbance. This is counterintuitive, as numerous other studies have demonstrated the deleterious effects of watershed disturbance on fish communities (Allan et al. 1997; Wang et al. 1997; Paul and Meyer 2001; Sutherland et al. 2002; Allan 2004; Walters et al. 2005; Moerke and Lamberti 2006; Infante and Allan 2010; Thornbrugh and Infante 2019). Bartram's Bass were negatively associated with increasing disturbance and were much more likely to be found in natural/forested habitats (Judson 2018). Declines in Guadalupe Bass and Shoal Bass were also linked to habitat degradations (Stormer and Maceina 2008, 2009; Garrett et al. 2015). Furthermore, streams in the Tallapoosa Basin with high agricultural land use had lower IBI scores for the community (Saalfield et al. 2012). However, most of the streams sampled in this study had little watershed disturbance. Good Tallapoosa Bass sites clearly had less disturbed watersheds, with nearly 80% of watersheds possessing a DI value less than two, compared to only 60% for poor sites. Only three creeks in the good Tallapoosa Bass sites had a DI value greater than three, with developed land use percentages greater than 25%; two had developed land use percentages greater than 60%. However, all three above had rock scores >4.25 and watershed areas <8.31 km^2. Sedimentation from agricultural land burying rocky substrates could be more detrimental to Tallapoosa Bass than urban disturbances (Berkman et al. 1986; Paragamian 1991; Sutherland et al. 2002; Infante and Allan 2010; Brewer and Rabeni 2011). Future studies should examine relative impacts of urban and agricultural land cover on Tallapoosa Bass to more comprehensively evaluate their relative threats to the species.

Tallapoosa Bass counts increased with percent pool. There was similarity between the histograms comparing the good and poor Tallapoosa Bass sites, but good sites had more percent pool in the 20-40% range. This range of percent pool may be the ideal range for Tallapoosa Bass. Redeye Bass are known to occur in areas with flow but when in pools they tend to occur near boulders and rocky outcrops (Leitner and Earley 2015). The lack of rocky substrate in the poor Tallapoosa Bass sites may have influenced the relationship with percent pool. The pools in the poor sites or sites without Tallapoosa Bass may not have enough rocky substrate compared to the good Tallapoosa Bass sites. Higher gradient bluff pools were associated with higher relative abundance of Smallmouth Bass in some Missouri streams (Brewer et al. 2007). I did not specify different types of pools, but a similar relationship could be found for Tallapoosa Bass as greater counts were associated with increasing gradient and pool. Pools at lower gradients may not be suitable for Tallapoosa Bass, because they are fluvial specialists that require adequate flow (Earley and Sammons 2015; Leitner and Earley 2015). Thus, there may be an optimal combination of pool and gradient for Tallapoosa Bass relative abundance. Greater nest counts of Neosho Smallmouth Bass were also positively associated with percent pool (Miller and Brewer 2021). Considering that Redeye Bass have been known to make nests at the heads of pools (Leitner and Earley 2015), greater percent pool could be important for Tallapoosa Bass spawning. Furthermore, numerous studies have shown that pools are an important refuge habitat for Smallmouth Bass and many other fish species during low flow conditions (Zorn and Seelbach 1995; Magoulick and Kobza

2003; Stradmeyer et al. 2008; Hafs et al. 2010; Archdeacon and Reale 2019). Residual pool depth was important for age-0 Smallmouth Bass abundance in smaller streams in the Ozark Highlands (Miller and Brewer 2020). Residual pool depth was not calculated during this study, but the greater percent of pool may represent a greater chance of refuge habitat during low flows similar to what was observed in late summer of 2019. The different roles of the mesohabitat types identified in this study (pool, run, riffle, shoal) in relation to Tallapoosa Bass distribution should be investigated further.

Stream gradient commonly influences fish distributions and abundances due to its impact on velocity, substrates, and number and composition of pools (Moyle and Cech 2000). Counts did increase with gradient in this study, although neither the linear nor quadratic term for gradient were statistically significant. Gradient has been found to be important for riverine Smallmouth Bass relative abundance (Brewer et al. 2007). The Piedmont region where Tallapoosa Bass are most commonly found typically has higher gradients than the Coastal Plain region (Boschung and Mayden 2004). Almost half of the good Tallapoosa Bass sites had gradients >5 m/km compared to only 18% of the poor sites. Both the linear and quadratic term for gradient were positive, indicating a slightly convex curvilinear relationship that increases faster at higher gradients. Redeye Bass are known to prefer higher gradient streams (Leitner and Earley 2015), which may have cooler temperatures and better DO levels (Moyle and Cech 2000). Although physicochemical requirements of Redeye Bass remain unknown, areas with faster current, greater amounts of rocky substrate, and high DO have been linked to greater abundances of a variety of aquatic organisms (Hawkins et al. 1982; Bond 1996; Moyle and Cech 2000). Gradient may not be statistically significant in the model, but there do seem to be differences in gradient between good and poor Tallapoosa Bass sites, suggesting gradient is important to some degree.

Relative abundance of Tallapoosa Bass appeared to decline seasonally during this study. May and June were the best months for Tallapoosa Bass capture. From June to July there was a large drop-off in counts and CPUE. There was a significant difference in CPUE from the early months (May and June) to the late months (July and August), suggesting seasonal changes in relative abundance of Tallapoosa Bass. For instance, one stream that was sampled in May 2019 yielded 46 Tallapoosa Bass, but when revisited in August for another project only five bass were found. Precipitation declined throughout the summer 2019 and in August that stream was characterized by fewer deep pools and lower discharge compared to May. High temperatures later in the summer could also coincide with the reduced flow, and as pools become shallow and warmer Tallapoosa Bass may be moving to deeper water. Movement patterns of Tallapoosa Bass in these tributary streams have been little examined, although Knight (2011) found that Tallapoosa Bass movement was primarily restricted to one shoal reach. However, Tallapoosa Bass in the mainstem Tallapoosa River exhibited long migrations in the spring, presumably related to spawning (Earley and Sammons 2015). Higher numbers of Tallapoosa Bass collected in May and June samples during my study could have been partly related to spawning, as some of the fish sampled displayed spawning colors. Cottrell (2018) similarly documented extensive movement of Shoal Bass into shoal areas during the spawning season in a Chattahoochee River tributary stream. Fish left that area after the spawn period and eventually congregated in remaining pools as water levels decreased in summer. It is unknown whether or not Tallapoosa Bass display similar behavior but anecdotal evidence from this study and reports from anglers suggest seasonal changes in Tallapoosa Bass behavior and movement that may be related to water levels and flow. Future studies should be conducted on Tallapoosa Bass movement and habitat use in smaller tributary streams to better understand spatial ecology of the species.

Occupancy model design typically involves surveying a site multiple times, but my study was designed to maximize the number of sites sampled throughout the field season. Therefore, a space-for-time approach was implemented for the occupancy model using spatial replicates. There are some concerns with potential pitfalls of this method, as a space-for-time approach has the potential to introduce positive bias in occurrence probability if sites are sampled without replacement (Kendall and White 2009). In sampling without replacement, each survey in site is sampled only once. In sampling with replacement, surveys are randomly drawn and can be sampled more than once. However, sampling without replacement is acceptable when the species is highly mobile and surveys are conducted in a sequential manner (Kendall and White 2009). Furthermore, simulation studies have shown that a space-for-time approach results in minimal to no bias in parameters, even when sampling without replacement (Guillera-Arroita et al. 2011; Kéry and Royle 2016). This aspect of occupancy modelling is an area that needs further research, especially in relation to fish movement (Kéry and Royle 2016; Potoka et al. 2016). Additionally, if seasonal shifts in Tallapoosa Bass relative abundance existed, this may have violated the closure assumption of occupancy modelling. If Tallapoosa Bass vacated stream reaches in the late summer due to low flows, then the assumption of the site staying occupied during the duration of the sampling season may have been violated. Occupancy season for drier years such as 2019 may need to be restricted to the spring/early summer months or use a flow covariate to model seasonal changes in occupancy, which was not measured during this study. Sampling over multiple years could help in understanding how relative abundance and occupancy many change from year to year depending on conditions.

V. Conclusions and Management Implications

Tallapoosa Bass are well distributed throughout the Piedmont physiographic region and both occupancy and detection probabilities were high. Occupancy was strongly associated with rocky substrate and majority of hydrologic soil group B, common in the Piedmont region. Counts were strongly associated with rocky substrate, majority of hydrologic soil group B, and DI for the watershed. Watershed area was not significant for counts in the relative abundance model, but anecdotal evidence suggests that smaller watersheds are preferred to some degree by Tallapoosa Bass. Comparisons between good Tallapoosa Bass sites and poor Tallapoosa Bass sites indicated slight differences in gradient and the amount of pool habitat, and these factors seem to partially influence Tallapoosa Bass abundance to some degree. There was some variation in these characteristics across sub-basins, and certain streams in several sub-basins possessed the ideal characteristics for Tallapoosa Bass occupancy and high relative abundances. Streams that should have high prioritization for management actions should have smaller watershed areas, large amounts of quality rocky substrate, medium percent pool, and medium to high gradients.

The LTW sub-basin potentially has the best overall assemblage of good streams. This was characterized by large amounts of complex rocky substrate, small watershed areas, and less amounts of LWD. This basin in particular should be prioritized for protection. Conversely, the TW sub-basin also contained many of these ideal characteristics but had few good Tallapoosa Bass populations. However, this basin appears to have less shoal habitat, which could potentially be an important component for Tallapoosa Bass life history. The Tallapoosa River mainstem in this area was also characterized by low catches of Tallapoosa Bass (Sammons et al. 2013). This sub-basin could warrant further investigation into Tallapoosa Bass distribution and factors leading to their decreased abundance compared to the LTW sub-basin. Specific creeks across the Tallapoosa River Basin that should be protected are Cohobodiah Creek (LTW sub-basin), Cutnose Creek (LTW sub-basin), Rocky Branch (MYT sub-basin), Town Creek (WM sub-basin), Jaybird Creek (WM sub-basin), Wedowee Creek (W sub-basin), Fox Creek (W sub-basin), Lost Creek (LTW sub-basin), Crooked Creek (WM sub-basin), and Lewis Creek (BT sub-basin). These creeks all have high relative abundances, large numbers of genetically pure fish (Matthew Lewis, Auburn University, unpublished data) and quality Tallapoosa Bass habitat. Town Creek, Rocky Branch, and Lewis Creek were all streams that had high relative abundances and fairly pure populations despite high levels of developed disturbance in the watershed and likely warrant special protection. Counts increase with disturbance in the relative abundance model, but warrants further study, specifically in relation to developed disturbance. Small, headwater urban streams surprisingly contained numerous Tallapoosa Bass, but streams with high coverage of natural/forested habitat in the watershed also yielded high counts, so more investigation into this area seems necessary. Determining whether agricultural or developed disturbance is more detrimental to Tallapoosa Bass is another potential study within the land use spectrum. The Tallapoosa River drainage seems to have little anthropogenic disturbance and disturbance was ultimately not important in either model, so land use ultimately may not have a serious impact on Tallapoosa Bass. Studies on the impacts of land use for other members of the Redeye Bass clade may prove to be more insightful.

Other topics that could use further research are a more extensive temperature study, investigating the effects of flow on movement, migration dynamics, spawning characteristics, influence of shoal and specific rocky substrates, influence of various mesohabitats, interactions with native Alabama Bass, diet, and influence of vegetative cover. Temperature was not important in either of my models but was measured only during the sample which may not have been a large enough temporal scale to detect effects. Water temperature typically has been found to be a large driver of fish distribution and abundance (Shuter and Post 1990; Moyle and Cech 2000; Brewer et al. 2007) and should be investigated further. The anecdotal observations of possible interactions among low discharge, higher temperatures, and Tallapoosa Bass abundance during my study highlight the dearth of knowledge regarding seasonal and annual movement dynamics of the species. Telemetry studies should be conducted on Tallapoosa River tributaries to help further understand seasonal movement dynamics and provide knowledge on Tallapoosa Bass spawning habitats and characteristics. Additionally, age-0 dynamics of the species are completely unknown but could be important to determine survival and recruitment dynamics as has been done for other black bass species (Goclowski 2010; Sammons and Goclowski 2010; Brewer 2013; Brewer et al. 2019; Haglund et al. 2019; Miller and Brewer 2020). The influence and importance of shoal habitat to Tallapoosa Bass also warrants further study. Pool was the only mesohabitat included in the models due to correlations, but more investigation into why pool is important and how it relates to other mesohabitats is needed. Relative abundance of Tallapoosa Bass and Alabama Bass were generally inversely related. Tallapoosa Bass and Alabama Bass appear to prosper in different stream sizes and watershed areas, and Alabama Bass appear to use LWD to a greater degree than Tallapoosa Bass. The interaction dynamics of these two co-evolved species is unknown in Tallapoosa River tributaries. Studies on their interactions and factors such as streams size that could be driving the separation of the two species is needed. Very little is known about diet of Tallapoosa Bass in tributary streams and how it relates to preferred habitats and should be investigated further. Redeye Bass have been noted to be found near vegetative cover (Leitner and Earley 2015), although bank vegetative cover was not important in this study, and Tallapoosa Bass were found across a broad range of bank vegetative cover scores. Further study is needed to understand the roles of both aquatic and terrestrial vegetative cover.

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VII. Tables

Table 1. List of sampling streams for Tallapoosa Bass in the Tallapoosa River Basin. Streams are listed from upstream to downstream and approximate location in the basin by sub-basin and county(ies) are given. Indented stream names followed by a (T) denote that they are tributaries of the stream named above them. Indented streams followed by an (S) indicate a secondary site on the same stream as above and are labeled differently to avoid confusion. Streams marked with an asterisk are sites that were discarded.

Location in Basin (Sub-Basin)	Stream Name	County(ies)
Tallapoosa Above L. Wedowee (TW)	Norman Creek	Cleburne
	Kemp Creek	Cleburne
	Macola Creek	Cleburne
	Silas Creek	Cleburne
	Verdin Creek	Cleburne
	Cane Creek	Cleburne
	Dynne Creek	Cleburne
	Chulafinnee Creek	Cleburne
	Lockhelooge Creek	Cleburne
	Ketchepedrakee Creek	Randolph/Clay
Little Tallapoosa Above L. Wedowee (LTW)	Lost Creek 2	Cleburne
	Cutnose Creek	Randolph
	Copper’s Rock Creek (T)	Randolph
	Cohobadiah Creek	Randolph/Cleburne
	Bear Creek	Randolph
Tributaries of L. Wedowee (W)	Buckhannon Creek	Randolph
	Pineywood Creek	Randolph
	Wedowee Creek	Randolph
	Frog Level Branch	Randolph
	Fox Creek	Randolph/Clay
	Lost Creek	Randolph/Clay
L. Wedowee to L. Martin (WM)	Crooked Creek	Randolph/Clay
	Cornhouse Creek	Randolph
	Wildcat Creek (T)	Randolph
	Hurricane Creek	Randolph/Clay
	Cedar Creek	Randolph/Clay
	High Pine Creek	Chambers/Randolph
	Town Creek (T)	Randolph
	High Pine Creek Upper (S)	Randolph
	Hodnett Mill Creek	Tallapoosa
	Chatahospee Creek	Tallapoosa/Chambers
	Allen Creek (T)	Tallapoosa/Chambers
	Eagle Creek	Tallapoosa
	Emuckfaw Creek	Tallapoosa/Clay

Tributaries of L. Martin, Yates Res, Thurlow Res (MYT)	Jaybird Creek	Tallapoosa
	Hillabee Creek	Tallapoosa
	Upper Hillabee Creek (S)	Tallapoosa
	Enitachopco Creek (T)	Tallapoosa/Clay
	Little Hillabee Creek (T)	Tallapoosa/Clay
	Whortleberry Creek (T)	Tallapoosa
	Elkahatchee Creek	Tallapoosa/Coosa
	Harold Creek (T)*	Tallapoosa/Coosa
	Sandy Creek	Tallapoosa/Chambers
	Chattasofka Creek (T)	Tallapoosa
	Blue Creek	Tallapoosa
	Oakachoy Creek	Coosa
	Wind Creek	Tallapoosa/Lee
	Channahatchee Creek	Elmore
	Sougahatchee Creek	Tallapoosa/Lee
	Rocky Branch (T)	Lee
Below Thurlow Dam (BT)	Uphapee Creek	Macon
	Wolf Creek (T)	Macon
	Choctafaula Creek (T)	Macon/Lee
	Chewacla Creek (T)	Macon/Lee
	Parkerson Mill Creek (T)	Lee
	Wallahatchee Creek*	Elmore
	Tumkeehatchee Creek	Elmore
	Chubbehatchee Creek	Elmore
	Lewis Creek	Elmore
	Harwell Mill Creek	Elmore

Table 2. Large Woody Debris habitat score descriptions based on GADNR Stream Team Protocol.

Description	**Score**
No woody debris encountered during transect	**1**
Wood very rare during the transect; less than 5% of the transect had woody debris	**2**
Wood rare during the transect; 5-10% of the transect had woody debris	**3**
Wood somewhat rare during the transect, 10-20% of the transect had woody debris OR 5-10% coverage and one cluster was considered complex, covering more than 2 m^2 in area with lots of interstitial spaces	**4**
Average woody debris encountered during the transect; about a third of the transect had woody debris	**5**
Higher than average woody debris encountered during the transect; approximately 50% of the transect had woody debris OR average density with at least one complex cluster	**6**
Wood commonly encountered during the transect; usually each grouping was < 10 m apart and overall about 66% of the transect had woody debris OR higher than average density with at least one complex cluster	**7**
Wood commonly encountered during the transect and one cluster was considered complex	**8**
Wood commonly encountered and two clusters were considered complex	**9**
Wood commonly encountered and three or more clusters were considered complex	**10**

Table 3. Rocky Substrate habitat score descriptions based on the GADNR Stream Team Protocol.

