EVALUATION OF ELECTROFISHING FOR INDEXING FISH ABUNDANCE IN FLORIDA LAKES

By

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To my brother, Staff Sergeant Mark Hangsleben

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Abstract of Thesis Presented to the Graduate School
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Electrofishing catch per unit effort (CPUE) data are commonly used to index temporal trends in abundance in fish monitoring programs, but the reliability of this index requires the assumption that the fraction of fish stock caught per unit effort (catchability, *q*) is relatively precise and constant through time. A wide range of biological, environmental, and technical factors can affect catchability, potentially violating these assumptions. To understand if CPUE data can be used to index abundance through time for Florida lakes, I evaluated how electrofishing catchability varies temporally with different biotic and abiotic factors in five small lakes in north central Florida. I also evaluated the influence of variable electrofishing catchability on the ability of a monitoring program to detect a true change in abundance in response to a perturbation, such as could occur following changes in water levels or disruption to vegetation via hurricane using a simulation. Lastly, I evaluated the effect of submersed aquatic vegetation on mean electrofishing catchability using a series of hatchery ponds. Electrofishing catchability in the lakes study varied season, lake, and species. Catchability was higher but substantially more variable for largemouth bass *Micropterus salmoides* and lake chubsucker *Erimyzon sucetta* than for bluegill *Lepomis*

macrochirus. Catchability was highly variable between years in the same season for both largemouth bass and lake chubsucker in some of the lakes, which could preclude the use of CPUE as a reliable index of abundance. Catchability for bluegill was low but precise; indicating that electrofishing CPUE could monitor abundance for this species. Simulation results revealed that statistical power decreased and the Type-I error rate (i.e., the probability of detecting a difference when in fact no difference occurred) increased substantially if *q* varies through time as I observed for largemouth bass and lake chubsucker. Type-I error rates were well above the expected value of 0.05, reaching as high as 0.7 for largemouth bass and 0.6 for lake chubsucker at high sample sizes. This resulted because increasing sample size improves the ability to detect real changes, but also increases the probability of detecting spurious changes due to variable *q* (i.e., Type-I error). Thus, variable catchability hinders our ability to use CPUE data to index trends in fish abundance. Mean electrofishing catchability in the hatchery pond study showed no difference between the pond treatments, indicating that relatively high coverages of submersed aquatic plants had no substantial influence on average electrofishing catchability. Mean catchability was higher for largemouth bass than bluegill, similar to the lake results. Mean catchability was more variable for both largemouth bass and bluegill in ponds with abundant vegetation than in those with low aquatic plant abundance. This suggests that abundant vegetation does not influence average *q* values, but it does increase the variability in electrofishing catchability and thus could increase the uncertainty in CPUE data used to index fish abundance. These results indicated that variable electrofishing catchability hinders our ability to detect trends in abundance using CPUE data for two of the three species I evaluated. Further

research should evaluate the temporal variability in electrofishing catchability and explore alternate sampling methods and data sources for their reliability for monitoring fishery trends.

CHAPTER 1

INTRODUCTION

Fish monitoring programs often seek to assess fish abundance and community composition. Most monitoring programs use catch data to evaluate temporal trends in fish community composition, and catch per unit effort (CPUE) data are often used as an index of abundance for individual fish species. The validity of using CPUE to index abundance relies on assuming a constant and linear relationship between CPUE and abundance as per (Harley et al. 2001):

$$CPUE = \frac{C}{E} = q \times N \tag{1}$$

where C = catch, E = effort, q = catchability, and N = abundance. For this relationship to hold true, q has to be relatively precise and constant through time. By rearranging equation 1, catchability is defined as the fraction of a fish stock collected (capture probability, C/N) per unit effort:

$$q = \frac{C/N}{E} \tag{2}$$

Electrofishing is widely used in fisheries management to characterize fish communities, including estimates of relative abundance, community composition, and size/age structure (Reynolds 1996). Electrofishing CPUE is easily obtained and is probably the most widely used relative abundance index in freshwater systems. However, the assumption that electrofishing CPUE is an index of abundance relies on q being relative precise and constant through time. Zalewski and Cowx (1990) argue that factors affecting q can be placed into three categories: biological (e.g. fish size,

abundance, species, etc.), environmental (e.g. water clarity and temperature, substrate, aquatic plants, season, etc.), and technical (e.g. personnel and equipment), and each of these could influence the ability of CPUE data to index fish abundance.

Factors affecting electrofishing catchability are interrelated and their combined effects can be difficult to isolate. Nonetheless, studies have showed that electrofishing catchability is influenced by fish abundance (McInerny and Cross 2000; Schoenebeck and Hansen 2005), habitat (Simpson 1978; Price and Peterson 2010), water clarity (Kirkland 1962; Simpson 1978; Gilliland 1987), water temperature (Danzmann et al. 1991), power output (Miranda and Dolan 2003), and personnel (Hardin and Conner 1992). Fisheries agencies often standardize factors they can control such as power output, the number of personnel, and sampling season.