Description	Score
No rocky substrate encountered	**1**
Very little rock encountered during transect, composed < 5% of the transect	**2**
Rock relatively rare during transect, composed 10-15% of the transect	**3**
Rocky substrate found in 25-30% of the transect but is mostly composed of small cobble or gravel with few boulders OR rock is rare in the transect but is grouped in 2-3 small rocky complexes covering around 2-3 m^2 each	**4**
Fine rocky substrate (cobble/gravel) comprises up to 50% of the transect OR substrate is mostly sandy but 4-6 isolated rocky complexes occur within transect	**5**
Fine rocky substrate comprises 60-75% of the transect OR boulder/bedrock substrate composes about 20-25% of the transect OR substrate is mostly sandy but more than 6 isolated rocky complexes occur within transect	**6**
Entire transect is composed of fine rocky substrate OR boulder/bedrock substrate composes about a third of the transect OR sandy substrate with more than 12 isolated rocky complexes within transect	**7**
Boulder/bedrock substrate comprises about half of the transect OR if less, multiple large rocky complexes exist within the transect, each covering more than 10 m^2	**8**
Boulder/bedrock substrate comprises about 66-75% of the transect OR if between 50-60%, multiple large rocky complexes exist within the transect, each covering more than 10 m^2	**9**
Virtually the entire transect contains rocky substrate, most of it composed of bedrock, boulders, and large rocky complexes	**10**

Table 4: Data summary for all variables collected in the field for the Tallapoosa River project for the main basin and the six sub-basins across 58 stream sites sampled between May 2019 and June 2020. Values are given as mean ± standard deviation (range) and are average values for the stream site. %PL is percent pool, %RN is percent run, %RF is percent riffle, and %SH is percent shoal. See methods for descriptions of sub-basins, Rock score, LWD score, Bank stability, and Vegetative cover.

	Sub-Basin						
Variable	TW	LTW	W	WM	MYT	BT	Tallapoosa
MSW (m)	6.71 ± 3.33 (2.00 – 12.50)	8.15 ± 1.88 (5.00 – 9.50)	7.30 ± 3.52 (3.50 – 11.20)	7.41 ± 2.84 (3.00 – 12.60)	14.29 ± 11.51 (4.40 – 48.00)	8.28 ± 4.27 (2.90 – 14.70)	9.25 ± 7.02 (2.00 – 48.00)
Rock score	6.02 ± 1.31 (4.25 – 7.60)	7.08 ± 1.57 (4.33 – 8.25)	5.82 ± 1.51 (3.60 – 7.83)	5.19 ± 2.12 (1.33 – 8.67)	5.20 ± 2.26 (1.50 – 9.00)	3.24 ± 1.46 (1.5 – 5.6)	5.261 ± 2.05 (1.33 – 9.00)
LWD score	2.88 ± 1.28 (1.20 – 5.75)	2.45 ± 0.13 (2.33 – 2.67)	2.84 ± 0.93 (1.80 – 4.00)	3.00 ± 1.09 (1.00 – 5.00)	3.31 ± 1.55 (1.50 – 7.83)	4.59 ± 2.31 (2.00 – 8.67)	3.24 ± 1.52 (1.00 – 8.67)
%PL	16.22 ± 10.45 (6.00 – 39.75)	8.39 ± 3.58 (4.17 – 11.67)	15.69 ± 9.54 (9.17 – 33.13)	23.13 ± 18.44 (3.33 – 76.67)	17.25 ± 7.66 (8.60 – 34.67)	18.10 ± 11.73 (6.00 – 40.00)	17.60 ± 12.11 (3.33 – 76.67)
%RN	55.52 ± 14.54 (29.00 – 81.67)	51.70 ± 17.01 (32.50 – 77.50)	50.58 ± 15.19 (35.00 – 73.00)	51.24 ± 17.72 (23.33 – 80.00)	52.86 ± 20.22 (5.00 – 83.00)	61.96 ± 14.92 (43.75 – 83.33)	54.03 ± 16.91 (5.00 – 83.33)
%RF	21.46 ± 14.27 (5.00 ± 55.00)	24.18 ± 11.73 (10.83 – 39.17)	16.23 ± 9.33 (7.50 – 33.60)	18.84 ± 13.11 (0.00 – 45.00)	8.88 ± 10.41 (0.00 – 32.50)	14.93 ± 12.81 (1.67 – 43.75)	16.30 ± 12.72 (0.00 – 55.00)
%SH	6.74 ± 7.63 (0.00 – 22.50)	15.73 ± 9.64 (0.00 – 24.17)	17.17 ± 17.07 (0.00 – 40.00)	6.78 ± 14.23 (0.00 – 53.33)	21.37 ± 21.11 (0.00 – 72.50)	4.78 ± 8.91 (0.00 – 23.00)	12.09 ± 15.84 (0.00 – 72.50)
Temperature (°C)	21.58 ± 3.18 (16.75 – 25.48)	18.93 ± 2.07 (16.16 – 20.90)	20.54 ± 3.04 (14.97 – 23.17)	23.16 ± 2.02 (17.80 – 26.23)	22.45 ± 3.06 (15.53 – 27.73)	22.99 ± 3.07 (15.78 – 26.66)	22.04 ± 2.97 (14.97 – 27.73)
DO (mg/L)	7.25 ± 1.37 (4.66 – 8.60)	8.56 ± 0.66 (7.61 – 9.36)	8.25 ± 0.55 (7.54 – 8.89)	7.54 ± 0.83 (5.82 – 8.80)	7.69 ± 0.64 (6.38 – 8.70)	7.51 ± 0.44 (7.08 – 8.14)	7.70 ± 0.89 (4.66 – 9.36)
Conductivity (mS)	0.061 ± 0.020 (0.036 – 0.098)	0.040 ± 0.0041 (0.035 – 0.047)	0.034 ± 0.0092 (0.024 – 0.050)	0.058 ± 0.029 (0.020 – 0.13)	0.071 ± 0.034 (0.030 – 0.18)	0.11 ± 0.069 (0.033 – 0.22)	0.066 ± 0.041 (0.020 – 0.22)
Turbidity (NTU)	7.93 ± 6.80 (1.75 – 19.68)	9.07 ± 2.89 (6.13 – 13.09)	6.83 ± 4.33 (2.56 – 13.26)	8.00 ± 6.92 (0.34 – 24.66)	9.13 ± 5.12 (3.59 – 21.91)	10.69 ± 9.15 (2.74 – 30.73)	8.67 ± 6.25 (0.34 – 30.73)

Max depth (m)	0.77 ± 0.24 (0.50 – 1.35)	0.77 ± 0.21 (0.48 – 0.99)	0.83 ± 0.17 (0.64 – 1.05)	1.02 ± 0.36 (0.57 – 1.87)	1.24 ± 0.59 (0.75 – 2.96)	0.99 ± 0.25 (0.68 – 1.33)	0.99 ± 0.41 (0.48 – 2.96)
Bank stability	3.74 ± 1.79 (0.50 – 6.60)	5.61 ± 0.90 (4.60 – 7.00)	3.89 ± 1.62 (0.70 – 5.31)	4.40 ± 1.99 (1.83 – 7.67)	5.02 ± 1.60 (2.40 – 7.83)	4.25 ± 1.74 (1.67 – 8.10)	4.35 ± 1.75 (0.50 – 9.00)
Vegetative cover	4.07 ± 1.14 (1.83 – 5.60)	5.67 ± 1.13 (4.20 – 7.25)	4.49 ± 1.68 (1.50 – 6.00)	4.51 ± 1.59 (2.42 – 8.33)	5.02 ± 1.60 (2.40 – 7.83)	4.35 ± 1.21 (2.83 – 6.80)	4.61 ± 1.46 (1.50 – 8.33)

Table 5: Data summary for all variables collected using the NHDPlus HR[a] in ArcMap for the Tallapoosa River project for the main basin and the six sub-basins across 58 sites sampled between May 2019 and June 2020. Values are given as mean ± standard deviation (range). WS refers to watershed, FP refers to the site floodplain, DI is disturbance index, MAF is mean annual flow, Ag is agricultural, and Dev is developed. See methods for calculations for land use, DI, distance to mainstem (dist mainstem), distance to downstream reservoir (dist down res), dams, soil groups, and geology. See methods for descriptions of sub-basins. Links to data sources are below corresponding to superscripts.

	Sub-Basin						
Variable	TW	LTW	W	WM	MYT	BT	Tallapoosa
%Ag FP[b,c]	25.75 ± 14.91 (2.94 – 47.41)	28.59 ± 17.71 (13.12 – 55.72)	12.23 ± 15.02 (4.08 – 10.06)	16.73 ± 21.09 (0.00 – 66.05)	7.40 ± 9.31 (0.00 – 26.54)	1.76 ± 3.70 (0.00 – 11.20)	14.11 ± 16.55 (0.00 – 66.05)
%Natural FP[b,c]	72.54 ± 15.34 (51.28 – 97.06)	70.39 ± 18.08 (42.95 – 86.88)	79.23 ± 24.89 (38.51 – 95.92)	82.34 ± 21.09 (33.95 – 100)	90.47 ± 11.20 (61.67 – 100)	97.19 ± 3.69 (88.44 – 100)	83.71 ± 17.93 (33.95 – 100)
%Dev FP[b,c]	1.71 ± 2.52 (0.00 – 8.36)	1.02 ± 0.65 (0.00 – 1.56)	8.54 ± 20.29 (0.00 – 49.91)	0.93 ± 2.33 (0.00 – 8.33)	2.13 ± 3.97 (0.00 – 15.00)	1.04 ± 1.37 (0.00 – 4.00)	2.19 ± 6.88 (0.00 – 49.91)
%Ag WS[b]	11.15 ± 7.59 (0.96 – 26.60)	26.30 ± 10.75 (13.24 – 40.80)	23.80 ± 7.18 (12.75 – 32.68)	15.87 ± 6.43 (5.06 – 28.17)	8.70 ± 3.09 (4.04 – 14.47)	13.77 ± 7.22 (2.20 – 27.32)	14.59 ± 8.53 (0.96 – 40.80)
%Natural WS[b]	85.17 ± 8.97 (67.74 – 98.29)	68.61 ± 11.69 (53.49 – 83.42)	69.48 ± 9.37 (60.50 – 84.70)	74.63 ± 16.34 (26.62 – 92.97)	80.37 ± 14.96 (32.71 – 90.22)	69.67 ± 20.45 (24.30 – 94.76)	76.11 ± 15.35 (24.30 – 98.29)
%Dev WS[b]	3.68 ± 1.79 (0.76 – 6.92)	5.10 ± 1.09 (3.35 – 5.91)	6.73 ± 5.49 (2.55 – 17.65)	9.50 ± 15.61 (1.97 – 61.02)	10.93 ± 16.21 (3.06 – 63.25)	16.56 ± 20.18 (3.04 – 66.17)	9.29 ± 13.89 (0.76 – 66.17)
DI FP	1.77 ± 0.41 (1.06 – 2.35)	1.73 ± 0.43 (1.28 – 2.37)	1.93 ± 1.49 (1.08 – 4.84)	1.50 ± 0.60 (1.00 – 2.90)	1.35 ± 0.42 (1.00 – 2.60)	1.13 ± 0.14 (1.00 – 1.38)	1.51 ± 0.65 (1.00 – 4.84)
DI WS	1.51 ± 0.27 (1.08 – 1.99)	1.95 ± 0.31 (1.52 – 2.32)	2.02 ± 0.44 (1.47 – 2.76)	2.04 ± 1.13 (1.25 – 5.69)	1.98 ± 1.14 (1.36 – 5.67	2.54 ± 1.44 (1.28 – 6.03)	2.00 ± 1.00 (1.08 – 6.03)
Gradient (m/km)	5.43 ± 4.89 (0.42 – 15.80)	4.54 ± 1.99 (2.69 – 7.36)	5.38 ± 3.49 (2.68 – 10.77)	5.34 ± 4.19 (0.68 – 15.52)	3.28 ± 2.73 (0.01 – 9.36)	3.48 ± 2.85 (0.75 – 8.52)	4.47 ± 3.57 (0.01 – 15.80)
Max elev (m)	291.9 ± 34.5 (256.0 – 375.8)	290.4 ± 7.3 (283.4 – 300.4)	290.3 ± 11.27 (279.2 – 311.7)	228.0 ± 45.2 (183.4 – 336.8)	184.6 ± 34.79 (119.4 – 250.7)	89.95 ± 31.6 (59.9 – 160.1)	218.2 ± 77.1 (59.9 - 375.8)

Min elev (m)	269.7 ± 18.5 (245.4 – 306.6)	268.3 ± 13.1 (249.8 – 285.4)	268.2 ± 24.05 (238.9 – 302.7)	213.2 ± 32.7 (175.6 – 276.7)	172.3 ± 33.20 (109.7 – 246.5)	78.3 ± 30.2 (54.9 – 148.1)	201.9 ± 71.2 (57.9 – 306.6)
Stream order	3.30 ± 0.82 (2 – 4)	3.60 ± 0.55 (3 – 4)	3.17 ± 0.98 (2 – 4)	3.54 ± 1.13 (2 – 5)	4.00 ± 1.13 (2 – 6)	3.78 ± 1.10 (2 – 5)	3.62 ± 1.02 (2 – 6)
Velocity (fps)	0.91 ± 0.06 (0.84 – 0.99)	0.94 ± 0.04 (0.89 – 0.97)	0.94 ± 0.097 (0.81 – 1.03)	0.95 ± 0.11 (0.76 – 1.17)	0.99 ± 0.21 (0.58 – 1.46)	1.01 ± 0.16 (0.86 – 1.38)	0.95 ± 0.14 (0.58 – 1.46)
MAF (cfs)	21.33 ± 21.64 (3.78 – 74.53)	17.68 ± 8.42 (7.34 – 27.72)	21.21 ± 17.76 (2.82 – 42.37)	31.08 ± 34.11 (3.10 – 114.88)	89.65 ± 124.18 (2.79 – 424.96)	87.52 ± 137.38 (5.16 – 433.18)	51.13 ± 88.47 (2.79 – 433.18)
Dist mainstem (km)	7.02 ± 9.38 (0.48 – 32.02)	4.21 ± 1.79 (2.21 – 6.23)	12.83 ± 7.17 (2.48 – 21.18)	14.01 ± 10.53 (1.45 – 32.84)	26.98 ± 22.34 (4.12 – 85.14)	23.37 ± 24.90 (0.37 – 73.32)	16.61 ± 17.88 (0.37 – 85.14)
Dams[c]	1.8 ± 3.01 (0 – 9)	1 ± 1.73 (0 – 4)	1.17 ± 1.60 (0 – 4)	4.31 ± 5.11 (0 – 12)	4.13 ± 3.60 (0 – 8)	7.56 ± 6.46 (0 – 13)	3.72 ± 4.56 (0 – 13)
Dist down res (km)	39.28 ± 26.07 (5.61 – 79.82)	24.81 ± 17.92 (2.98 – 51.96)	7.62 ± 4.89 (1.28 – 13.94)	53.77 ± 29.22 (2.67 – 106.97)	20.39 ± 22.75 (2.63 – 80.47)	197.0 ± 37.97 (133.9 – 257.2)	57.59 ± 67.03 (1.28 – 257.22)
%Soil group A WS[e,f]	0 ± 0 (0 – 0)	0 ± 0 (0 – 0)	0 ± 0 (0 – 0)	0 ± 0 (0 – 0)	0.17 ± 0.65 (0.00 – 2.57)	41.89 ± 36.36 (0.00 – 100)	7.13 ± 21.53 (0.00 – 100)
%Soil group B WS[e,f]	96.94 ± 8.86 (71.83 – 100)	100 ± 0 (100 – 100)	95.14 ± 11.90 (70.85 – 100)	97.16 ± 7.48 (74.65 – 100)	95.45 ± 7.36 (79.41 – 100)	7.49 ± 11.69 (0.00 – 33.05)	82.80 ± 33.63 (0.00 – 100)
%Soil group C WS[e,f]	3.06 ± 8.86 (0.00 – 28.17)	0 ± 0 (0 – 0)	4.86 ± 11.90 (0.00 – 29.15)	1.95 ± 7.03 (0.00 – 25.35)	4.12 ± 7.15 (0.00 – 20.59)	44.86 ± 31.45 (0.00 – 95.63)	9.49 ± 20.54 (0.00 – 95.63)
%Soil group D WS[e,f]	0 ± 0 (0 – 0)	0 ± 0 (0 – 0)	0 ± 0 (0 – 0)	0.88 ± 3.19 (0.00 – 11.52)	0.26 ± 0.75 (0.00 – 2.75)	1.97 ± 3.30 (0.00 – 10.04)	0.57 ± 2.07 (0.00 – 11.52)
%Geology metamorphic[e]	86.86 ± 12.05 (67.45 – 100)	97.69 ± 5.16 (88.46 – 100)	36.32 ± 48.11 (0.00 – 100)	83.87 ± 19.48 (33.03 – 100)	79.16 ± 22.89 (15.16 – 100)	22.67 ± 27.92 (0.00 – 79.86)	69.94 ± 34.67 (0.00 – 100)
%Geology schist[d]	36.08 ± 28.83 (0 – 100)	92.97 ± 15.71 (64.87 – 100)	34.86 ± 48.84 (0.00 – 99.60)	57.31 ± 40.22 (0.00 – 100)	19.59 ± 21.92 (0.00 – 53.43)	14.54 ± 22.84 (0.00 – 70.05)	38.01 ± 37.65 (0.00 – 100)

[a] https://viewer.nationalmap.gov/basic/

[b] https://nassgeodata.gmu.edu/CropScape/

[c] https://www.epa.gov/enviroatlas/forms/enviroatlas-data-download
[d] https://connectivity.sarpdata.com/
[e] https://datagateway.nrcs.usda.gov/
[f] https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/geo/?cid=nrcs142p2_053629

Table 6: Total black bass captured and CPUE (fish/hr) per species for each sub-basin and the Tallapoosa River drainage across the 58 sites sampled between May 2019 and June 2020. TAL is Tallapoosa Bass, ALB is Alabama Bass, LMB is Largemouth Bass, and HYB is hybrids. CPUE is given as mean ± SD (range) and N is the total count of each species. Superscripts denote significant differences between sub-basins at the $P = 0.1$ significance level. See methods for description of sub-basins.

	Sub-Basin						
	TW^{bc}	LTW^{a}	W^{ab}	WM^{ab}	MYT^{abc}	BT^{c}	Tallapoosa
Sites	10	5	6	13	15	9	58
Transects	55	33	34	59	75	41	297
TAL							
N	28	116	75	98	127	8	452
CPUE	1.66 ± 1.87	14.73 ± 12.00	7.79 ± 6.30	6.94 ± 11.74	6.63 ± 11.86	1.15 ± 3.44	5.81 ± 9.68
	(0.00 – 4.52)	(3.58 – 31.71)	(0.00 – 18.36)	(0.00 – 42.84)	(0.00 – 45.47)	(0.00 – 10.32)	(0.00 – 45.47)
ALB							
N	7	4	4	14	37	41	107
CPUE	0.50 ± 1.08	0.41 ± 0.67	0.36 ± 0.42	0.86 ± 1.84	1.29 ± 2.36	2.56 ± 3.27	1.08 ± 2.08
	(0.00 – 3.04)	(0.00 – 1.53)	(0.00 – 1.01)	(0.00 – 6.28)	(0.00 – 8.74)	(0.00 – 8.60)	(0.00 – 8.74)
LMB							
N	16	3	3	27	22	33	104
CPUE	1.04 ± 1.98	0.48 ± 1.07	0.28 ± 0.46	2.05 ± 4.19	1.13 ± 1.46	2.03 ± 2.08	1.32 ± 2.44
	(0.00 – 6.45)	(0.00 – 2.38)	(0.00 – 1.10)	(0.00 – 13.98)	(0.00 – 4.93)	(0.00 – 5.72)	(0.00 – 13.98)
HYB							
N	3	1	3	11	23	6	47
CPUE	0.12 ± 0.38	0.10 ± 0.23	0.28 ± 0.47	1.05 ± 2.47	0.89 ± 1.67	0.30 ± 0.62	0.57 ± 1.49
	(0.00 – 1.19)	(0.00 – 0.51)	(0.00 – 1.15)	(0.00 – 6.91)	(0.00 – 5.57)	(0.00 – 1.72)	(0.00 – 6.91)
Total bass	54	124	85	150	209	88	710

Table 7: Correlation matrix for all covariates for the detection sub-model used to model the occupancy status of Tallapoosa Bass in 58 stream sites sampled between May 2019 and June 2020. All variables were measured at the transect scale. Categorical covariates (Gear type) were dummy coded to allow for correlation analysis. Effort was measure as seconds of effort. Max depth is in meters and Turbidity is in NTU.

	Effort	Max depth	Turbidity	LWD
Effort	-	-	-	-
Max depth	0.38	-	-	-
Turbidity	0.17	0.19	-	-
LWD score	0.20	0.33	0.29	-
Gear Type	-0.09	-0.35	-0.51	-0.19

Table 8: Summary statistics and data sources for all variables used to model the occupancy status of Tallapoosa Bass in 58 stream sites sampled between May 2019 and June 2020. SD is standard deviation. Gear type (backpack or canoe), MPSB (majority pct hydrologic soil group B, Yes or No), and Year (2019 or 2020) are categorical variables. Temperature was converted to a categorical variable with Warm and Cool categories.

Variable	Mean ± SD	Range	Data Source
Detection: transect scale			
Seconds of effort	1048 ± 435.13	326 - 3212	Field-collected
Gear type	N/A	N/A	Field-collected
Max depth (m)	1.00 ± 0.52	0.30 – 4.80	Field-collected
LWD score	3.29 ± 1.72	1.00 – 10.00	Field-collected
Turbidity (NTU)	9.14 ± 7.15	0.06 – 48.86	Field-collected
Occupancy: site scale			
Rock score	5.261 ± 2.05	1.33 – 9.00	Field-collected
Pool habitat (%)	17.60 ± 12.11	3.33 – 76.67	Field-collected
Stream temperature (°C)	22.04 ± 2.97	14.97 – 27.73	Field-collected
Gradient (m/km)	4.46 ± 3.57	0.01 – 15.80	NHDPlus HR[a]
Occupancy: watershed scale			
Watershed area (km^2)	92.54 ± 165.84	3.97 – 924.34	NHDPlus HR[a]
Disturbance index for the watershed	2.00 ± 1.00	1.08 – 6.03	NHD Plus HR[a]; CropNASS[b]
Dams (Total # in stream network)	3.72 ± 4.56	0 – 13	SARP[c]
MPSB	N/A	N/A	NHDPlus HR[a]; USDA NRCS SSURGO/STATSGO2[d,e]
Year	N/A	2019-2020	Field-collected

[a] https://viewer.nationalmap.gov/basic/
[b] https://nassgeodata.gmu.edu/CropScape/
[c] https://connectivity.sarpdata.com/
[d] https://datagateway.nrcs.usda.gov/
[e] https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/geo/?cid=nrcs142p2_053629

Table 9: Correlation matrix for all continuous covariates for the occurrence sub-model used to model the occupancy status of Tallapoosa Bass in 58 stream sites sampled between May 2019 and June 2020. Disturbance index for the watershed (DI-Shed) and watershed area (Area, km^2) were measured at the watershed level. Dams is the number of dams in the stream network until the confluence with the mainstem Tallapoosa River. Percent pool, rock score, max depth (Depth), and site gradient (Gradient, m/m) were averaged over the transects and represent the site scale. MPSB (majority pct hydrologic soil group B, Yes or No), and Year (2019 or 2020), and TempCat (temperature category, Warm or Cool) are categorical variables and were dummy coded to allow for correlation analysis.

	DI-Shed	%Pool	Rock score	Area	Gradient	Dams	Depth	MPSB	TempCat
DI-Shed	-	-	-	-	-	-	-	-	-
%Pool	-0.054	-	-	-	-	-	-	-	-
Rock score	-0.038	-0.374	-	-	-	-	-	-	-
Area	-0.238	0.148	-0.276	-	-	-	-	-	-
Gradient	-0.36	-0.182	0.513	-0.566	-	-	-	-	-
Dams	0.480	0.108	0.283	0.285	-0.154	-	-	-	-
Depth	<0.001	0.423	-0.327	0.720	-0.414	0.317	-	-	-
MPSB	-0.254	-0.031	0.419	-0.161	0.074	-0.363	-0.050	-	-
TempCat	-0.029	-0.048	-0.121	0.267	-0.214	0.255	-0.108	-0.070	-
Year	-0.499	0.138	0.035	0.241	-0.224	-0.224	-0.068	0.035	0.012

Table 10: Top full models for the occupancy model after adding the top occurrence sub-models to the top detection sub-model. Coefficients are on the logit scale and indicate increments of one standard deviation and mean levels of continuous covariates. Int(p) is the intercept for the detection sub-model, Depth is maximum depth (m) for each survey, Sec is seconds of effort for each survey, GT represents the backpack gear type with canoe gear as the reference, and Trap represents the trap effect of 0 for surveys with trap effect of 1 as the reference. Int(Ψ) is the intercept for the occupancy sub-model, Rock is the average rock score for the site, MPSB is No for majority pct hydrologic soil group B at the site with Yes as the reference, Temp is cool streams with warm as the reference, and dams is the number of dams in the site network until the confluence with the Tallapoosa River. Chi-square (χ^2), *P*-value, and c-hat are from the MacKenzie and Bailey (2004) goodness-of-fit test. K is the number of model parameters, QAICc is Quasi-likelihood Akaike's information criterion adjusted for small sample size, ΔQAICc is the difference in QAICc score between the given model and the top model, and w_i is the model weight. Model in bold is the model that explains the most variance with the fewest number of parameters and was selected as the final model.

	Detection sub-model					Occurrence sub-model					Goodness-of-fit test						
Model	Int(p)	Depth	Sec	GT	Trap	Int (Ψ)	Rock	MPSB	Temp	Dams	χ^2	*P*-value	c-hat	K	QAICc	ΔQAICc	w_i
2	1.084	-0.43	0.25	-0.63	-0.85	3.23	2.41	-3.09		-1.26	126.54	0.182	1.11	10	275.82	0.00	0.34
1	**1.094**	**-0.47**	**0.22**	**-0.68**	**-0.74**	**1.96**	**1.43**	**-2.90**			**133.53**	**0.104**	**1.17**	**9**	**276.00**	**0.19**	**0.31**
3	1.060	-0.41	0.24	-0.57	-0.83	4.26	3.07	-3.57	-3.87	-1.50	126.02	0.188	1.11	11	276.41	0.59	0.25
4	1.077	-0.44	0.22	-0.63	-0.78	2.48	1.79	-3.20	-1.40		131.11	0.135	1.14	10	278.33	2.51	0.10

Table 11: Coefficients, standard errors (SE), probabilities, and 95% confidence intervals (CI) for the top occupancy model used to model the occupancy status of Tallapoosa Bass in 58 stream sites sampled between May 2019 and June 2020. Coefficients and corresponding CIs are given on the logit scale and indicate increments of one standard deviation and mean levels of continuous covariates. The probability column and its corresponding CIs for the intercept are on the probability scale. The intercepts on the probability scale are the average detection and occupancy probabilities at mean levels of all continuous covariates and in the reference category for categorical variables. Effort was measured as second of effort. Gear Type-BP is gear type for backpack with canoe as the reference, Trap-0 is trap factor of 0 with 1 as the reference, and MPSB-N is majority pct hydrologic soil group B for the category No with Yes as the reference. Significant variables are denoted with an asterisk ($P \leq 0.05$).

Parameter	Coefficient ± SE	95% CI	Probability	95% CI	*P*-value
Detection sub-model (p)					
Intercept	1.09 ± 0.27	0.57, 1.62	0.75	0.64, 0.83	<0.001*
Max depth (m)	-0.47 ± 0.22	-0.89, -0.036			0.030*
Effort	0.22 ± 0.19	-0.15, 0.59			0.239
Gear type-BP	-0.68 ± 0.36	-1.38, 0.027			0.061
Trap-0	-0.74 ± 0.35	-1.43, -0.054			0.037*
Occupancy sub-model (Ψ)					
Intercept	1.96 ± 0.76	0.46, 3.45	0.88	0.61, 0.97	0.010*
Rock score	1.43 ± 0.64	0.18, 2.69			0.026*
MPSB-N	-2.90 ± 1.32	-5.48, -0.31			0.028*

Table 12: Correlation matrix for all continuous variables used to model the relative abundance of Tallapoosa Bass in 58 stream sites sampled between May 2019 and June 2020. Disturbance index for the watershed (DI-Shed) and watershed area (Area, km^2) were measured at the watershed level. Effort (seconds of effort) percent pool habitat, maximum depth (Max depth, m), Rock score, and transect gradient (Gradient, m/km) were measured at the transect level. Gear type (Canoe or backpack), MPSB (majority pct hydrologic soil group B, Yes or No), and Year (2019 or 2020), and TempCat (temperature category, Warm or Cool) are categorical variables and were dummy coded to allow for correlation analysis.

	Effort	%PL	Max depth	Rock score	Gradient	Area	DI-Shed	Gear type	TempCat	Year
Effort	-	-	-	-	-	-	-	-	-	-
% Pool	0.152	-	-	-	-	-	-	-	-	-
Max depth	0.382	0.458	-	-	-	-	-	-	-	-
Rock score	-0.084	-0.398	-0.254	-	-	-	-	-	-	-
Gradient	-0.277	-0.116	-0.292	0.326	-	-	-	-	-	-
Area	0.438	0.100	0.578	-0.209	-0.469	-	-	-	-	-
DI-Shed	0.059	-0.059	0.012	<0.001	0.094	-0.187	-	-	-	-
Gear type	0.092	0.032	0.360	-0.057	-0.331	0.743	-0.172	-	-	-
TempCat	0.201	0.010	0.100	-0.195	-0.166	0.278	-0.049	0.159	-	-
Year	-0.105	0.109	-0.070	0.048	-0.133	0.177	0.481	0.220	-0.021	-
MPSB	-0.091	-0.010	-0.042	0.351	0.123	-0.146	-0.271	0.151	-0.115	0.036

Table 13: Summary statistics and data sources for all variables used to model the relative abundance of Tallapoosa Bass in 58 stream sites sampled between May 2019 and June 2020. SD is standard deviation. Gear type (backpack or canoe), MPSB (majority pct hydrologic soil group B, Yes or No), and Year (2019 or 2020) are categorical variables. Temperature was converted to a categorical variable with Warm and Cold categories.

Variable	Mean ± SD	Range	Data Source
Transect scale:			
Seconds of effort	1048 ± 435.13	326 - 3212	Field-collected
Max depth (m)	1.00 ± 0.52	0.30 – 4.80	Field-collected
Rock score	5.29 ± 2.42	1.00 – 10.00	Field-collected
Pool habitat (%)	17.5 ± 14.17	0 – 90	Field-collected
Gradient (m/km)	3.89 ± 3.40	0.01 – 18.03	NHDPlus HR[a]
Site scale:			
Stream temperature (°C)	22.04 ± 2.97	14.97 – 27.73	Field-collected
Watershed scale:			
Watershed area (km^2)	92.54 ± 165.84	3.97 – 924.34	NHDPlus HR[a]
Disturbance index for the watershed	2.00 ± 1.00	1.08 – 6.03	NHDPlus HR[a]; CropNASS[b]
MPSB	N/A	N/A	NHDPlus HR[a]; USDA NRCS SSURGO/STATSGO 2[d,e]
Year	N/A	2019-2020	Field-collected

[a] https://viewer.nationalmap.gov/basic/

[b] https://nassgeodata.gmu.edu/CropScape/

[c] https://datagateway.nrcs.usda.gov/

[d] https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/geo/?cid=nrcs142p2_053629

Table 14: Top relative abundance models from the all-subsets analysis with the zero-inflation model added in. Coefficients are on the natural log scale and indicate increments of one standard deviation and mean levels of continuous covariates. Coefficients for the zero-inflation model are given on the logit scale. RS is the rock score, AR is watershed area (km^2), DI is disturbance index for the watershed, PL is percent pool, S is seconds of effort, G is transect gradient (m/km) and G^2 is the quadratic term for gradient, D is max depth (m), T denotes Cool streams with Warm as the reference, Y is year 2020 with 2019 as the reference, and MB is majority pct hydrologic soil group B for the category No with Yes as the reference,. K is the number of model parameters, AICc is Akaike's information criterion adjusted for small sample size, ΔAICc is the difference in AICc score between the given model and the top model, and w_i is the model weight.

	Abundance model												Zero-inflation model						
Model	Int	RS	AR	DI	PL	S	G	G^2	D	T	Y	MB	Int	RS	MB	K	AIC$_c$	ΔAIC$_c$	w_i
1	-3.02	0.37		0.44	0.23	0.44	0.40	0.24	-0.20			2.64	-5.51	-4.52	-0.59	12	799.47	0.00	0.23
2	-3.47	0.37		0.43	0.24	0.41	0.42	0.24	-0.21	0.54		2.67	-5.61	-4.63	-0.61	13	800.42	0.95	0.15
3	-3.04	0.33		0.43	0.14	0.42	0.45	0.25				2.67	-5.25	-4.33	-0.51	11	800.43	0.96	0.15
4	-3.08	0.28		0.42		0.45	0.46	0.26				2.70	-5.22	-4.32	-0.48	10	800.51	1.04	0.14
7	-2.70	0.40		0.47	0.26	0.40			-0.21			2.55	-5.53	-4.59	-0.74	10	800.64	1.17	0.13
5	-2.85	0.35		0.53	0.22	0.45	0.44	0.25	-0.19		-0.50	2.54	-5.31	-4.58	-0.82	13	800.77	1.30	0.12
9	-2.97	0.34	-0.35	0.37	0.16	0.43						2.80	-4.07	-1.90	1.39	10	801.42	1.95	0.09

Table 15: Coefficients, standard errors (SE) and 95% confidence intervals (CI) for the top model used to model the relative abundance Tallapoosa Bass surveyed in 58 stream sites sampled between May 2019 and June 2020. Coefficients and CI are given on the natural log scale and indicate increments of one standard deviation and mean levels of continuous covariates. Coefficients for the zero-inflation model are on the logit scale. DI-Shed is disturbance index for the watershed, %PL is percent pool, and Seconds is seconds of effort. Temp-W denotes Warm streams with Cool as the reference. Year2020 is a categorical variable with 2019 as the reference. MPSB is majority pct hydrologic soil group B for the category Yes with No as the reference. Transect gradient^2 refers to the quadratic term for gradient. Significant variables are denoted with an asterisk ($P \leq 0.05$).

Parameter	Coefficient ± SE	95% CI	*P*-value
Abundance model			
Intercept	-3.03 ± 1.04	-5.06, -0.99	0.004*
Rock Score	0.35 ± 0.13	0.10, 0.61	0.007*
Watershed area (km^2)	-0.03 ± 0.12	-0.26, 0.20	0.794
DI-Shed	0.44 ± 0.18	0.10, 0.80	0.013*
%PL	0.18 ± 0.13	-0.07, 0.44	0.148
Seconds	0.43 ± 0.13	0.18, 0.68	<0.001*
Transect gradient (m/km)	0.34 ± 0.29	-0.21, 0.89	0.243
Transect gradient^2	0.19 ± 0.14	-0.08, 0.47	0.178
Max depth (m)	-0.12 ± 0.13	-0.38, 0.13	0.337
Temp-W	0.08 ± 0.26	-0.43, 0.59	0.764
Year2020	-0.06 ± 0.25	-0.55, 0.43	0.804
MPSB	2.65 ± 1.01	0.67, 4.63	0.009*
Zero-inflation model			
Intercept	-5.30 ± 3.54	-12.24, 1.64	0.136
Rock Score	-4.26 ± 2.50	-9.16, 0.64	0.089
MPSB	-0.44 ± 2.86	-6.05, 5.17	0.878

VIII. Figures

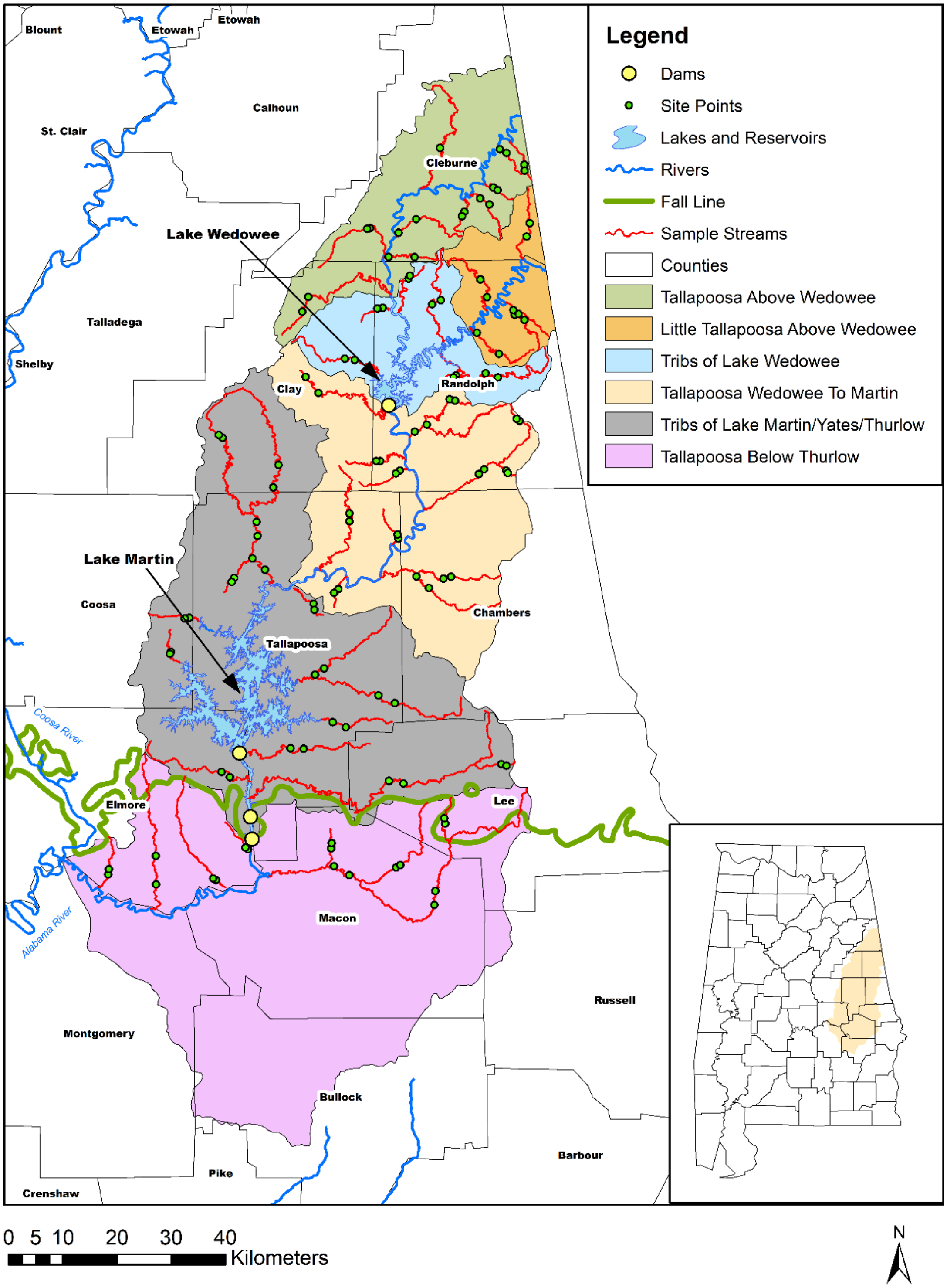


Figure 1: Map of the Tallapoosa River drainage study area in Alabama. The Fall Line separates the Piedmont Upland and Coastal Plain physiographic regions. Shaded areas refer to specific subbasins. Sample streams are in red and site points for all 58 sites are in green. Counties are also labeled for reference.