However, many of these factors are difficult to standardize (e.g. habitat and water clarity), influence catchability, and thus could influence effectiveness of CPUE data to monitor fish abundance. For example, electrofishing catchability has been shown to vary by species. For example, Price and Peterson (2010) found electrofishing capture efficiencies to vary by species in streams. Electrofishing catchability can also vary by the habitat preference of a species. For example fish species that are located in the littoral zone (e.g. bluegill *Lepomis macrochirus*) are more susceptible to electrofishing than species located in the limnetic zone (e.g. gizzard shad *Dorosoma cepedianum*). Fish size is another factor that has been shown to effect electrofishing (Dolan and Miranda 2003). Dolan and Miranda (2003) also suggested that many of the inconsistencies in electrofishing immobilization thresholds for species may be the result

of differences in body sizes. Fish species also exhibit season specific habitat use, which can affect electrofishing catchability.

Many monitoring programs standardize by season to make their catches less variable because fish species change habitats across seasons. For example, Mesing and Wicker (1986) showed that largemouth bass *Micropterus salmoides* in two Florida lakes moved to inshore areas to spawn, making them more susceptible to electrofishing. Coutant (1975) also showed that largemouth bass typically move to shallow water to spawn, but will move to deeper cooler water when temperatures exceed a certain threshold, making them less susceptible to electrofishing. Water temperatures also change by season and Danzmann et al. (1991) showed a positive relationship between catchability of largemouth bass and bluegill with water temperatures.

Other factors shown to affect electrofishing catchability are habitat characteristics (e.g., abundance of submersed vegetation, woody debris, etc.), which vary across water bodies. For example, water clarity can affect electrofishing CPUE for largemouth bass (Kirkland 1962; Simpson 1978; Gilliland 1987) and bluegill (Simpson 1978). Other studies have also linked water clarity with a change in fish habitat selection (Miner and Stein 1996). Simpson (1978) found that electrofishing *q* increased in ponds with cover relative to those devoid of cover. Price and Peterson (2010) also found that electrofishing capture efficiency for 50 stream dwelling species varied by habitat characteristics and habitat complexity. Abundance of aquatic macrophytes has also been shown to affect electrofishing catchability (Chick et al. 1999; Bayley and Austen 2002).

Understanding how *q* varies for a given set of conditions is important to understanding whether CPUE can reliably index fish abundance. An ability to reliably index fish abundance is a key tool to assess fish population responses to management actions such as changes in harvest regulations or unplanned actions such as nonnative species introductions. The purpose of this study was to evaluate how electrofishing catchability may vary for fishes in Florida lakes. I hypothesized electrofishing catchability would vary by species, season, presence of aquatic vegetation, and water body (i.e., differences in depth, water clarity, etc.). Thus, my objectives were to 1) evaluate how *q* varied across lakes that differed in habitat characteristics, within and between seasons for three different fish species, 2) evaluate how *q* varied with the presence or absence of abundant submersed vegetation using a hatchery pond experiment, 3) evaluate the effects of the observed variation in *q* on the ability to monitor abundance in fish stocks with CPUE data from boat electrofishing.

CHAPTER 2
METHODS

Objective 1: Variation in *q* Across Lakes and Seasons for Different Fish Species

I used five Florida lakes for objective 1, to evaluate how electrofishing catchability varied by season and species. None of these lakes had high coverages of submersed aquatic macrophytes, so objective 2 was addressed with a separate pond study. The lakes used for objective 1 ranged in size from 3.6 to 21 ha, mean depth from 1.86 to 4.64 m and average secchi depth from 0.98 to 5.23 m (Table 2-1). Average width of floating and emergent vegetation ranged from 5.8 to 17.1 m, percent area coverage (PAC) ranged from 21 to 66 percent, and percent volume inhabited (PVI) ranged from 4.8 to 18 percent (Table 2-1). Average emergent plant biomass ranged from 1.2 to 6.35-kg wet weight/m^2, average floating-leaved plant biomass ranged from 0.01 to 4.64-kg wet weight/m^2, and average submersed plant biomass ranged from 0.1 to 3.51-kg wet weight/m^2 (Table 2-1). All plant species observed while sampling in each transect were listed according to the frequency that they occurred (Appendix A). All aquatic vegetation sampling took place July 27-29, 2010 and followed Florida LAKEWATCH aquatic plant sampling procedures (Florida LAKEWATCH 2009).