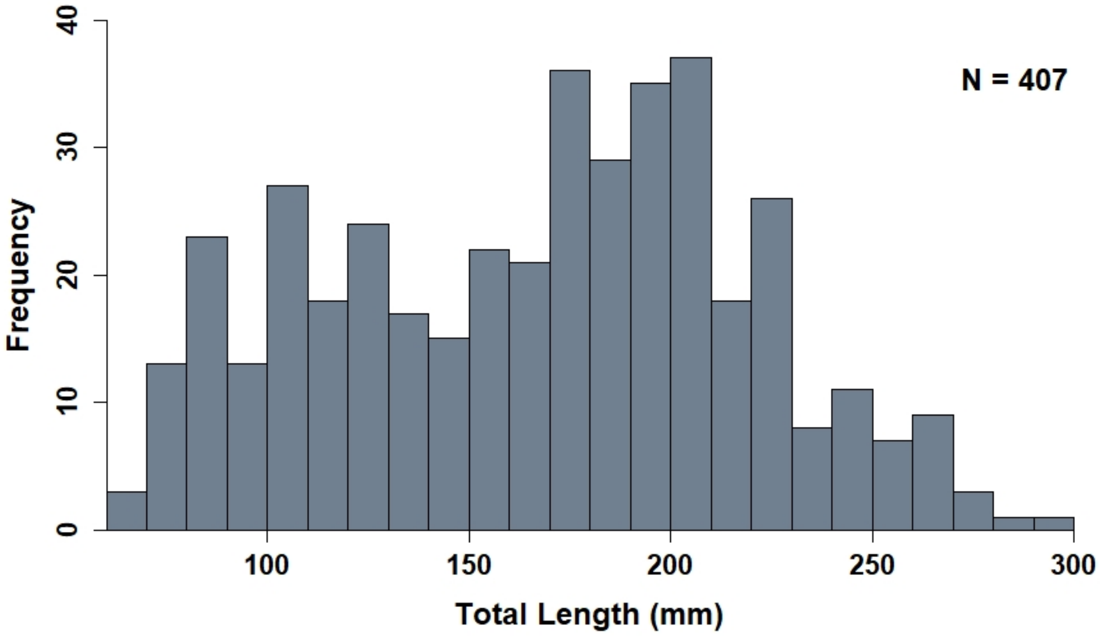


Figure 2: Length-frequency of Tallapoosa Bass (10-mm bins) collected throughout the entire Tallapoosa River drainage over the 58 sites.

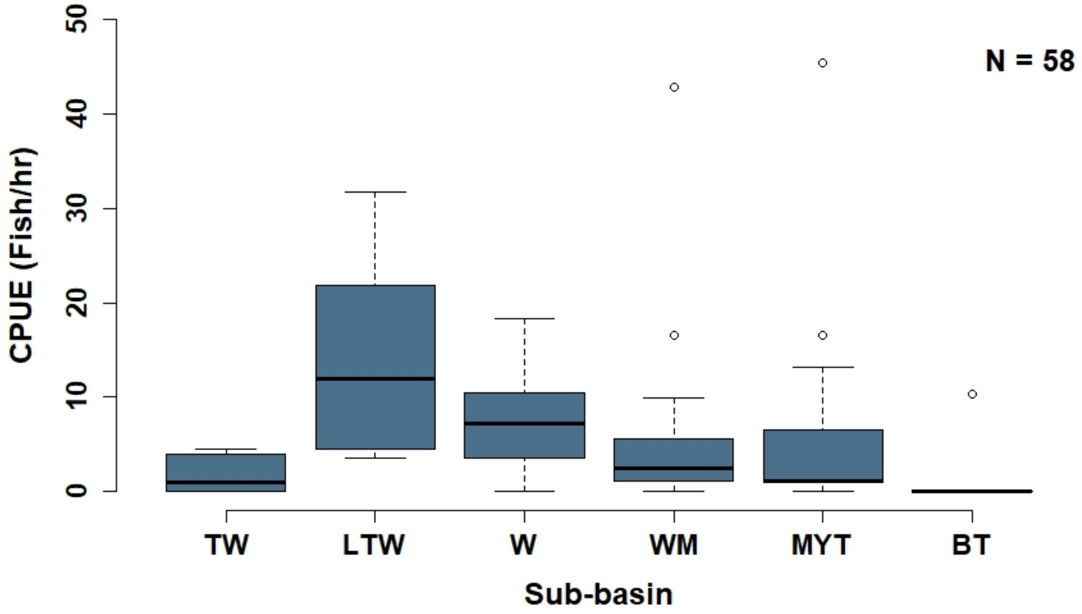


Figure 3: Mean CPUE of Tallapoosa Bass for all sites in each sub-basin of the Tallapoosa River drainage. Only the 58 sites used for analysis are included. Sub-basins are the Tallapoosa River Basin above Lake Wedowee (TW), the Little Tallapoosa River Basin above Lake Wedowee (LTW), Tributaries of Lake Wedowee (W), the Tallapoosa River Basin between Lake Wedowee and Lake Martin (WM), Tributaries of Lake Martin, Yates Reservoir, and Thurlow Reservoir (MYT), and the Tallapoosa River Basin below Thurlow Dam (BT). The black lines are the median, the edges of the box are the 25 (Q1) and 75% (Q3) quartiles and represent the interquartile range (IQR), the whiskers represent Q1 - 1.5*IQR and Q3 + 1.5*IQR, and the dots are outliers.

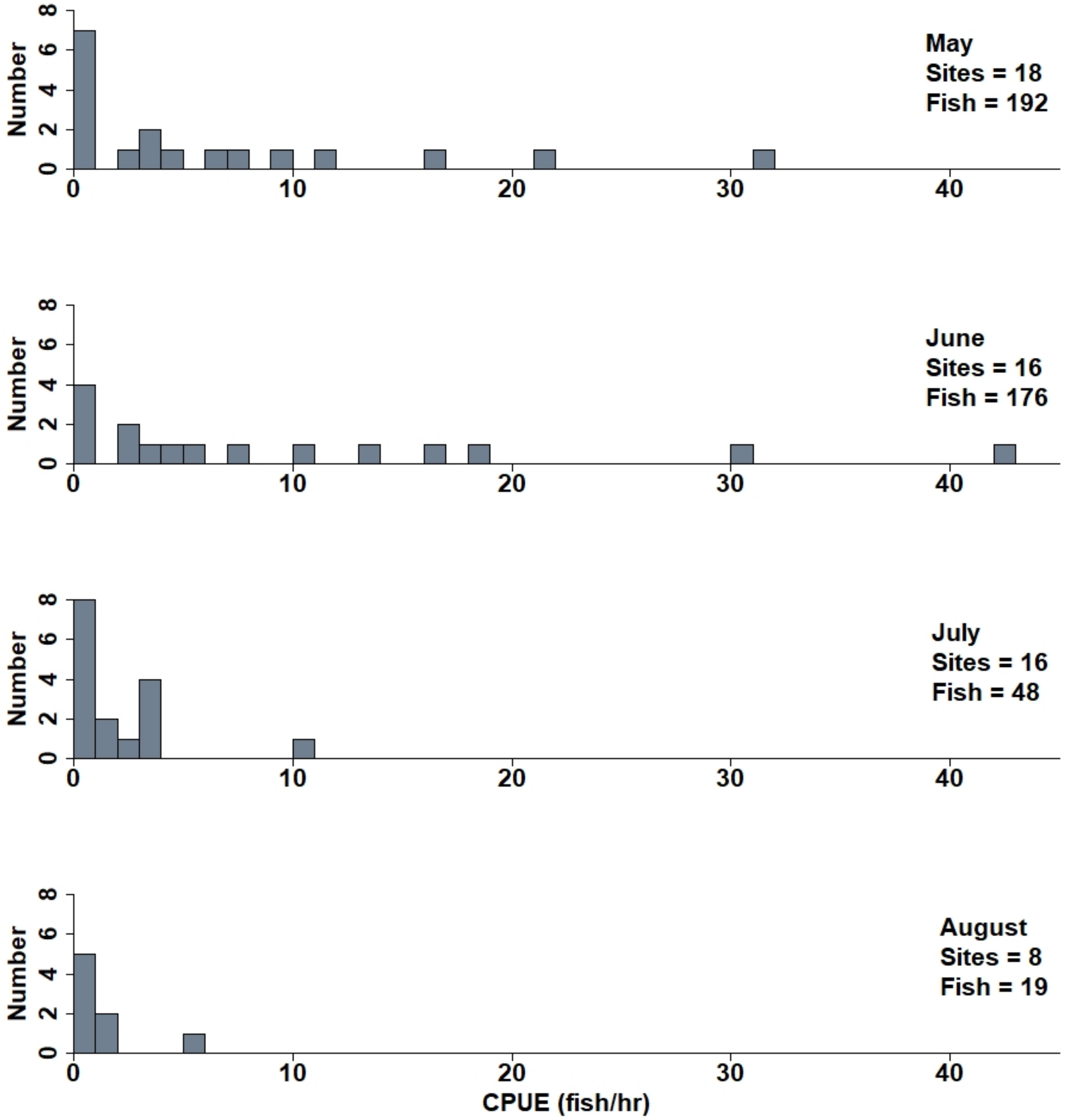


Figure 4: Tallapoosa Bass CPUE (1 fish/hr bins) at 58 sites in the Tallapoosa River drainage over four months in 2019 and 2020.

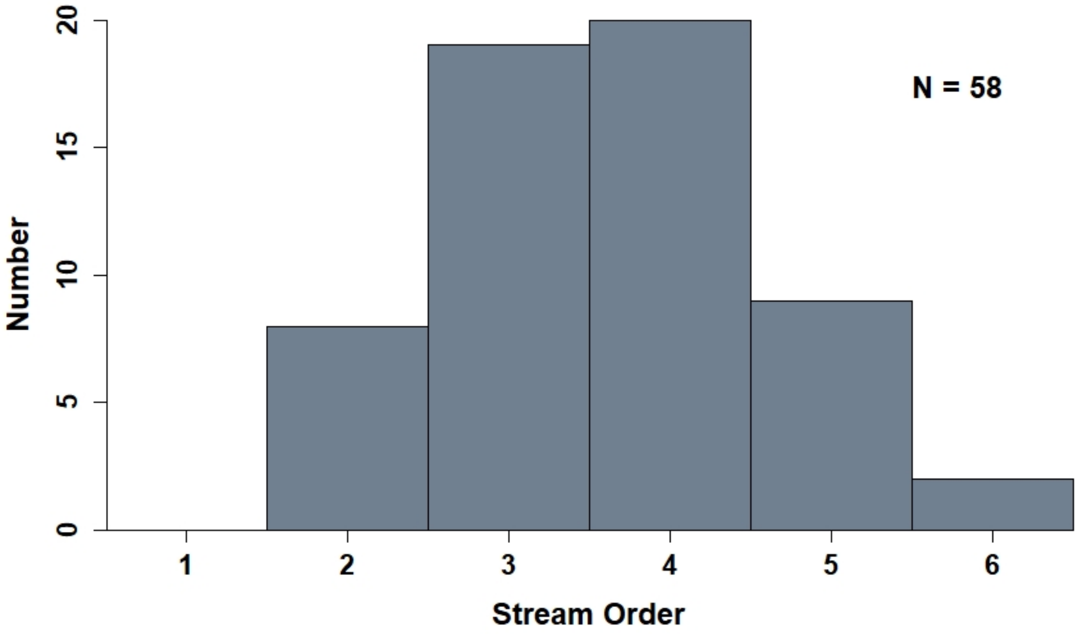


Figure 5: Stream orders of the 58 streams sampled throughout the Tallapoosa River drainage.

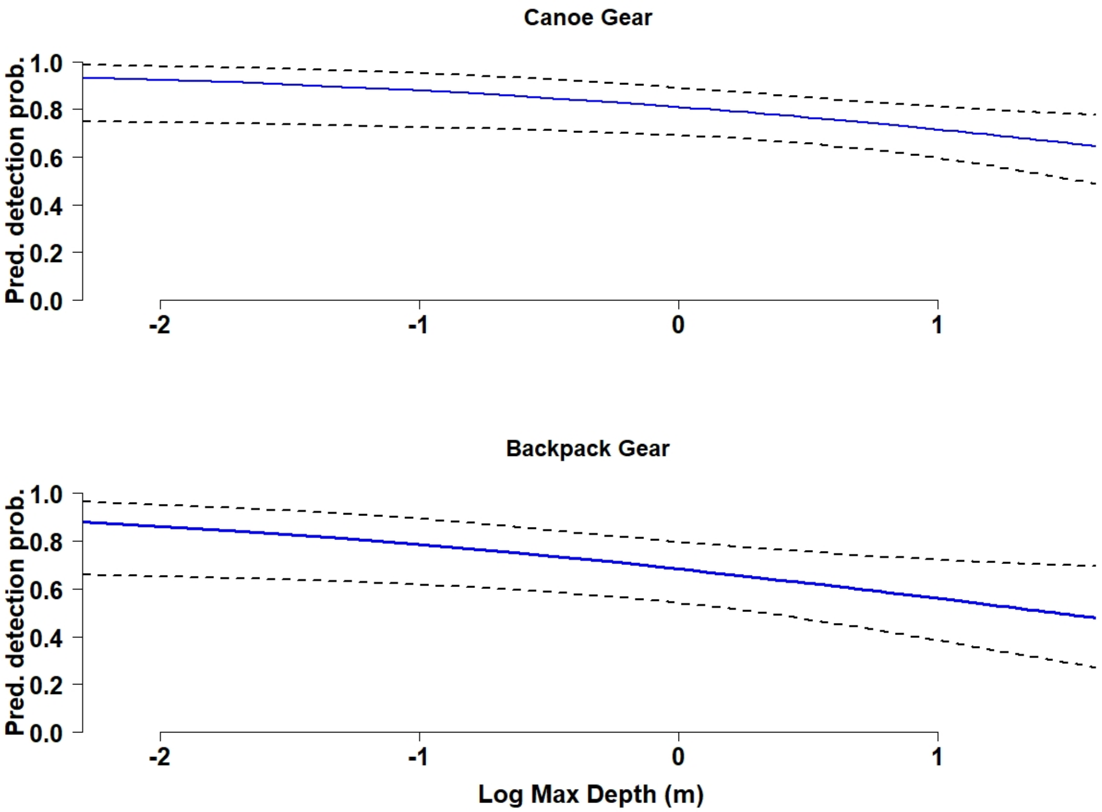


Figure 6: Relation between log$_e$-transformed depth and predicted detection probability of Tallapoosa Bass using canoe gear and backpack gears. All comparisons are made in the scenario when bass are more likely to be detected after the first survey. Dotted lines represent the 95% CI.

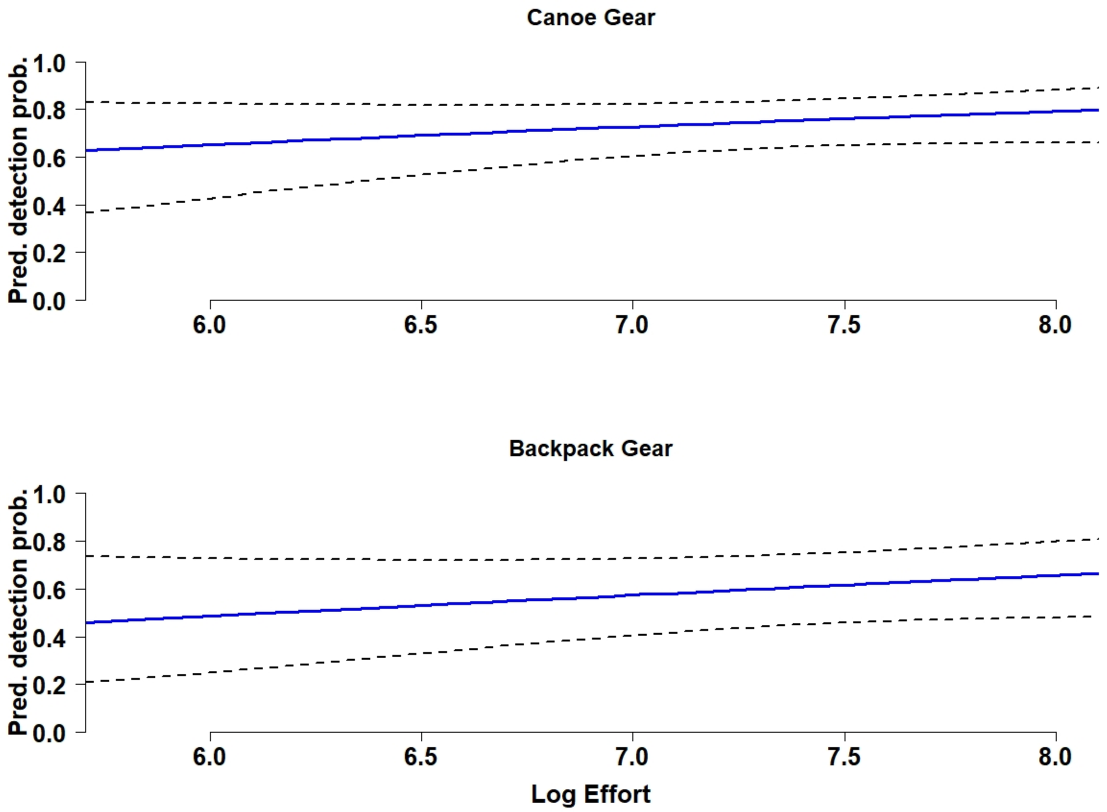
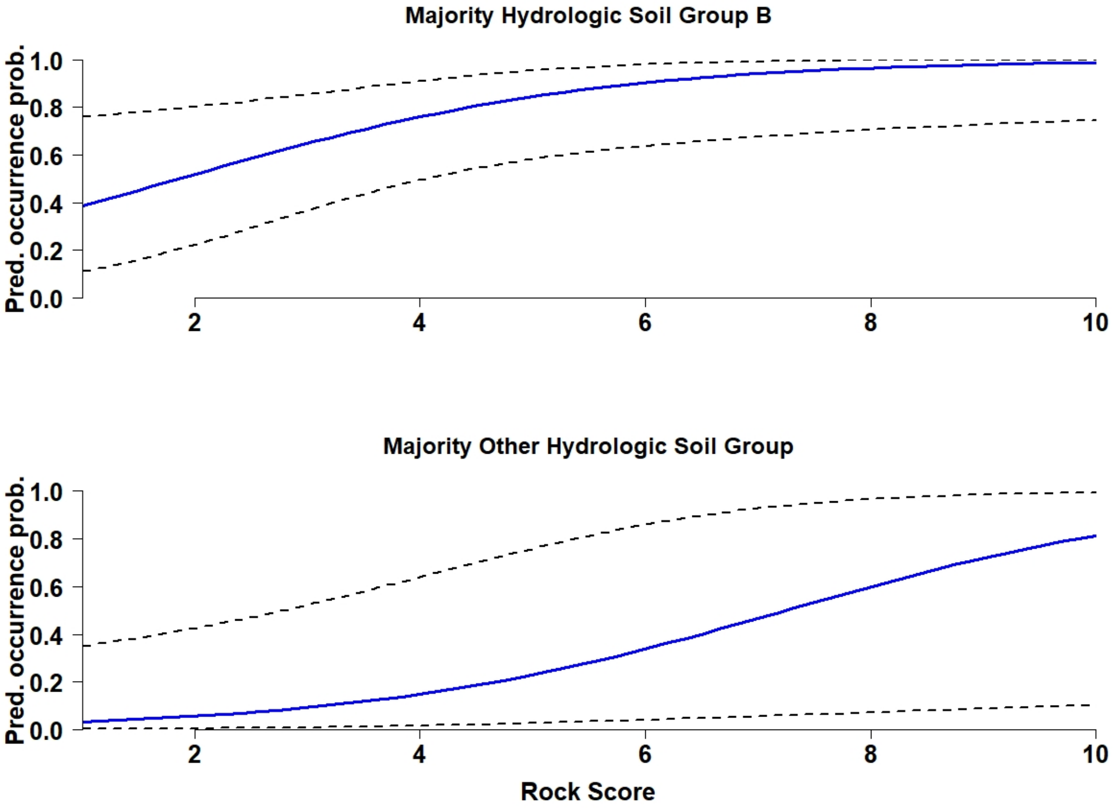
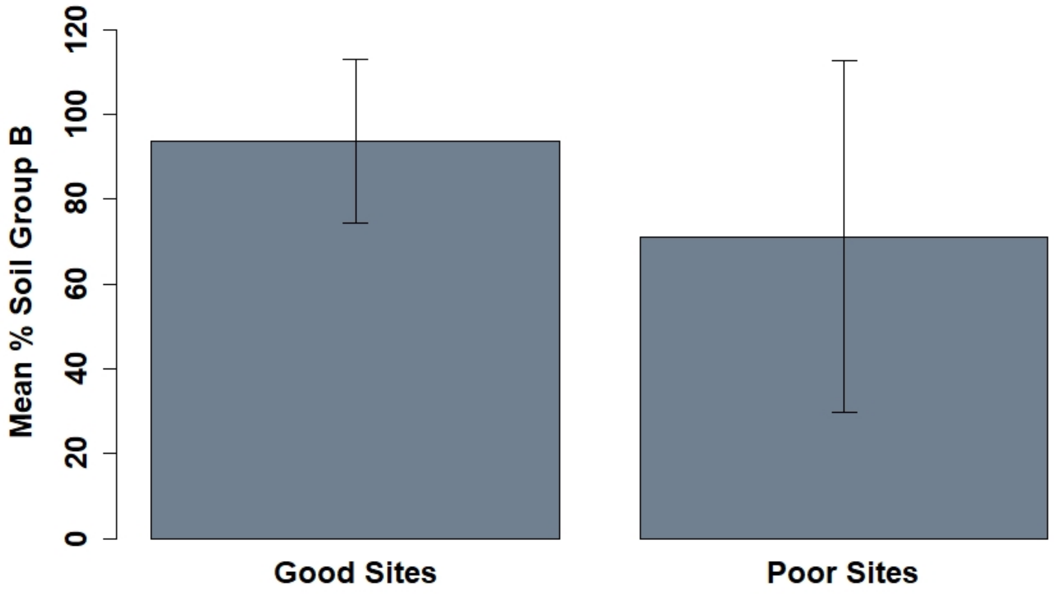


Figure 7: Relationship between $\log_e$-transformed effort in seconds and predicted detection probability using canoe gear and backpack gears. All comparisons are made in the scenario when bass are more likely to be detected after the first survey. Dotted lines represent the 95% CI.


Majority Hydrologic Soil Group B

Majority Other Hydrologic Soil Group

Figure 8: Relationship between rock score and predicted occurrence probability for streams with a majority percent (>50%) of hydrologic soil group B and streams with a majority percent of any other hydrologic soil group. Soil group B is a class of soils with moderately high runoff potential and is the dominant soil group in the Piedmont region of the Tallapoosa River drainage. Dotted lines represent the 95% CI.



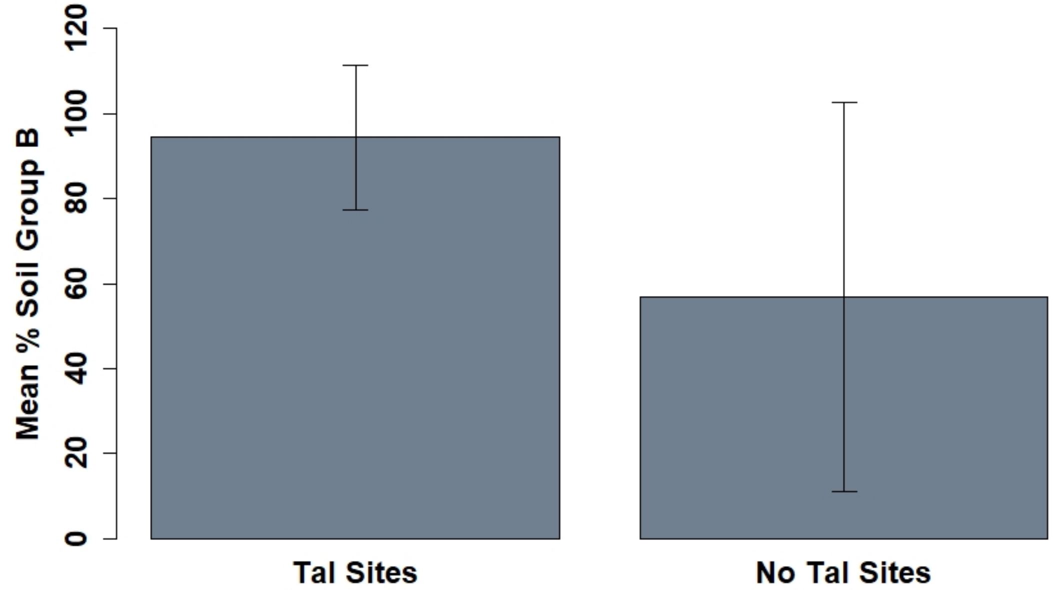


Figure 9: Comparison of mean percent hydrologic soil group B for good (≥3 bass) and poor (<3) Tallapoosa Bass sites and for sites where no Tallapoosa Bass were caught and sites where at least one Tallapoosa Bass was caught. Soil group B is a class of soils with moderately high runoff potential and is the dominant soil group in the Piedmont region of the Tallapoosa River drainage. Error bars represent one standard deviation.

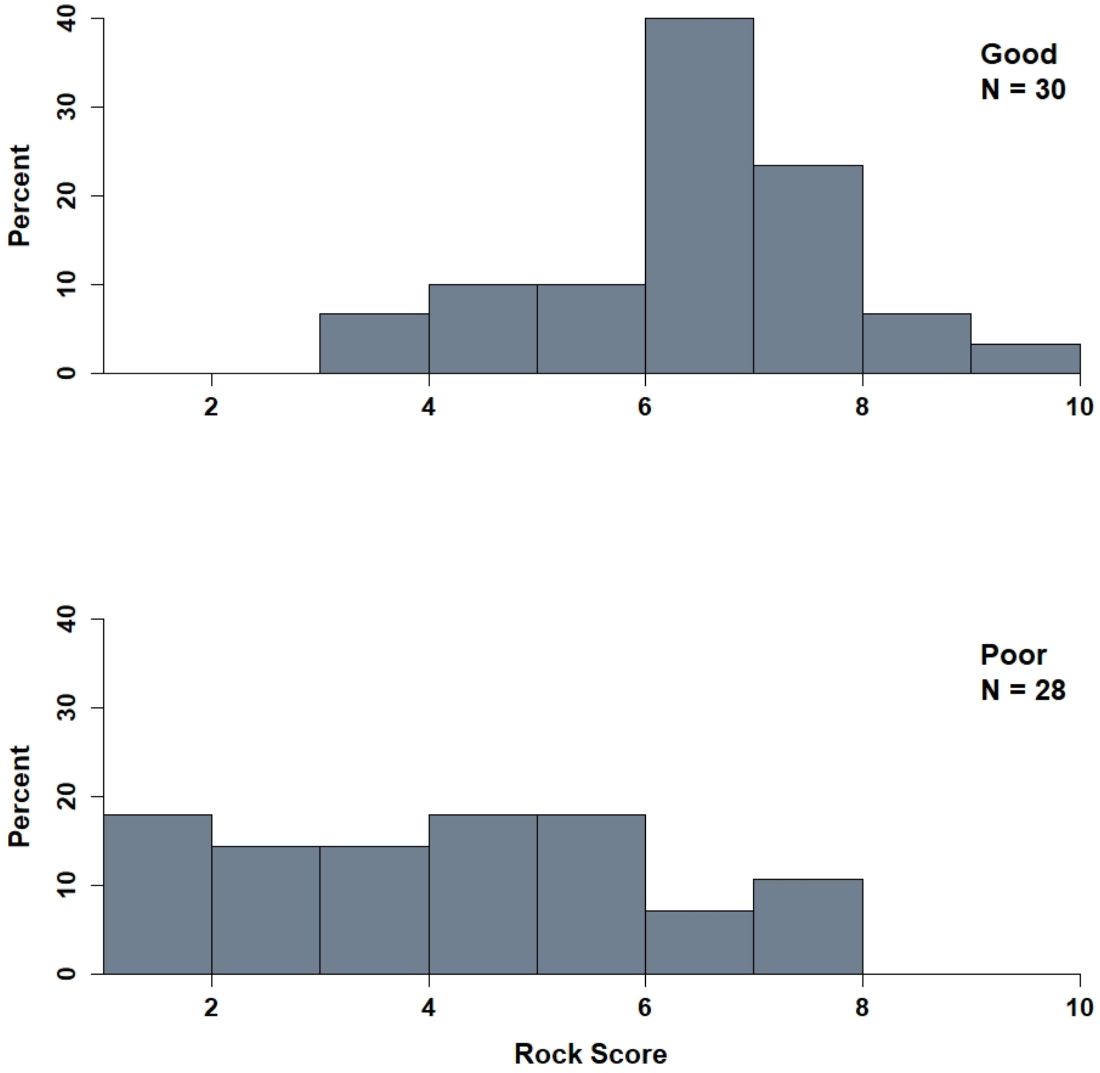


Figure 10: Mean rock score for good (≥3 bass) and poor (<3) Tallapoosa Bass sites.

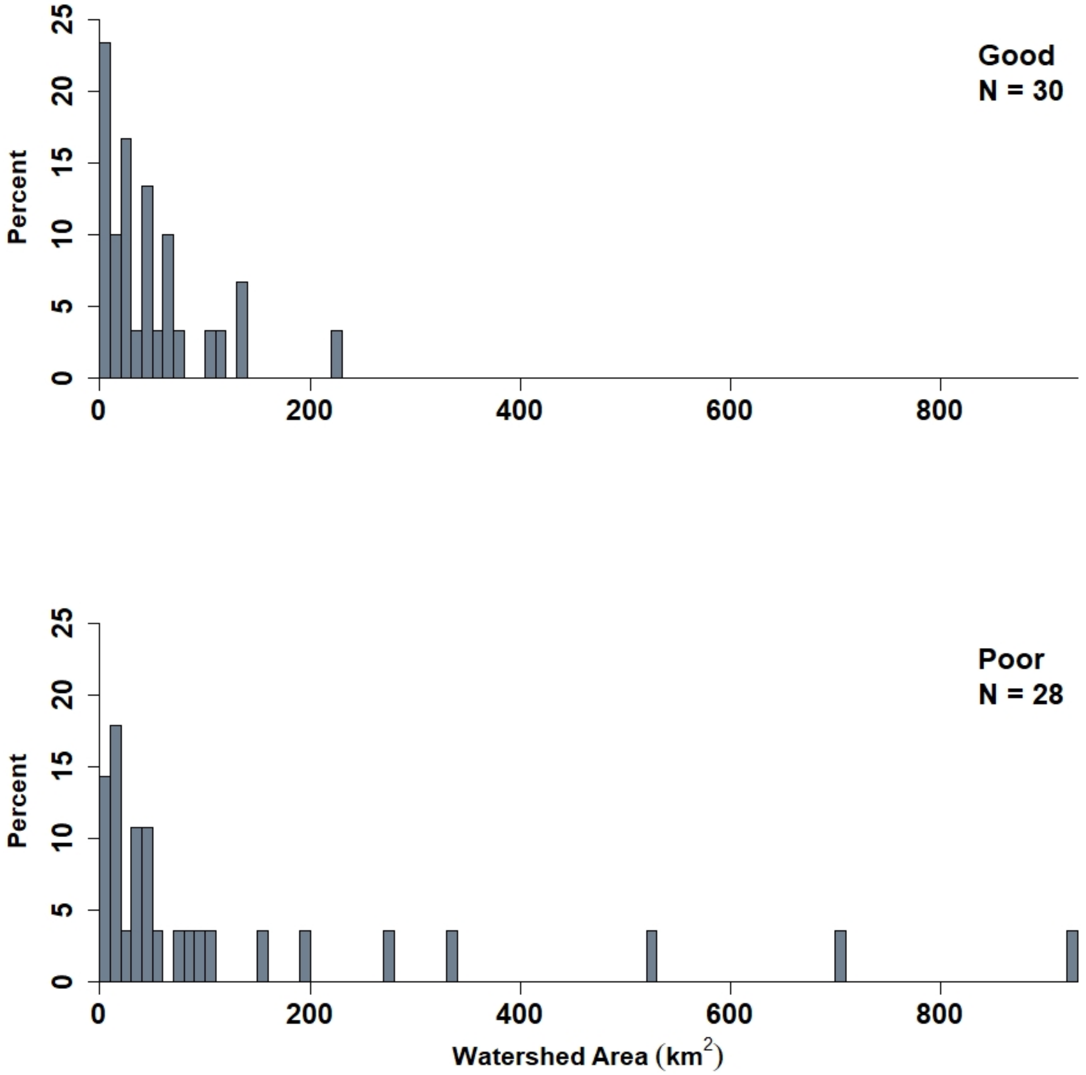


Figure 11: Watershed area (10-km^2 bins) for good (≥3 bass) and poor (<3) Tallapoosa Bass sites.