My approach to estimate *q* was to establish marked fish populations in all lakes, and then conduct standardized electrofishing using Florida Fish and Wildlife Commission (FWC) protocols (Bonvechio 2009) to obtain estimates of catchability for each species. Marked populations of fish were established in each lake using electrofishing and angling. Marking events were done with a 4.88-m aluminum boat equipped with a Smith Root VIA generator powered pulsator (GPP), one boom with eight droppers made of ¼-inch stainless steel cable, and 1-2 netters. All species were

identified and measured for total length (TL) to the nearest millimeter (mm). Largemouth bass greater than 249-mm TL received a passive integrated transponder (PIT) tag and a right pelvic fin clip (RP2). Largemouth bass were PIT tagged in the abdominal cavity following the procedure developed by Harvey and Campbell (1989). Largemouth bass between 100-mm and 249-mm TL received a left pelvic fin clip (LP2). Bluegill and lake chubsucker *Erimyzon sucetta* greater than 49-mm TL received a LP2 clip.

I estimated short-term tagging mortality for each size group to adjust the marked population available for recapture. Subsamples of fish from each 50-mm length group were placed in holding pens. Holding pens consisted of a PVC rectangular frame measuring 3.0 m by 1.25 m. The mesh measured 19.3-mm stretched and extended a depth of approximately 1.5 m. Fish were held for 48 h and then evaluated for mortality. Tagging mortality was estimated for each cage replicate as the number of fish dead at the end of the experiment divided by the total number of fish found alive at the end of the experiment. Mean tagging mortality and associated confidence intervals were obtained using 1,000 nonparametric bootstrap simulations, resampling the mortality estimates of the cage replicates with replacement using Poptools software (Hood 2009). Confidence intervals were approximated as the 2.5 and 97.5 percentile of the bootstrap samples.

Electrofishing catchability was measured during recapture events that were conducted following FWC sampling program protocols. Recapture trips were conducted two times in fall (early December) of 2009, spring (February-March), and summer (June) and three times in fall of 2010 and then in the spring of 2011. Catchability was

not evaluated in three of the lakes in the fall of 2009 due to lower numbers of marked fish, as the project was just underway. Electrofishing was done using a 5.5-m boat equipped with a Smith Root 9.0 GPP, two booms with eight droppers made from ¼-inch stainless steel cable, and two netters. A recapture event was defined as one circle around the entire perimeter of each lake, broken down into 600-second transects to mimic FWC protocol. Catchability was measured using only marked fish, but unmarked fish captured during recapture events were also marked for future recapture events. Electrofishing power settings and driving pattern followed FWC's standardized sampling manual for lentic systems (Bonvechio 2009). Catchability for each recapture event was calculated for the entire lake by taking the number of recaptures (*R*) divided by the total number of marks available (M_a), multiplying by the area (*A*) of the lake per 10 ha, then dividing by the effort (*E*) in hours (M. Lauretta, University of Florida, personal communication):

$$q = \frac{R \times A}{M_a \times E} \tag{3}$$

Equation 3 corrects values of *q* for lake size and sampling effort, such that they were comparable across lakes.

Because this study spanned about two years, it was important to correct the number of tagged fish available for natural mortality between mark and recapture events. Expected rates of natural mortality were used to adjust marks available through time following Lorenzen (2000), which predicts natural mortality to decrease with fish length as:

$$M_l = M_r \left(\frac{l}{l_r}\right)^c \tag{4}$$

where M_l is the instantaneous natural mortality rate at length l, M_r is the instantaneous natural mortality rate at reference length l_r, and c is the allometric exponent of the mortality-length relationship. I set the allometric exponent of the mortality-length relationship (c) to -0.4 (Gwinn and Allen 2010), which causes a gradual decline in natural mortality with fish length. Reference mortalities for largemouth bass and bluegill were obtained from the literature for Florida systems (Renfro et al. 1997; Crawford and Allen 2006). Reference lengths were also obtained from the literature and were based on the age of fish used in the mortality estimates and the length at age of fish in the study lakes (Canfield and Hoyer 1992). Each species was separated into two length groups based on natural breaks in length frequency data. Natural mortality (M_l) for each length group was calculated using median lengths (l) from each length group and reference values (summarized in Table 2-2).

Only one previous study has estimated instantaneous total natural mortality for lake chubsucker (Winter 1984). I suspected that their mortality estimates measured in Nebraska would not be appropriate for lake chubsucker populations in Florida, and thus I obtained an empirical estimate from fish at my study lakes. Lake chubsucker instantaneous natural mortality was obtained using a linear regression model developed by Hoenig (1983 cited by Hewitt and Hoenig 2005):

$$ln(M) = 1.44 - 0.982 \times ln(t_{max}) \quad (5)$$

where M is the instantaneous natural mortality rate and t_{max} is the maximum age observed. Because Eberts et al. (1998) showed no significant difference in length at age between male and female lake chubsucker, maximum age was obtained by taking sagittal otoliths from a sample of the largest lake chubsucker captured from each lake.