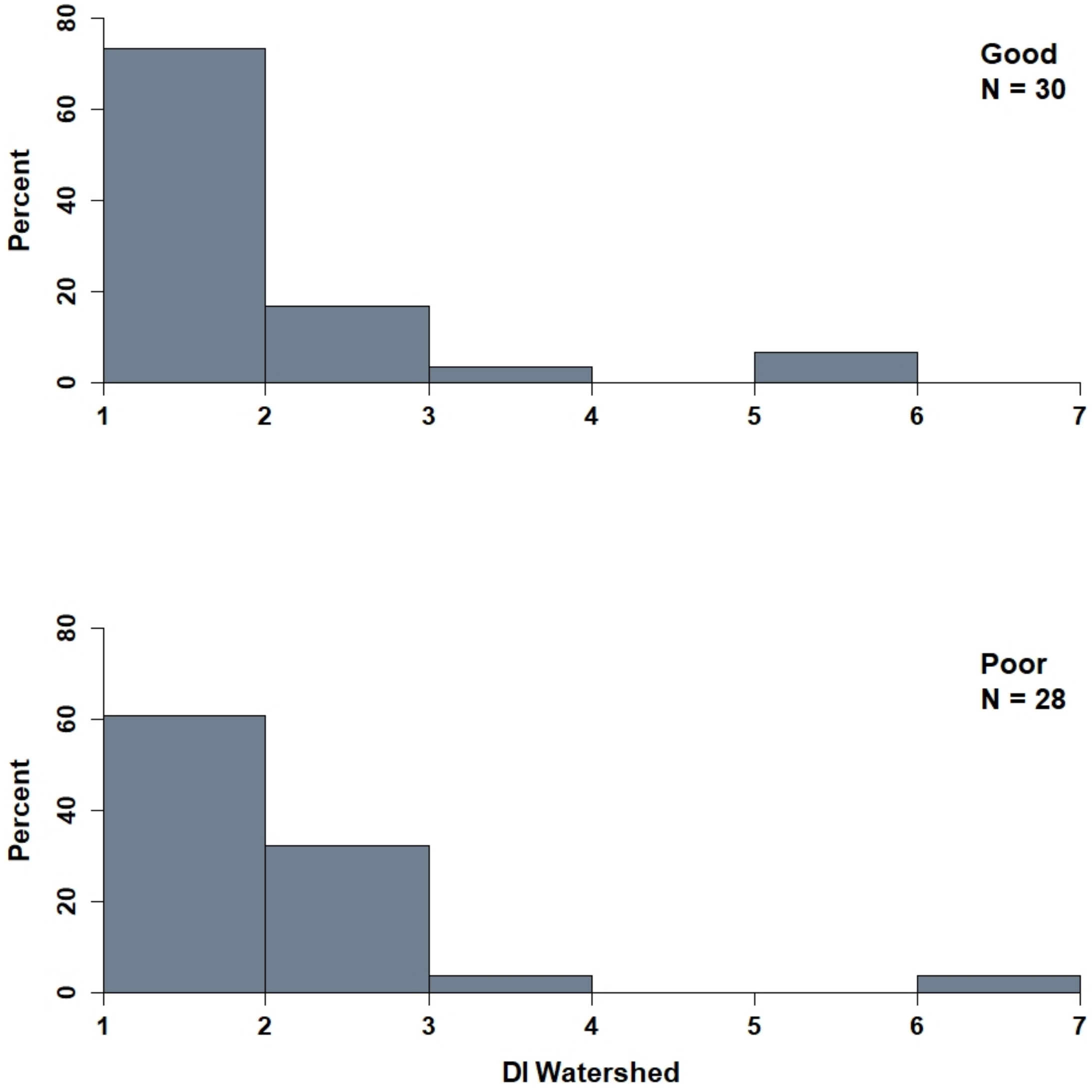


Figure 12: Watershed disturbance index (DI) values for good (≥3 bass) and poor (<3) Tallapoosa Bass sites.

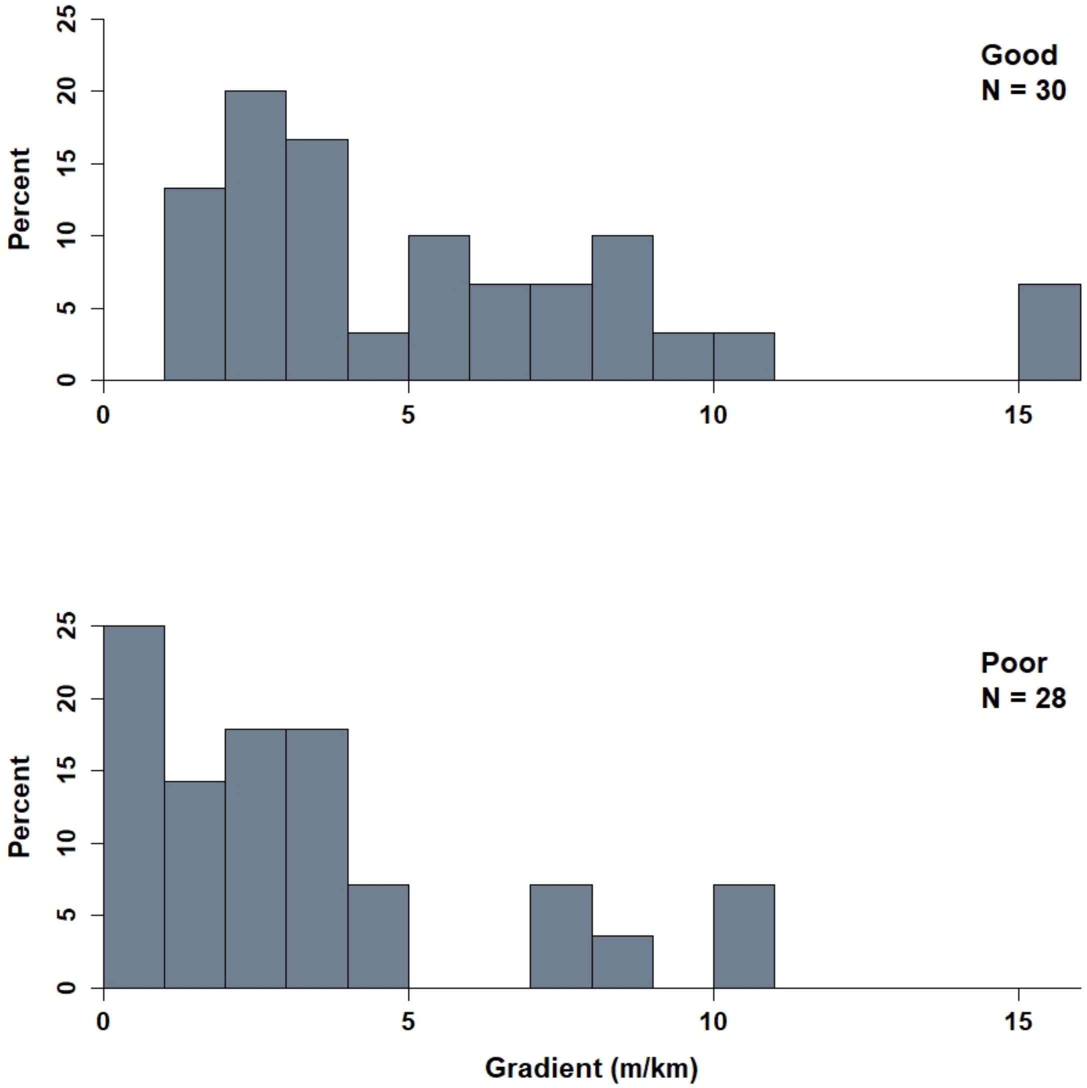


Figure 13: Site gradient (1-m/km bins) for good (≥3 bass) and poor (<3) Tallapoosa Bass sites.

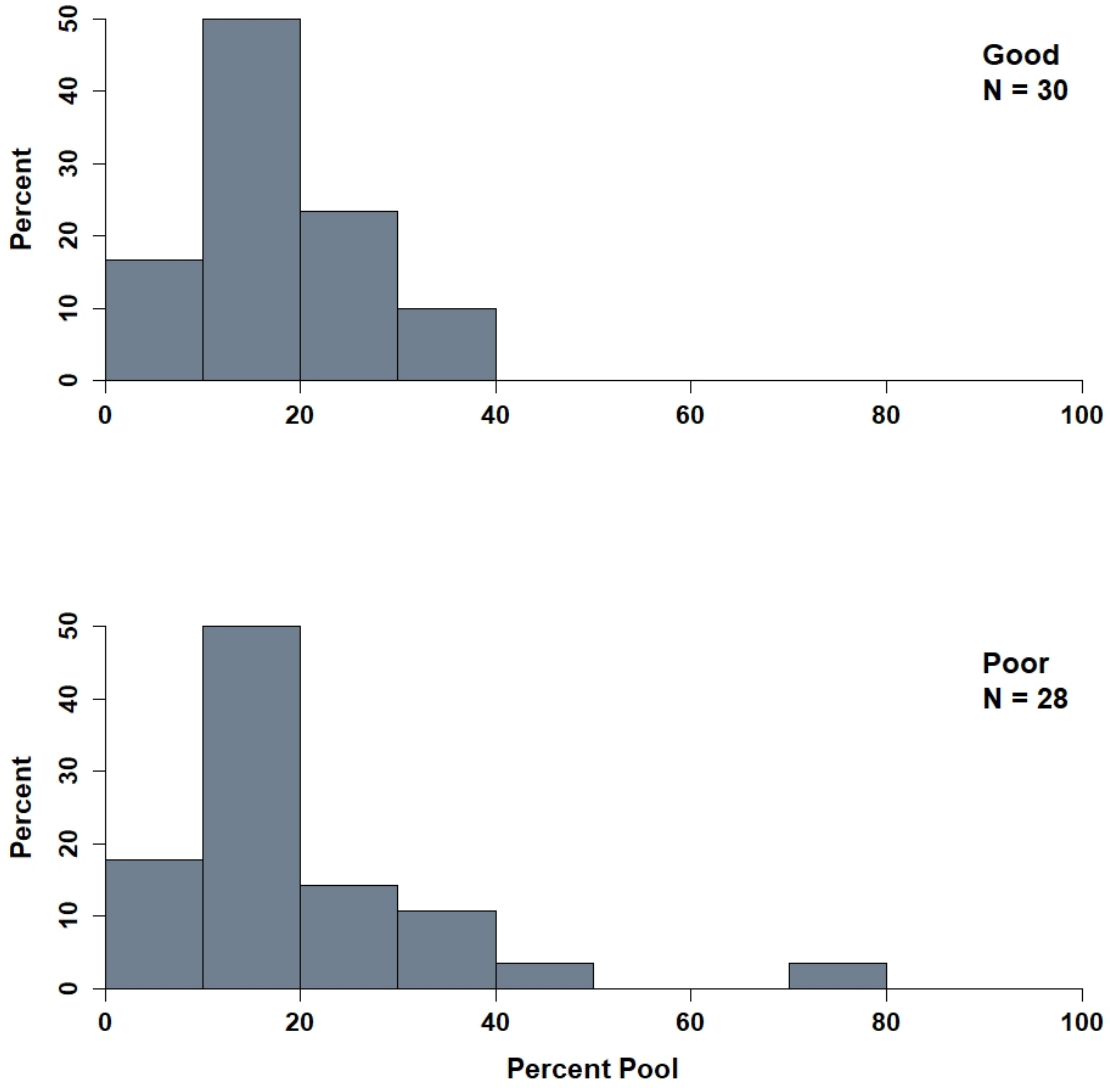


Figure 14: Figure 12: Percent pool (10% bins) for good (≥3 bass) and poor (<3) Tallapoosa Bass sites.

IX. Appendices

IX.1. Tallapoosa Project Sampling Datasheet

Date:________ Stream:___________________ MSW:_____ Trans #:__ Trans Duration:_____

WPT:______/______ Start:____________/_____________ End:___________/____________

EF time:_________ HAB: ____%PL ____%RN ____%RF ____%SH

Temp:______ DO:_______ Cond: ________ Turb:________ Max Depth:_______ pH: ____

LWD:_____ Rock:_____ RBank:_____ LBank:_____ RVeg:_____ LVeg:_____ Notes: ____

SP	**TL**	**WT**	**Fin Clip ID**	**Notes**	**SP**	**TL**	**WT**	**Fin Clip ID**	**Notes**

IX.2. Tallapoosa Project Sampling Protocol

1. START OF FLOAT

- Write down date and stream name (repeat for every datasheet).
- Prior to sampling, use the laser range finder to obtain 5 stream widths (in meters) and average for the Mean Stream Width (MSW) and write down on datasheet.
- Multiply MSW by 90 seconds to obtain minimum length of timed transect for canoe streams in minutes and multiply by 40 meters to obtain minimum length of transect in meters for backpack streams and record to datasheet under trans duration.

2. START OF SAMPLING TRANSECT

- Record transect number (first of the day is 1, second is 2, etc.).
- Mark Start of sampling transect on GPS and write down the LAT/LONG and Waypoint number
- Record temp, DO, pH, turbidity, and conductivity.

3. DURING SAMPLING TRANSECT

- Use stopwatch to record transect time for canoe streams.
- Sample all the best habitat available. Focus on catching only bass.
- Observe the types of mesohabitats sampled (Pool = PL, Run = RN, Riffle = RF, and Shoal = SH) and keep a mental note of the percentages of each along the sampling transect.
- Observe bank stability and bank vegetative protection on the bank that is being sampled, and observe rocky substrate and large woody debris (LWD) for the sampling transect only (the section of the stream you are actively sampling). Use the provided habitat assessment protocols to come up with a score number.
- Record depth using the depth sounder or meter stick at several pools to get an estimate of max depth.

4. END OF SAMPLING TRANSECT

- Mark End of sampling transect on GPS and write down the LAT/LONG and Waypoint number.
- Write down the EF time in seconds for backpack sites and the stopwatch time for canoe streams
- Write down percent mesohabitats, max depth, and score numbers for bank stability, bank vegetation, rocky substrate, and LWD.
- Record species (Alabama Bass = ALB, Redeye = RED, Largemouth = LMB, write potential hybrids in the notes column), weight in grams, and total length (front of head to end of caudal fin) in millimeters for every black bass. Write down any short notes in the notes column or longer ones on back of datasheet.

- Indicate whether or not a fin clip was taken (Y or N) and if yes then record Fin Clip ID. The ID numbers start at 1 and go until infinity. ID numbers are continuous across streams and transects; for example, if one transect ends at 20, the next transect will begin at 21, and if one stream ends at 30, the next stream will start at 31. Examples of a yes and ID number will look like:

Y, 1	**Y, 112**

- Estimate approximately 10 MSW minimum from the end of the current transect until the start of the next one and repeat protocol beginning at step 2.

IX.3. List of Coordinates for Canoe Sites. Coordinates for the start and end points for the canoe sites, and the coordinates for the bridge access for put-in and take-out. All canoe streams were sampled from upstream to downstream. Transect lengths ranged from 86.68 m to 861.70 m.

	Site Start		Site End		Access Put-in		Access Take-out	
Stream	Lat	Long	Lat	Long	Lat	Long	Lat	Long
Silas Creek	33.59204	-85.41554	33.6023	-85.43381	33.59176	-85.41553	33.60230	-85.43381
Bear Creek	33.34351	-85.3976	33.3788	-85.44144	33.34373	-85.39687	33.37681	-85.44388
Cohobadiah Creek	33.4677	-85.43391	33.43789	-85.42083	33.46783	-85.43457	33.43182	-85.43111
Cutnose Creek	33.39957	-85.34676	33.40825	-85.36605	33.39966	-85.34624	33.41256	-85.37054
Cane Creek	33.68655	-85.51331	33.65919	-85.52153	33.68706	-85.5132	33.65367	-85.53165
Wind Creek	32.68748	-85.78523	32.68858	-85.81102	32.68711	-85.78427	32.67309	-85.85045
Dynne Creek	33.56778	-85.56111	33.54541	-85.59602	33.56788	-85.56072	33.53990	-85.59866
Crooked Creek	33.30597	-85.78089	33.27933	-85.75566	33.30629	-85.78102	33.27670	-85.74691
Pineywood Creek	33.4333	-85.51268	33.42624	-85.52982	33.43403	-85.51258	33.42136	-85.5382
Chattasofka Creek	32.82103	-85.74501	32.81068	-85.76286	32.82264	-85.74445	32.80543	-85.77390
High Pine Creek	33.15164	-85.42786	33.14362	-85.43806	33.15228	-85.42700	33.12486	-85.46981
Oakachoy Creek	32.84861	-86.04671	32.84527	-86.04903	32.84911	-86.04678	32.83402	-86.04032
Sandy Creek	32.76321	-85.60548	32.77615	-85.63801	32.76272	-85.60457	32.78219	-85.64737
Cornhouse Creek	33.22605	-85.54121	33.21468	-85.56471	33.22577	-85.54093	33.21063	-85.57136
Wedowee Creek	33.30442	-85.39993	33.31133	-85.42426	33.30410	-85.39947	33.30729	-85.43306
Blue Creek	32.72316	-85.70203	32.73186	-85.72816	32.72325	-85.70126	32.73140	-85.72819
Ketchepedrakee Creek	33.41436	-85.78751	33.43898	-85.77544	33.41388	-85.78711	33.44122	-85.77093

Fox Creek	33.33621	-85.70335	33.33418	-85.68373	33.33648	-85.70371	33.33291	-85.67586
Chattahospee Creek	32.95475	-85.53793	32.97388	-85.56213	32.95402	-85.53802	32.98354	-85.57624
Allen Creek	32.97316	-85.49423	32.96932	-85.50925	32.97348	-85.49358	32.98073	-85.53298
Emuckfaw Creek	33.07882	-85.694392	33.065632	-85.69437	33.07896	-85.69471	33.05523	-85.69477
Channahatchee Creek	32.64893	-85.94701	32.64035	-85.93047	32.64981	-85.94723	32.63582	-85.92804
Hillabee Creek	33.00432	-85.88605	32.98543	-85.86148	33.00518	-85.89038	32.98478	-85.86064
Enitachopco Creek	33.15977	-85.83479	33.12225	-85.84503	33.16005	-85.83505	33.11298	-85.83486
Chubbehatchee Creek	32.50917	-86.07561	32.4618	-86.0752	32.51041	-86.07512	32.44863	-86.07935
Chewacla Creek	32.45053	-85.52685	32.42784	-85.52954	32.45096	-85.52651	32.42295	-85.53036
Uphapee Creek	32.47749	-85.69591	32.49215	-85.72601	32.47740	-85.69559	32.49051	-85.74218
Lost Creek 2	33.5607	-85.33532	33.5385	-85.3418	33.56158	-85.33574	33.53498	-85.34863
Upper Hillabee Creek	33.06489	-85.87808	33.04131	-85.87626	33.06641	-85.88011	33.03657	-85.87818
Sougahatchee Creek	32.62939	-85.58921	32.63398	-85.61777	32.62674	-85.58797	32.61934	-85.63364

IX.4. List of Coordinates for Backpack Sites. Coordinates for the start and end points for the backpack sites, and the coordinates for the bridge access. All backpack streams were sampled from downstream to upstream. Lockhelooge Creek was accessed from two bridges and each line is for a separate access point; the bold coordinates indicate the lowest start point to the highest upstream endpoint and the most downstream access point. Transect lengths ranged from 140 m to 328 m.