Sectioned otoliths were aged by two readers and disagreements were evaluated by a third reader. The maximum age was used in equation 5 to obtain an estimate of natural mortality which was used with the mean length of lake chubsucker from all lakes as the reference values in equation 4 (Table 2-2).

I evaluated the effects of lake, season, and species on catchability with a logistic model formulated as:

$$logit(q) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_i x_i \qquad (6)$$

where q is the catchability, β_0 is the intercept, $\beta_{1\ldots i}$ is the slope of the variable of interest and $x_{1\ldots i}$ is the variable of interest (e.g., lake type). My catch data conformed to a negative binomial distribution, which explains catch data with a dispersion parameter k that is estimated when fitted to the data. The parameters $\beta_{1\ldots i}$ were estimated iteratively by maximizing the negative binomial log-likelihood function:

$$\mathrm{LL}(\mathrm{x}|\lambda, \mathrm{k}) = \frac{\Gamma(k+x)}{\Gamma(k)x!}\left(\frac{k}{k+\lambda}\right)^k \left(\frac{\lambda}{k+\lambda}\right)^x \qquad (7)$$

where k is the dispersion parameter, x is the observed catch (i.e., recaptures) and λ is the predicted catch. Predicted catch λ was given by:

$$\lambda = \hat{q} \times E \times M_a \qquad (8)$$

where $\hat{q}$ is the predicted catchability from equation 6, E is the effort (hrs per 10 ha) and M_a is the adjusted number of marks available for each recapture event (adjusted for natural mortality).

To evaluate my hypothesis that electrofishing q varied by species, season, and lake I confronted my data with nine models: 1) null model where q is constant across all variables, models 2-5) q varies by single factors season, lake, year, or species, models 6-8) season by species interaction, lake by season interaction, and species by lake

interaction, and model 9) *q* varies by a season, lake and species interaction. Akaike's information criterion (AIC) was used to evaluate which model explained the observed variation in $\hat{q}$ the best (Akaike 1973, cited by Anderson 2008). Akaike's information criterion is given by:

$$\mathrm{AIC} = -2\mathrm{LL} + 2\mathrm{p} \tag{9}$$

where *p* is the number of estimated parameters in the model. Akaike's information criterion was used because it selects the most parsimonious model, considering the tradeoff between the variance explained by the model versus the number of parameters. Anderson (2008) suggested that models with ΔAIC values less then four have a lot of empirical support, and Bolker (2008) suggested that models with ΔAIC values less then two apart are essentially equivalent. Therefore, I considered models that had ΔAIC values close to zero and had ΔAIC values less than two apart and chose the model with fewest parameters. Model probabilities were also calculated for each model following Anderson (2008) and are conditional of the model set. If interaction models were chosen, I considered sub-models to evaluate the interactions.

Objective 2: Effects of Submersed Vegetation on *q*

Evaluating catchability in hatchery ponds allowed us to compare how *q* varies between ponds with abundant submersed vegetation and those with little to no vegetation. The lake study could not be used to evaluate the effects of vegetation on electrofishing catchability because submersed aquatic plant abundance was low and very similar among lakes (Table 2-1). Electrofishing catchability was evaluated for largemouth bass (100-470 mm TL) and bluegill (50-230 mm TL) in ten hatchery ponds approximately 0.4 hectares in size with a maximum depth of two meters. Ponds were

grouped into two categories, ponds with abundant vegetation (N=6) and ponds with little to no vegetation (N=4). The abundant-vegetation ponds had percent area coverage ranging from 50-95% of primarily hydrilla *Hydrilla verticillata*, where the low-vegetation ponds had little to no aquatic vegetation due to grass carp stocking. The abundant-vegetation ponds were electrofished three times in September of 2009 following the same recapture protocol as the lake sampling. The low-vegetation ponds were electrofished twice at the end of July 2010 following the same protocols. All species were identified and measured for total length to the nearest millimeter. Each pond was then drained to obtain true abundances for each fish species (see Allen et al. In Press for details of the pond draining). Observed catchability was estimated for each pond using equation 2. I compared the mean *q* for each species between the two groups of ponds to explore effects of submersed vegetation on the average catchability, as well as the variation in catchability.

Objective 3: Evaluating the Effects of Variable *q* on the Ability to Monitor Abundance in Fish Stocks with CPUE Data from Boat Electrofishing

I evaluated how the observed variation in *q* would influence the use of electrofishing CPUE data to detect changes in relative abundance with a simulation. This simulation is designed to inform resource managers how variable *q* affects statistical power and the Type-I error rate. I assumed that variability in *q* among the lakes and seasons from the small lakes study (objective 1) would approximate the variability expected in one lake over time. Because my lakes varied moderately in vegetation abundance, depth, and water clarity (Table 2-1, Appendix A), I felt this assumption was reasonable as it could approximate the variation in depth, water clarity,

and littoral habitat complexity that would occur with changes in water level and water chemistry though time.

The simulation estimated the expected statistical power and Type-I error rates when comparing CPUE between two blocks of years. Estimating the Type-I error rate, observe a change when a change has not occurred, and the statistical power, observe a change when one has occurred, is important to natural resource managers because it shows them with what probability they can detect a change of a certain size and with what probability that change is correct. To predict the Type-I error and statistical power I simulated multi-year datasets of electrofishing catch under the hypotheses of both constant and variable catchability. Catch was simulated as a random draw from a negative binomial distribution such that multiple draws for a given year would represent samples from multiple electrofishing transects. The negative binomial draws were expressed as:

$$C_n \sim nbin(q_y, \lambda, k)_{n=1\ldots N} \tag{10}$$

where q_y is the catchability in year y, λ is the expected average catch, and k is the negative binomial dispersion parameter that influences the variation in C_n across replicate samples ($n = 1\ldots N$). Higher values of k decrease the variation among multiple draws and vice versa, allowing me to mimic common among-transect variation in electrofishing catches of fish for Florida lakes. Variation in q among years was simulated by drawing a separate value of q_y from a beta distribution parameterized to mimic the predicted variability in q from the best AIC model from the small lakes study (objective 1).

Parameter inputs for the simulation were the expected average catch λ, the shape parameters of the beta distribution (a and b), and the negative binomial dispersion parameter k. I set λ and k to 500 and 1, respectively. I chose these values because they produced catches similar to what you would expect from electrofishing catch data in Florida. I set the shape parameters of the beta distribution to values that would produce similar coefficients of variation to the q values predicted by equation 6 for each species.

To evaluate the ability of a monitoring program to detect a change in abundance in response to a perturbation, such as could occur following water level changes and/or disruption to vegetation, I induced a 100% (doubling) increase in the population for the second half of the simulated blocks of years of the dataset. I compared the average catch pre- and post- change for each dataset with a two tailed t-test with equal variance to determine the probability that the 100% increase in the population would be detected (i.e., statistical power). I repeated this analysis with zero change in the population between blocks of years to determine with what probability a spurious change in relative abundance would be detected (i.e., Type-I error rate). A test was considered significant if the α value was less than 0.05. I evaluated the effects of evaluating pre- and post-evaluation periods of 3, 5, and 10 years with sample sizes (i.e., electrofishing transects) ranging from six to 90. The analysis was repeated on 1,000 simulated datasets to evaluate the influence of variable catchability on statistical power and Type-I error rates.

Table 2-1. Size, mean depth, average secchi depth, average width of emergent and floating leaved zone, percent area coverage and volume infested, and average emergent, floating-leaved, and submersed biomass in each of the five lakes sampled.

Lake	Size (ha)	Average depth (m)	Average secchi depth (m)	Average width of emergent and floating-leaved zone (m)	Percent area covered	Percent volume infested	Average emergent plant biomass (kg wet wt/m^2)	Average floating-leaved plant biomass (kg wet wt/m^2)	Average submersed plant biomass (kg wet wt/m^2)
Devils Hole	11.5	4.64	4.48	10.60	66.4	4.8	6.35	4.24	3.51
Speckled Perch	12.6	1.86	1.57	9.20	21.0	7.4	2.27	1.64	0.77
Big Fish	3.0	3.25	3.02	4.10	28.2	1.7	0.76	0.03	3.49
Keys Pond	3.6	2.92	2.90	5.80	39.6	5.2	1.20	0.01	0.60
Johnson's Pond	20.8	2.45	0.98	17.10	36.9	18.0	5.31	4.64	0.10

Table 2-2. Instantaneous natural mortality rates for each species and length group with reference values and lengths used to correct for the number of tags present at each sampling event.

Species	Length group (mm)	Median length (mm)	M	Reference M	Reference length (mm)
Bass	100-249	145	0.71	0.52 for ages 3-6 (Renfro et al. 1997)	325 for age 4-5 (Canfield and Hoyer 1992)
	250+	325	0.53		
Bluegill	50-149	80	0.71	0.5 for ages 2-6 (Crawford and Allen 2006)	195 for age 4 (Canfield and Hoyer 1992)
	150+	170	0.52		
Lake chubsucker	50-209	125	0.86	0.62 *	275 *
	210+	290	0.61		

*Estimated in this study

CHAPTER 3
RESULTS

Objective 1: Variation in *q* Across Lakes and Seasons for Different Fish Species

Extensive effort (i.e., over 25 electrofishing boat trips per lake) was exerted to establish marked populations of each species at each lake (Table 3-1). Total unadjusted number of marked and recaptured fish from both marking and recapture events varied by lake, with more fish marked and recaptured in the large lakes (Table 3-2). Lake chubsucker was not collected at Big Fish Lake, and very few were marked at Johnson Pond (Table 3-2).