	Site Start		Site End		Access Point	
Stream	Lat	Long	Lat	Long	Lat	Long
Kemp Creek	33.68373	-85.39397	33.67755	-85.38097	33.68394	-85.3943
Lockhelooge Creek-2*	**33.50528**	**-85.61609**	33.50719	-85.6106	**33.50406**	**-85.61678**
Lockhelooge Creek-1*	33.50758	-85.56886	**33.50489**	**-85.56463**	33.50782	-85.568999
High Pine Creek Upper	33.23159	-85.35717	33.23549	-85.36311	33.231455	-85.356913
Buckhannon Creek	33.46869	-85.57636	33.47385	-85.57359	33.468499	-85.576914
Wolf Creek	32.52176	-85.73134	32.53062	-85.7304	32.521697	-85.730899
Copper's Rock Creek	33.41607	-85.36841	33.40965	-85.35812	33.41662	-85.36838
Jaybird Creek	32.92883	-85.76542	32.9188	-85.76378	32.929445	-85.765674
Norman Creek	33.6579	-85.34571	33.64834	-85.3448	33.657878	-85.345242
Harwell Mill Creek	32.4779	-86.16893	32.48685	-86.1677	32.47736	-86.169009
Wildcat Creek	33.26821	-85.49575	33.26591	-85.48483	33.268236	-85.495815
Hurricane Creek	33.16603	-85.63382	33.16583	-85.64123	33.16561	-85.632046
Eagle Creek	32.95313	-85.71672	32.94667	-85.7252	32.953382	-85.716446
Verdin Creek	33.58002	-85.46539	33.57269	-85.47002	33.580349	-85.465258
Lost Creek	33.42053	-85.62807	33.41948	-85.63861	33.420682	-85.627873
Macola Creek	33.62028	-85.40725	33.61593	-85.3989	33.620329	-85.407534
Rocky Branch	32.66122	-85.39661	32.65849	-85.38643	32.661081	-85.397178

Whortleberry Creek	32.9715	-85.92207	32.96512	-85.92709	32.971612	-85.922098
Parkerson Mill Creek	32.56261	-85.50729	32.57161	-85.50898	32.562429	-85.507171
Frog Level Branch	33.30809	-85.48299	33.30482	-85.48809	33.308342	-85.482826
Town Creek	33.14962	-85.38419	33.14551	-85.38121	33.149635	-85.384193
Lewis Creek	32.52022	-85.89513	32.52306	-85.90001	32.520388	-85.894853
Elkahatchee Creek	32.90516	-86.01055	32.90417	-86.01986	32.905035	-86.010219
Little Hillabee Creek	33.20471	-85.94545	33.20936	-85.95318	33.204759	-85.945186
Hodnett Mill Creek	33.03665	-85.59815	33.04368	-85.59941	33.036605	-85.598312
Cedar Creek	33.14991	-85.59489	33.14517	-85.60237	33.149785	-85.594624
Chulafinnee Creek	33.55316	-85.65273	33.55212	-85.65856	33.553348	-85.652835
Choctafaula Creek	32.48974	-85.60378	32.49361	-85.59558	32.489814	-85.603897
Tumkeehatchee Creek	32.46936	-85.95749	32.47174	-85.96295	32.469236	-85.957301

Appendix IX.5. Occupancy Model Code

```
rm(list=ls(all=TRUE))

#loading necessary packages
library(readxl)
library(usdm)
library(MuMIn)

#setting working directory
setwd("~/Tallapoosa_Project_R")
setwd("C:/Users/malam/OneDrive/Documents/Tallapoosa_Project_R")


####transforming and rechecking correlations for final model candidate variables####

#reading in data for detection covariate list
taldet<- read_excel("TallapoosaModelRData.xlsx", sheet = "detcovs")
#checking for skew in detection covariates
hist(taldet$sec)
taldet$sec=log(taldet$sec)
hist(taldet$sec) #transformation helps

hist(taldet$depth)
taldet$depth=log(taldet$depth)
hist(taldet$depth) #transformation helps

hist(taldet$turb)
taldet$turb=log(taldet$turb)
hist(taldet$turb) #transformation does not help, leave this one as is

hist(taldet$lwd)
taldet$lwd=log(taldet$lwd)
hist(taldet$lwd) #distribution is fine, do not transform, the transformation makes it worse

#read in the detection data again with dummy-coded categorical variables to check
correlations again
catdetcovs<- read_excel("TallapoosaModelRData.xlsx", sheet = "catdetcovs")
#checking correlations first for reference
cor(catdetcovs[,2:6])
#transforming necessary skewed covariates
catdetcovs$depth=log(catdetcovs$depth)
catdetcovs$sec=log(catdetcovs$sec)

#turning data into a dataframe
catdetcovs=as.data.frame(catdetcovs)
```

```
#checking correlations and variance inflation factors
cor(catdetcovs[,2:6])
vif(catdetcovs[,2:6])
#based on above results all variables are safe

#reading in data for occurrence covariates
talocc<- read_excel("TallapoosaModelRData.xlsx", sheet = "rocccovs")
#checking skew for continuous covariates
hist(talocc$area)
talocc$area=log(talocc$area)
hist(talocc$area) #transformation helps

hist(talocc$dished)
talocc$dished=log(talocc$dished)
hist(talocc$dished) #transformation helps

hist(talocc$ravgrock) #does not need a transformation

hist(talocc$ravgpl)
talocc$ravgpl=log(talocc$ravgpl)
hist(talocc$ravgpl) #transformation helps

hist(talocc$ravgdepth)
talocc$ravgdepth=log(talocc$ravgdepth)
hist(talocc$ravgdepth) #transformation helps

hist(talocc$sitegradient)
talocc$sitegradient=log(talocc$sitegradient)
hist(talocc$sitegradient) #transformation does not help much

hist(talocc$dams) #extra zeros, but overall I think distribution is ok

#read in the occurrence data again with dummy-coded categorical variables to check
correlations again
catocccovs<- read_excel("TallapoosaModelRData.xlsx", sheet = "catocccovs")
#check correlations first for reference
cor(catocccovs[1:10])
#transforming necessary skewed covariates
catocccovs$area=log(catocccovs$area)
catocccovs$dished=log(catocccovs$dished)
catocccovs$ravgpl=log(catocccovs$ravgpl)
catocccovs$ravgdepth=log(catocccovs$ravgdepth)
#turning data into a dataframe
catocccovs=as.data.frame(catocccovs)
```

```
#checking correlations and variance inflation factors
cor(catocccovs[1:10])
vif(catocccovs[c(1:10)])
#transforming site gradient because its relationship with area dramatically changed
catocccovs$sitegradient=log(catocccovs$sitegradient)
#rechecking correlations again
cor(catocccovs[1:10])
vif(catocccovs[c(1:10)])
#based on above results, all variables are safe, except max depth which will be removed
due to its high correlation with area. site gradient is no longer too highly correlated with
area


######Reading in occupancy model code######
library(unmarked)
library(AICcmodavg)
tals<-read.csv("TalUnmarked.csv")
head(tals) #checking data to make sure it looks good
summary(tals)

#Define y for modeling. This defines which columns the y (detection) variable should be:
rys=tals[,16:21] #detections after updated genetic data. using reduced transects since very
few sites have 7 or 8 transects
rys

#transform variables based on above analysis
tals[,108:115]=log(tals[,108:115]) #log-transforming depth
tals[,108:115]
tals[,51:58]=log(tals[,51:58]) #log-transforming sec
tals[,51:58]
tals$sitegradient=log(tals$sitegradient)
tals$area=log(tals$area)
tals$ravgpl=log(tals$ravgpl)
tals$dished=log(tals$dished)

#turning detections, trap factor, and year into factors so they don't standardize
tals$year=as.factor(tals$year)

tals$tr1=as.factor(tals$tr1)
tals$tr2=as.factor(tals$tr2)
tals$tr3=as.factor(tals$tr3)
tals$tr4=as.factor(tals$tr4)
tals$tr5=as.factor(tals$tr5)
tals$tr6=as.factor(tals$tr6)
```

```
tals$trap1=as.factor(tals$trap1)
tals$trap2=as.factor(tals$trap2)
tals$trap3=as.factor(tals$trap3)
tals$trap4=as.factor(tals$trap4)
tals$trap5=as.factor(tals$trap5)
tals$trap6=as.factor(tals$trap6)

#standardize dataframe
sdtals=stdize(tals,binary="omit",center=TRUE,scale=TRUE)

#define detection covariates, ones measured for each survey, have multiple columns in excel file
#put in all of the variables in the spreadsheet, pick out the ones I need later
rdetcvtalsd=
list(sec=sdtals[,c("z.sec1","z.sec2","z.sec3","z.sec4","z.sec5","z.sec6")],pl=sdtals[,c("z.pl1","z.pl2","z.pl3","z.pl4","z.pl5","z.pl6")],rf=sdtals[,c("z.rf1","z.rf2","z.rf3","z.rf4","z.rf5","z.rf6")],temp=sdtals[,c("z.temp1","z.temp2","z.temp3","z.temp4","z.temp5","z.temp6")],turb=sdtals[,c("z.turb1","z.turb2","z.turb3","z.turb4","z.turb5","z.turb6")],depth=sdtals[,c("z.depth1","z.depth2","z.depth3","z.depth4","z.depth5","z.depth6")],lwd=sdtals[,c("z.lwd1","z.lwd2","z.lwd3","z.lwd4","z.lwd5","z.lwd6")],rock=sdtals[,c("z.rock1","z.rock2","z.rock3","z.rock4","z.rock5","z.rock6")],veg=sdtals[,c("z.veg1","z.veg2","z.veg3","z.veg4","z.veg5","z.veg6")],bank=sdtals[,c("z.bank1","z.bank2","z.bank3","z.bank4","z.bank5","z.bank6")],translength=sdtals[,c("z.translength1","z.translength2","z.translength3","z.translength4","z.translength5","z.translength6")],transgradient=sdtals[,c("z.transgradient1","z.transgradient2","z.transgradient3","z.transgradient4","z.transgradient5","z.transgradient6")],transmaf=sdtals[,c("z.transmaf1","z.transmaf2","z.transmaf3","z.transmaf4","z.transmaf5","z.transmaf6")],transvel=sdtals[,c("z.transvel1","z.transvel2","z.transvel3","z.transvel4","z.transvel5","z.transvel6")],trap=tals[,c("tr1","tr2","tr3","tr4","tr5","tr6")],ttrap=tals[,c("trap1","trap2","trap3","trap4","trap5","trap6")])

#define site covariates; these are the ones measured once for each site, same exact value for every survey
#put in all of the variables in the spreadsheet, pick out the ones I need later
rocccvtalsd<-
sdtals[,c("date","stream","sub_basin","gear_type","z.sitelength","z.pctb","z.distmain","z.diflood","z.dished","z.meta","z.ravgpl","z.avgrf","z.ravgrock","z.avgtemp","z.ravgdepth","z.avglwd","z.area","z.avgvel","z.avgmaf","z.sitegradient","z.avgsec","z.bankavg","z.vegavg","talstream","z.schist","month","z.doy","z.avgrn","z.avgsh","pctbmaj",'z.propb','z.dams','z.ddres',"res","abovefall","z.dlink","tempcat","year")]

#create unmarked data frame using defined variables
rumftalsd<-unmarkedFrameOccu(y=rys,siteCovs=rocccvtalsd, obsCovs = rdetcvtalsd)
summary(rumftalsd)
```

```
####detection models####
rtalmodsd<-
occu(~1+sec+turb+lwd+gear_type*depth+gear_type*translength+gear_type*sec+I(depth
^2)~1 , rumftalsd)
summary(rtalmodsd) #interactions and quadratics are not significant, remove to save
degrees of freedom

rtalmodsd<-occu(~1+sec+turb+lwd+gear_type+depth~1 , rumftalsd)
summary(rtalmodsd) #final most-complex detection model

occ_gofdet <- mb.gof.test(rtalmodsd, nsim = 1000, plot.hist = FALSE) #checking
goodness-of-fit for most-complex detection model
# hide the chisq table to give simpler output
# occ_gof1$chisq.table <- NULL
print(occ_gofdet) #good fit, overdispersed

modellist=dredge(rtalmodsd,rank=QAICc,chat=1.11) #running the all-subsets analysis,
rank using QAIC and c-hat from above gof test
modellist

#best model in the subset with effort in it. Reduced to two variables of greatest effect and
seconds of effort to save degrees of freedom for the occurrence side, trap added in
rtalmodsd<-occu(~1+sec+gear_type+depth+trap~1 , rumftalsd)
summary(rtalmodsd)


####Occurrence sub-model####
rtalmodsdocc<-
occu(~1~1+z.ravgpl+I(z.ravgpl^2)+z.ravgrock+z.area+z.dished+z.sitegradient+pctbmaj+
tempcat+z.dams+year+z.area*z.dished, rumftalsd)
summary(rtalmodsdocc) #quadratic not significant and interaction causes convergence
issues. remove from model

#most complex occurrence submodel.
rtalmodsdocc<-
occu(~1~1+z.ravgpl+z.ravgrock+z.area+z.dished+z.sitegradient+pctbmaj+tempcat+z.da
ms+year, rumftalsd)
summary(rtalmodsdocc)

occsgoffull <- mb.gof.test(rtalmodsdocc, nsim = 1000, plot.hist = FALSE)
# hide the chisq table to give simpler output
# occ_gof4$chisq.table <- NULL
print(occsgoffull) #decent fit, but overdispersed
```

```
rdredgeq=dredge(rtalmodsdocc,rank = QAICc, chat=1.44) ##running the all-subsets analysis, rank using QAICc and c-hat from above gof test
rdredgeq #results in 4 top models within 2 units


####full occupancy models####
####adding in top 4 occurrence sub-models to top detection model. releveling certain variables to obtain ideal reference categories. I want Yes for pctbmaj since Piedmont streams are Yes category, and I want Canoe for gear type since I believe it is the best gear. I want trap 1 so I am getting average detection probability for when we were more likely to keep detecting bass.
smod1<-occu(~1+depth+sec+relevel(gear_type,ref="C")+relevel(trap,ref="1")~1+z.ravgrock+relevel(pctbmaj,ref="Y"), rumftalsd)
summary(smod1)

smod2<-occu(~1+depth+sec+relevel(gear_type,ref="C")+relevel(trap,ref="1")~1+z.ravgrock+relevel(pctbmaj,ref="Y")+z.dams, rumftalsd)
summary(smod2)

smod3<-occu(~1+depth+sec+relevel(gear_type,ref="C")+relevel(trap,ref="1")~1+z.ravgrock+relevel(pctbmaj,ref="Y")+z.dams+relevel(tempcat,ref="W"), rumftalsd)
summary(smod3)

smod4<-occu(~1+depth+sec+relevel(gear_type,ref="C")+relevel(trap,ref="1")~1+z.ravgrock+relevel(pctbmaj,ref="Y")+relevel(tempcat,ref="W"), rumftalsd)
summary(smod4)


#full global model. keeping detection model constant throughout this process to leave more degrees of freedom for the occurrence sub-model, the side I most care about
stalmodsdglobal<-occu(~1+depth+sec+gear_type+trap~1+z.ravgpl+z.ravgrock+z.area+z.dished+z.sitegradient+pctbmaj+tempcat+z.dams+year, rumftalsd)
summary(stalmodsdglobal)

#gof test for full global model
socc_gof_global <- mb.gof.test(stalmodsdglobal, nsim = 1000, plot.hist = FALSE)
# hide the chisq table to give simpler output
#occ_gof_global$chisq.table <- NULL
print(socc_gof_global) #good fit, but overdispersed
```

```
#ranking top 4 full models using QAICc and c-hat from global full model due to
overdispersion
QAICc(smod1,smod2,smod3,smod4,chat=1.15)

#not actually using this for an average, but it ranks them in order and shows the delta and
the model weight within the model set, and the log-likelihood of each model
smodavg<- model.avg(smod1,smod2,smod3,smod4,rank = QAICc, rank.args =
alist(chat=1.15))
summary(smodavg)

#goodness of fit tests for top full models
soccgof1 <- mb.gof.test(smod1, nsim = 1000, plot.hist = FALSE)
print(soccgof1)
soccgof2 <- mb.gof.test(smod2, nsim = 1000, plot.hist = FALSE)
print(soccgof2)
soccgof3 <- mb.gof.test(smod3, nsim = 1000, plot.hist = FALSE)
print(soccgof3)
soccgof4 <- mb.gof.test(smod4, nsim = 1000, plot.hist = FALSE)
print(soccgof4)

#all models above have adequate fit and overdispersion
#top occupancy model. explains equal variance as other top models within 2 QAICc units
with fewest number of parameters.
smod1<-
occu(~1+depth+sec+relevel(gear_type,ref="C")+relevel(trap,ref="1")~1+z.ravgrock+rele
vel(pctbmaj,ref="Y"), rumftalsd)
summary(smod1)

#top model is overdispersed, so multiply covariance matrix by the square root of c-hat
from the full global model to inflate SEs and obtain more accurate confidence intervals
smod1@estimates@estimates$state@covMat=smod1@estimates@estimates$state@cov
Mat*sqrt(1.15) #inflating SEs for occupancy covariates, global c-hat was 1.15
smod1@estimates@estimates$det@covMat=smod1@estimates@estimates$det@covMat
*sqrt(1.15) #inflating SEs for detection covariates, global c-hat was 1.15
summary(smod1) #checking summary

#define anti-logit function to turn intercepts into probability
antilogit <- function(x) { exp(x) / (1 + exp(x) ) }
antilogit(1.094) #0.75, average detection probability at mean levels of depth and seconds,
in trap factor category of 1 (likely to detect fish on subsequent surveys) and in gear type
category of canoe (using canoe gear)
antilogit(1.96) #0.88, average occupancy probability at mean levels of rock score and in
the Yes category for pctbmaj (stream has a majority percent of soil group B)
```

```
#variations of model 1
#backpack reference
smod1<-
occu(~1+depth+sec+gear_type+relevel(trap,ref="1")~1+z.ravgrock+relevel(pctbmaj,ref=
"Y"), rumftalsd)
summary(smod1)
antilogit(0.415) #0.60, average detection probability at mean levels of depth and seconds,
in trap factor category of 1 (likely to detect fish on subsequent surveys) and in gear type
category of backpack (using backpack gear)

#trap 0 reference for canoe
smod1<-
occu(~1+depth+sec+relevel(gear_type,ref="C")+trap~1+z.ravgrock+relevel(pctbmaj,ref=
"Y"), rumftalsd)
summary(smod1)
antilogit(0.355) #0.59, average detection probability at mean levels of depth and seconds,
in trap factor category of 0 (NOT likely to detect fish on subsequent surveys) and in gear
type category of canoe (using canoe gear)

#trap 0 reference for backpack
smod1<-occu(~1+depth+sec+gear_type+trap~1+z.ravgrock+relevel(pctbmaj,ref="Y"),
rumftalsd)
summary(smod1)
antilogit(-0.324) #0.42, average detection probability at mean levels of depth and
seconds, in trap factor category of 0 (NOT likely to detect fish on subsequent surveys)
and in gear type category of backpack (using backpack gear)

#no reference for soil
smod1<-
occu(~1+depth+sec+relevel(gear_type,ref="C")+relevel(trap,ref="1")~1+z.ravgrock+pct
bmaj, rumftalsd)
summary(smod1)
antilogit(-0.94) #0.28, average occupancy probability at mean levels of rock score and in
the NO category for pctbmaj (stream does not have a majority percent of soil group B)


####confidence intervals for top occupancy model####
#reset model to desired reference categories and re-inflate standard errors
smod1<-
occu(~1+depth+sec+relevel(gear_type,ref="C")+relevel(trap,ref="1")~1+z.ravgrock+rele
vel(pctbmaj,ref="Y"), rumftalsd)
summary(smod1)
```

```
#top model is overdispersed, so multiply covariance matrix by the square root of c-hat from the full global model to inflate SEs and obtain more accurate confidence intervals
smod1@estimates@estimates$state@covMat=smod1@estimates@estimates$state@covMat*sqrt(1.15) #inflating SEs for occupancy covariates, global c-hat was 1.15
smod1@estimates@estimates$det@covMat=smod1@estimates@estimates$det@covMat*sqrt(1.15) #inflating SEs for detection covariates, global c-hat was 1.15
summary(smod1) #checking summary

#extracting coefficients from the top occupancy model
coefsocc=smod1@estimates@estimates$state@estimates
coefsdet=smod1@estimates@estimates$det@estimates

#vector of SEs from the top occupancy model
occse=c(0.76,0.64,1.32)
detse=c(0.27,0.22,0.19,0.36,0.35)

#upper and lower limits, cbind for ease of interpretation
occupper=coefsocc+1.96*occse
occlower=coefsocc-1.96*occse
occCI=cbind(occlower,coefsocc,occupper) #confidence intervals surrounding coefficient estimates
occCI

#confidence intervals for the intercept average occurrence probability
antilogit(0.47) #lower
antilogit(3.45) #upper

detupper=coefsdet+1.96*detse
detlower=coefsdet-1.96*detse
detCI=cbind(detlower,coefsdet,detupper) #confidence intervals surrounding coefficient estimates
detCI

#confidence intervals for the intercept average detection probability
antilogit(0.57) #lower
antilogit(1.62) #upper

####making graphs to show predicted relationship between continuous covariates and detection/occurrence probabilities####

#sequence of rock data, standardize it
rocks=seq(1,10,length.out = 58)
strockspred=stdize(rocks)
rockspred=rocks #keeping not-standardized data to plot against
mean(strockspred) #checking standardization
sd(strockspred)
```

```
#new data frame for predictions for MPSB-yes sites, majority soil group B
stnewdat<-data.frame(z.ravgrock=strockspred,pctbmaj=factor("Y",levels=c("N","Y")))
stpred.occ<- predict(smod1,type="state",newdata=stnewdat) #using predict function
stpred.occ #checking predictions

#new data frame for predictions for MPSB-no sites, NO majority soil group B
n.stnewdat<-data.frame(z.ravgrock=strockspred,pctbmaj=factor("N",levels=c("N","Y")))
n.stpred.occ<- predict(smod1,type="state",newdata=n.stnewdat) #using predict function
n.stpred.occ #checking predictions

#creating double plot of rock predictions
par(mfrow=c(2,1))
plot(stpred.occ[[1]] ~ rockspred, type = "l", lwd = 3, col = "blue", ylim = c(0,1),
    las = 1, ylab = "Pred. occurrence prob.", xlab = "", main="Majority Hydrologic Soil
Group B",cex.lab=1.6,cex.axis=1.6,font.lab=2,cex.main=1.5,frame=FALSE) #plotting
prediction occupancy probability versus rock score not-standardized
lines(rockspred, stpred.occ[,3], lty=2, lwd = 2) #upper and lower confidence intervals
lines(rockspred, stpred.occ[,4], lty=2, lwd = 2)

plot(n.stpred.occ[[1]] ~ rockspred, type = "l", lwd = 3, col = "blue", ylim = c(0,1),
    las = 1, ylab = "Pred. occurrence prob.", xlab = "Rock Score", main="Majority Other
Hydrologic Soil
Group",cex.lab=1.6,cex.axis=1.6,font.lab=2,cex.main=1.5,frame=FALSE) #plotting
prediction occupancy probability versus rock score not-standardized
lines(rockspred, n.stpred.occ[,3], lty=2, lwd = 2)
lines(rockspred, n.stpred.occ[,4], lty=2, lwd = 2) #upper and lower confidence intervals
par(mfrow=c(1,1))

#for detection side
depths=seq(0.1,5,length.out = 58)
depths=log(depths)
stdepthpred=stdize(depths)
depthpred=depths #non-standardized data to show plot relationship better

mean(stdepthpred) #checking standardizations
sd(stdepthpred)

secs=seq(300,3300,length.out = 58)
secs=log(secs)
stsecpred=stdize(secs)
secpred=secs #non-standardized data to show plot relationship better

mean(stsecpred) #checking standardizations
sd(stsecpred)
```

```
#depth predictions, canoe reference
dnewdat1=data.frame(depth=stdepthpred,sec=0,gear_type=factor("C",levels=c("C","BP"
)),trap=factor("1",levels=c("1","0")))
pred.det1<- predict(smod1,type="det",newdata=dnewdat1)
pred.det1

#depth predictions, backpack reference
dnewdat2=data.frame(depth=stdepthpred,sec=0,gear_type=factor("BP",levels=c("C","BP
")),trap=factor("1",levels=c("1","0")))
pred.det2<- predict(smod1,type="det",newdata=dnewdat2)
pred.det2

#depth plot
par(mfrow=c(2,1))
plot(pred.det1[[1]] ~ depthpred, type = "l", lwd = 2, col = "blue", ylim = c(0,1),
    las = 1, ylab = "Pred. detection prob.", xlab = "",main="Canoe
Gear",cex.lab=1.6,cex.axis=1.6,font.lab=2,cex.main=1.5,frame=FALSE) #plotting
prediction detection probability versus log-transformed depth, not-standardized
lines(depthpred, pred.det1[,3], lty=2, lwd = 2) #upper and lower confidence intervals
lines(depthpred, pred.det1[,4], lty=2, lwd = 2)

plot(pred.det2[[1]] ~ depthpred, type = "l", lwd = 3, col = "blue", ylim = c(0,1),
    las = 1, ylab = "Pred. detection prob.", xlab = " Log Max Depth (m)",main="Backpack
Gear",cex.lab=1.6,cex.axis=1.6,font.lab=2,cex.main=1.5,frame=FALSE) #plotting
prediction detection probability versus log-transformed depth, not-standardized
lines(depthpred, pred.det2[,3], lty=2, lwd = 2) #upper and lower confidence intervals
lines(depthpred, pred.det2[,4], lty=2, lwd = 2)
par(mfrow=c(1,1))

#seconds predictions, canoe reference
snewdat1=data.frame(depth=0,sec=stsecpred,gear_type=factor("C",levels=c("C","BP")),t
rap=factor("1",levels=c("1","0")))
pred.det.s1<- predict(smod1,type="det",newdata=snewdat1)
pred.det.s1

#seconds predictions, backpack reference
snewdat2=data.frame(depth=0,sec=stsecpred,gear_type=factor("BP",levels=c("C","BP"))
,trap=factor("1",levels=c("1","0")))
pred.det.s2<- predict(smod1,type="det",newdata=snewdat2)
pred.det.s2
```

```
#seconds plot
par(mfrow=c(2,1))
plot(pred.det.s1[[1]] ~ secpred, type = "l", lwd = 3, col = "blue", ylim = c(0,1),
     las = 1, ylab = "Pred. detection prob.", xlab = "",main="Canoe Gear",cex.lab=1.6,cex.axis=1.5,font.lab=2,cex.main=1.5,frame=FALSE) #plotting prediction detection probability versus log-transformed seconds, not-standardized
lines(secpred, pred.det.s1[,3], lty=2, lwd = 2) #upper and lower confidence intervals
lines(secpred, pred.det.s1[,4], lty=2, lwd = 2)

plot(pred.det.s2[[1]] ~ secpred, type = "l", lwd = 3, col = "blue", ylim = c(0,1),
     las = 1, ylab = "Pred. detection prob.", xlab = "Log Effort",main="Backpack Gear",cex.lab=1.5,cex.axis=1.6,font.lab=2,cex.main=1.5,frame=FALSE) #plotting prediction detection probability versus log-transformed seconds, not-standardized
lines(secpred, pred.det.s2[,3], lty=2, lwd = 2) #upper and lower confidence intervals
lines(secpred, pred.det.s2[,4], lty=2, lwd = 2)
par(mfrow=c(1,1))
```