Tagging mortality was negligible for largemouth bass, lake chubsucker, and large bluegill. No lake chubsucker or large bluegill died in cage experiments and very few bass died resulting in tagging mortalities of 1% or less. Tagging mortality for bluegill 50-100 mm and 101-150 mm in length averaged 19 % and 2 % respectively. Thus, only bluegill less than 150 mm were corrected for short term tagging mortality.

My analysis of lake chubsucker otoliths indicated that the maximum age of lake chubsucker was seven years. Using equation 4 and this maximum age obtained from the sectioned otoliths, I estimated total instantaneous natural mortality (*M*) at 0.62 for lake chubsucker. This estimate was used as the reference mortality in equation 3. The instantaneous natural mortality rate for each length group was 0.86 for lake chubsucker between 50-209 mm and 0.61 for lake chubsucker greater than 210 mm. Natural mortality rates used for largemouth bass and bluegill are shown in Table 2.

Akaike's information criterion indicated that the variation in electrofishing catchability in the lake study was best explained by the species, season, lake interaction model (Table 3-3) with a model probability of 0.99, indicating that the three way

interaction model had substantially more support than any other model. This model indicated that *q* varied significantly among species, seasons, and lakes but that the differences were not consistent across the levels of each treatment. The species and lake interaction model had marginal support with a ΔAIC value of 8.5; however, all the other models had very little support (i.e., ΔAIC >10, Table 3-3).

To dissect this three-way interaction of species, season, and lake, I evaluated how *q* varied among season and lake for each species. Although the season and lake interaction model had the lowest ΔAIC value for largemouth bass; the lake model had substantial support with a ΔAIC value of 1.89 (Table 3-4, Figure 3-1). Because a ΔAIC < 2 indicates that the models are essentially equivalent, I selected the model that included only the lake variable (fewer parameters), as the best model to explain how *q* varied for largemouth bass. All other models for largemouth bass had very little support (i.e., ΔAIC > 10). Electrofishing catchability varied substantially across lakes for largemouth bass, with Devils Hole and Big Fish Lakes having the lowest *q* values and Johnson Pond the highest (Figure 3-1).

The season model and the season x lake interaction model both had substantial support for explaining how *q* varied for lake chubsucker (ΔAIC = 0.00 and 0.03, respectively, Table 3-5, Figure 3-2). I selected the model including only season as a variable because it has the lowest number of parameters. Thus, electrofishing catchability for lake chubsucker varied by season. Lake chubsucker *q* values were marginally higher in spring than in the other seasons (Figure 3-2), but also exhibited high variability similar to the largemouth bass data. All other models for lake chubsucker had marginal support.

The null model had the most support for bluegill (Table 3-6), which indicated that *q* did not vary among lakes and seasons for bluegill (Figure 3-3). Values of *q* were consistently low across all lakes for bluegill (Figure 3-3) and did not vary with lake or season. Thus, my results showed differences in catchability among the species with largemouth bass varying by lake, lake chubsucker varying by season and bluegill catchability as constant across seasons and lakes.

Objective 2: Effects of Submersed Vegetation on *q*

My evaluation of the effects of submersed vegetation on catchability corroborated the results of my AIC model selection because mean electrofishing catchability was greater and more variable for largemouth bass than for bluegill (Figure 3-4). Mean electrofishing catchability for largemouth bass and bluegill was slightly higher in ponds with abundant vegetation than in ponds with little to no vegetation (Figure 3-4); however, 95% confidence intervals overlapped. Additionally, the 95% confidence interval for catchability for both species in ponds with abundant vegetation was much larger than in ponds with little to no vegetation. This indicated that catchability for largemouth bass and bluegill was more variable in ponds with abundant vegetation than in those with scarce plants. Thus, submersed aquatic vegetation tended to affect the variability of electrofishing catchability but did not influence the mean *q* values.