Appendix IX.6. Relative Abundance Model Code

```
rm(list=ls(all=TRUE))

#loading necessary packages
library(readxl)
library(usdm)
library(MuMIn)

#setting working directory
setwd("~/Tallapoosa_Project_R")
setwd("C:/Users/malam/OneDrive/Documents/Tallapoosa_Project_R")

#reading in data for counts covariates
TalInfo<- read_excel("TallapoosaModelRData.xlsx", sheet = "Tallapoosa")
TalData<- as.data.frame(TalInfo)

#checking variables for skew
hist(TalData$area)
TalData$area=log(TalData$area)
hist(TalData$area) #transformation helps

hist(TalData$transgradient)
TalData$transgradient=log(TalData$transgradient)
hist(TalData$transgradient) #transformation only flips the skew

hist(TalData$depth)
TalData$depth=log(TalData$depth)
hist(TalData$depth) #transformation helps

hist(TalData$pl)
TalData$pl=log(TalData$pl+1) #small constant for zero values
hist(TalData$pl) #transformation helps

hist(TalData$dished)
TalData$dished=log(TalData$dished)
hist(TalData$dished) #transformation helps

hist(TalData$sec)
TalData$sec=log(TalData$sec)
hist(TalData$sec) #transformation helps

hist(TalData$rock) #no transformation needed
```

```
#read in the data again with dummy-coded categorical variables to check correlations again
catpoisson<- read_excel("TallapoosaModelRData.xlsx", sheet = "catpoisson")
#check correlations first for reference
cor(catpoisson[1:12])
#transform necessary variables
catpoisson$area=log(catpoisson$area)
catpoisson$depth=log(catpoisson$depth)
catpoisson$pl=log(catpoisson$pl+1)
catpoisson$sec=log(catpoisson$sec)
catpoisson$dished=log(catpoisson$dished)

#turning data into dataframe
catpoisson=as.data.frame(catpoisson)
#checking correlations
cor(catpoisson[1:12])
vif(catpoisson[1:12])
#transgradient is now highly correlated with area, transform gradient to recheck relationship
catpoisson$transgradient=log(catpoisson$transgradient)
#recheck correlations
cor(catpoisson[1:12])
vif(catpoisson[1:12])
#geartype is highly correlated with area, remove geartype and try again
cor(catpoisson[c(1:8,10:12)])
vif(catpoisson[c(1:8,10:12)])
#all variables now look safe, nothing too highly correlated


####Loading in data for model code####
TalInfo<- read_excel("TallapoosaModelRData.xlsx", sheet = "Tallapoosa")
TalData<- as.data.frame(TalInfo)
library(glmmTMB)
#converting to factors so they don't standardize, make categorical variables factors
TalData$geartype=as.factor(TalData$geartype)
TalData$subbasin=as.factor(TalData$subbasin)
TalData$totaltalgen=as.factor(TalData$totaltalgen)
TalData$year=as.factor(TalData$year)
TalData$pctBmaj=as.factor(TalData$pctBmaj)
TalData$tempcat=as.factor(TalData$tempcat)

#checking distribution of count data
hist(TalData$totaltalgen,breaks=seq(-0.5,35,1)) #looks pretty overdispersed, probably negative binomial
```

```
#transforming necessary variables
TalData$area=log(TalData$area)
TalData$transgradient=log(TalData$transgradient)
TalData$pl=log(TalData$pl+1)
TalData$dished=log(TalData$dished)
TalData$depth=log(TalData$depth)
TalData$sec=log(TalData$sec)

#standardizing data
sdtaldata=stdize(TalData,binary="omit",center=TRUE,scale=TRUE)

#converting back to numeric for running model
sdtaldata$totaltalgen=as.numeric(as.character(sdtaldata$totaltalgen))

#checking distribution of count data
hist(sdtaldata$totaltalgen,breaks=seq(-0.5,35,1)) #looks pretty overdispersed, probably
negative binomial


#trying a model with negative binomial distribution
talabund3 <-
glmmTMB(totaltalgen~z.sec+z.depth+pctBmaj+z.pl+I(z.pl^2)+z.rock+z.area*z.dished+t
empcat+year+z.transgradient+I(z.transgradient^2)+(1|stream)+(1|subbasin),
zi=~z.rock+pctBmaj, sdtaldata, family=nbinom2)
summary(talabund3) #pl quadratic not important, remove. Interactions not considered to
save degrees of freedom

#Final variable list, full zi model
talabund3 <-
glmmTMB(totaltalgen~z.sec+z.depth+pctBmaj+z.pl+z.rock+z.area+z.dished+tempcat+y
ear+z.transgradient+I(z.transgradient^2)+(1|stream)+(1|subbasin), zi=~z.rock+pctBmaj,
sdtaldata, family=nbinom2)
summary(talabund3)

#checking nbinom1, not as good
talabund4 <-
glmmTMB(totaltalgen~z.sec+z.depth+pctBmaj+z.pl+z.rock+z.area+z.dished+tempcat+y
ear+z.transgradient+I(z.transgradient^2)+(1|stream)+(1|subbasin), zi=~z.rock+pctBmaj,
sdtaldata, family=nbinom1)
summary(talabund4)

AICc(talabund3,talabund4) #comparing AICc scores of nbinom models
summary(model.avg(talabund3,talabund4)) #not using for coefficients, but using to find
out delta AICc and model weight if the two models are considered together
```

```
#top model for all subsets analysis. no zi model due to convergence issues, will add back in later
talabundcat <- glmmTMB(totaltalgen~z.sec+z.depth+pctBmaj+z.pl+z.rock+z.area+z.dished+tempcat+year+z.transgradient+I(z.transgradient^2)+(1|stream)+(1|subbasin), sdtaldata, family=nbinom2)
summary(talabundcat)

#running the all-subsets analysis
abundmodcat<-dredge(talabundcat,rank=AICc)
abundmodcat
write.csv(abundmodcat,"abundmodcat.csv") #turning into csv for ease of organizing

#adding in zi formula to all top models within 2 AICc units
tab1 <- glmmTMB(totaltalgen~z.sec+z.rock+z.dished+pctBmaj+z.transgradient+I(z.transgradient^2)+z.depth+z.pl+(1|stream)+(1|subbasin), sdtaldata, family=nbinom2, zi=~z.rock+pctBmaj)
summary(tab1)

tab2 <- glmmTMB(totaltalgen~z.sec+z.rock+z.dished+pctBmaj+z.transgradient+I(z.transgradient^2)+tempcat+z.depth+z.pl+(1|stream)+(1|subbasin), sdtaldata, family=nbinom2, zi=~z.rock+pctBmaj)
summary(tab2)

tab3 <- glmmTMB(totaltalgen~z.sec+z.rock+z.dished+pctBmaj+z.transgradient+I(z.transgradient^2)+z.pl+(1|stream)+(1|subbasin), sdtaldata, family=nbinom2, zi=~z.rock+pctBmaj)
summary(tab3)

tab4 <- glmmTMB(totaltalgen~z.sec+z.rock+z.dished+pctBmaj+z.transgradient+I(z.transgradient^2)+(1|stream)+(1|subbasin), sdtaldata, family=nbinom2, zi=~z.rock+pctBmaj)
summary(tab4)

tab5 <- glmmTMB(totaltalgen~z.sec+z.rock+z.dished+pctBmaj+z.transgradient+I(z.transgradient^2)+year+z.depth+z.pl+(1|stream)+(1|subbasin), sdtaldata, family=nbinom2, zi=~z.rock+pctBmaj)
summary(tab5)
```

```
tab6 <-
glmmTMB(totaltalgen~z.sec+z.rock+z.dished+pctBmaj+z.transgradient+I(z.transgradient^2)+z.area+z.depth+z.pl+(1|stream)+(1|subbasin), sdtaldata, family=nbinom2, zi=~z.rock+pctBmaj)
summary(tab6)

tab7 <-
glmmTMB(totaltalgen~z.sec+z.rock+z.dished+pctBmaj+z.depth+z.pl+(1|stream)+(1|subbasin), sdtaldata, family=nbinom2, zi=~z.rock+pctBmaj)
summary(tab7)

tab8 <-
glmmTMB(totaltalgen~z.sec+z.rock+z.dished+pctBmaj+z.area+z.depth+z.pl+(1|stream)+(1|subbasin), sdtaldata, family=nbinom2, zi=~z.rock+pctBmaj)
summary(tab8)

tab9 <-
glmmTMB(totaltalgen~z.sec+z.rock+z.dished+pctBmaj+z.area+z.pl+(1|stream)+(1|subbasin), sdtaldata, family=nbinom2, zi=~z.rock+pctBmaj)
summary(tab9)

#generating model selection table for top models
modelscat<- model.sel(tab1,tab2,tab3,tab4,tab5,tab6,tab7,tab8,tab9,rank=AICc)
modelscat

#generating model selection table for top models within 2 AICc units, 6 and 8 discarded due to now being >2AICc units
modelscat<- model.sel(tab1,tab2,tab3,tab4,tab5,tab7,tab9,rank=AICc)
modelscat

#averaging all top models to obtain model coefficients, 6 and 8 discarded
abundavgcat<- model.avg(tab1,tab2,tab3,tab4,tab5,tab7,tab9,rank=AICc)
summary(abundavgcat)
print(abundavgcat)

#confidence intervals
ests=abundavgcat$coefficients[1,] #full coefficients from the average
SEs=c(1.04,0.13,0.13,0.18,1.01,0.28,0.14,0.13,0.13,3.54,2.50,2.86,0.26,0.25,0.12) #SEs from the abund avg output
uppers=ests+1.96*SEs #upper confidence interval
lowers=ests-1.96*SEs #lower confidence interval
CIS=cbind(lowers,ests,uppers,SEs) #confidence intervals surrounding coefficient estimates
CIS
```