Objective 3: Evaluating the Effects of Variable *q* on the Ability to Monitor Abundance in Fish Stocks with CPUE Data from Boat Electrofishing

Simulations were only run for largemouth bass and lake chubsucker because the best model for bluegill was the null model where *q* was constant across seasons and lakes. Because catchability is constant for bluegill Type-I error rates will not increase and statistical power will increase with sample size. Furthermore, constant *q* infers that

electrofishing CPUE could be used to index abundance for bluegill; although given the low *q* values obtaining adequate sample size for size/age information could be more difficult for bluegill than for largemouth bass and lake chubsucker. Sample size (i.e., number of electrofishing transects) and the number of sample years influenced the reliability of CPUE data to index largemouth bass and lake chubsucker abundance. Variable catchability affected the ability to detect changes in abundance by reducing the probability of detecting a real change (i.e., statistical power) and by increasing the probability of detecting a spurious change (i.e., Type-I error rate; Figures 3-5 and 3-6). This pattern was true for both largemouth bass and lake chubsucker, however, there was a higher increase in Type-I error rate for largemouth bass. For example, the highest α realized for largemouth bass under variable *q* was approximately 70% (Figure 3-5) where the highest α realized for lake chubsucker under variable *q* was approximately 55% (Figure 3-6). My model inputs resulted in a coefficient of variation of *q* of 58% for largemouth bass and a coefficient of variation of *q* of 28% for lake chubsucker. Thus, the higher the levels of variation in catchability results in a higher Type-I error rate.

Increased sample size increased both statistical power and Type-I error rate; whereas the number of years pre- and post-perturbation influenced statistical power (Figures 3-5 and 3-6). For example, Type-I error rates for largemouth bass increased from approximately 15% at small sample sizes to approximately 70% for very large sample sizes when comparing between two years (Figure 3-5). Type-I error rates remained unchanged as the number of years compared increased (Figure 3-5). Conversely, statistical power for largemouth bass increased when sample size

increased but also increased as the number of years compared increased (Figure 3-5). Thus, with the variability in catchability I observed, increasing sample size for a given year will improve statistical power but the probability of finding spurious differences in abundance (Type-I error) also increases substantially. Increasing the number of sample years increased the statistical power but had no influence on the Type-I error rate, meaning that more sample years improved the reliability of CPUE data for indexing abundance. Further simulations with a tenfold increase in the population increased statistical power but had no effect on the Type-I error rate. Thus, by increasing the size of the change to be detected the probability of seeing a change when one has not occurred does not decrease.

Table 3-1. Number of marking and recapture events with each gear type in each lake.

	Electrofishing		Angling
Lake	Marking events	Recapture events	Marking events
Devils Hole	15	14	7
Speckled Perch	16	14	2
Big Fish	17	12	5
Keys	17	12	5
Johnson's Pond	18	12	0

Table 3-2. Numbers of fish marked and recaptured with each gear type in each lake before adjusting for tagging and natural mortality.

		Electrofishing		Angling		Total	
Lake	Species	Marked	Recaptured	Marked	Recaptured	Marked	Recaptured
Devils Hole	Largemouth bass	838	233	59	24	897	257
	Bluegill	1,629	67	0	0	1,629	67
	Lake chubsucker	866	502	0	0	866	502
Speckled Perch	Largemouth bass	786	327	18	4	804	331
	Bluegill	1,574	73	0	0	1,574	73
	Lake chubsucker	535	276	0	0	535	276
Big Fish	Largemouth bass	419	137	18	3	437	140
	Bluegill	1,351	56	0	0	1,351	56
	Lake chubsucker	0	0	0	0	0	0
Keys	Largemouth bass	118	55	25	10	143	65
	Bluegill	1,236	42	3	0	1,239	42
	Lake chubsucker	549	316	0	0	549	316
Johnson's Pond	Largemouth bass	816	264	0	0	816	264
	Bluegill	1,701	29	0	0	1701	29
	Lake chubsucker	88	6	0	0	88	6

Table 3-3. Models used in all species AIC comparison, ΔAIC values, and model probabilities.

Model	Negative Loglikelihood	Parameters	AIC	Δ AIC	Wi
Species*season*lake	-382.75	10	785.50	0.00	0.99
Species*lake	-389.05	8	794.10	8.60	0.01
Species*season	-395.18	6	802.36	16.86	0.00
Species	-401.11	4	810.23	24.72	0.00
Lake*season	-445.37	8	906.74	121.24	0.00
Lake	-448.28	6	908.56	123.05	0.00
Season	-453.47	4	914.94	129.43	0.00
Year	-455.42	3	916.85	131.35	0.00
Null	-457.31	2	918.62	133.12	0.00

Table 3-4. Models used in largemouth bass AIC comparison, ΔAIC values, and model probabilities.

Model	Negative Loglikelihood	Parameters	AIC	Δ AIC	Wi
Season*lake	-157.24	8	330.48	0.00	0.72
Lake	-160.18	6	332.36	1.89	0.28
Season	-168.73	4	345.46	14.99	0.00
Null	-171.17	2	346.34	15.87	0.00

Table 3-5. Models used in lake chubsucker AIC comparison, ΔAIC values, and model probabilities.

Model	Negative Loglikelihood	Parameters	AIC	Δ AIC	Wi
Season	-116.62	4	241.24	0.00	0.50
Season*lake	-113.64	7	241.27	0.04	0.49
Null	-123.36	2	250.73	9.49	0.00
Lake	-120.65	5	251.30	10.06	0.00

Table 3-6. Models used in bluegill AIC comparison, ΔAIC values, and model probabilities.

Model	Negative Loglikelihood	Parameters	AIC	Δ AIC	Wi
Null	-103.49	2	210.98	0.00	0.64
Season	-103.04	4	214.09	3.11	0.13
Lake	-100.75	6	213.50	2.52	0.18
Season*lake	-100.09	8	216.18	5.20	0.05

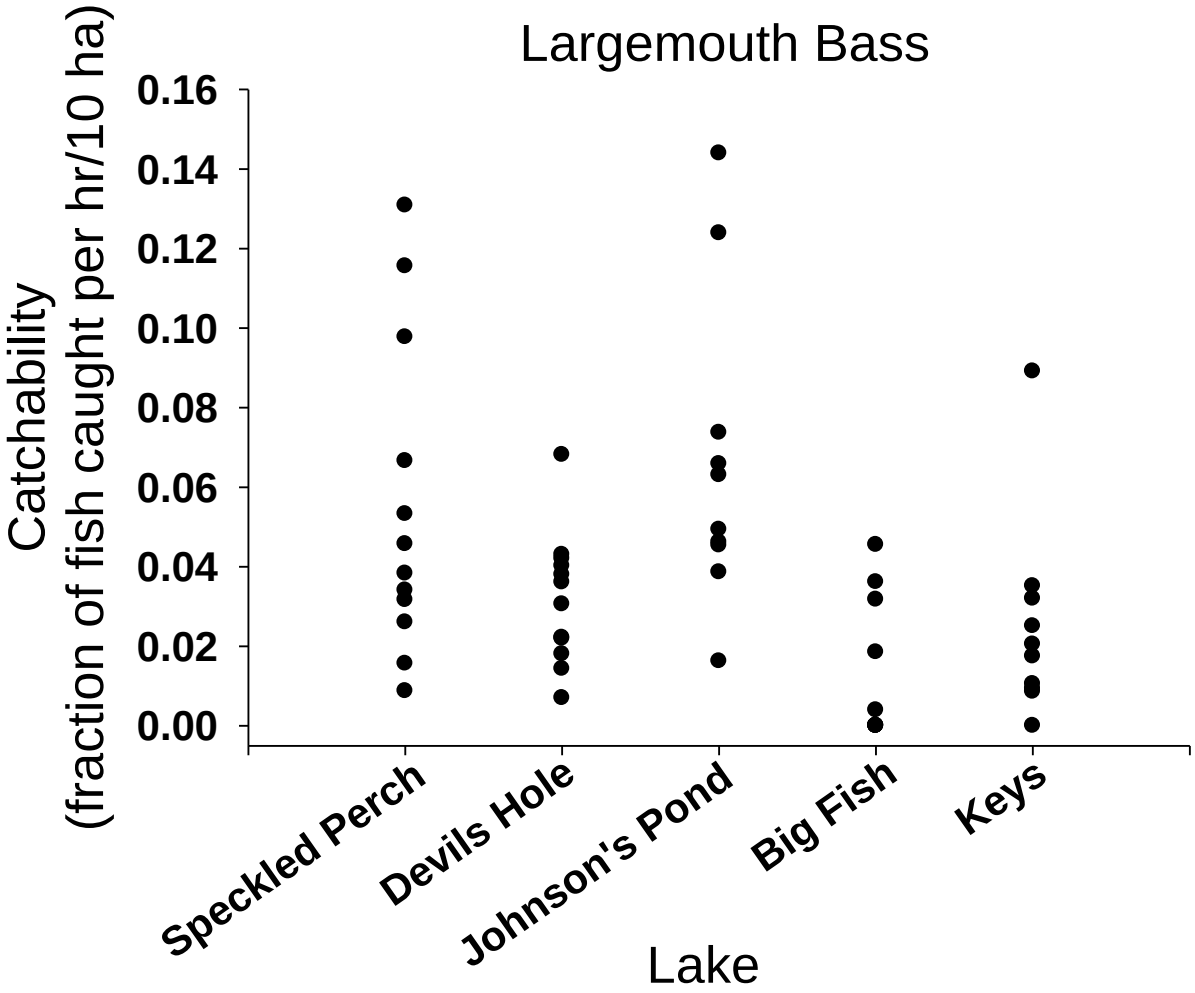

Figure 3-1. Observed catchability (fraction of fish caught per unit effort) for largemouth bass in Lakes Speckled Perch, Devils Hole, Johnson's Pond, Big Fish, and Keys.

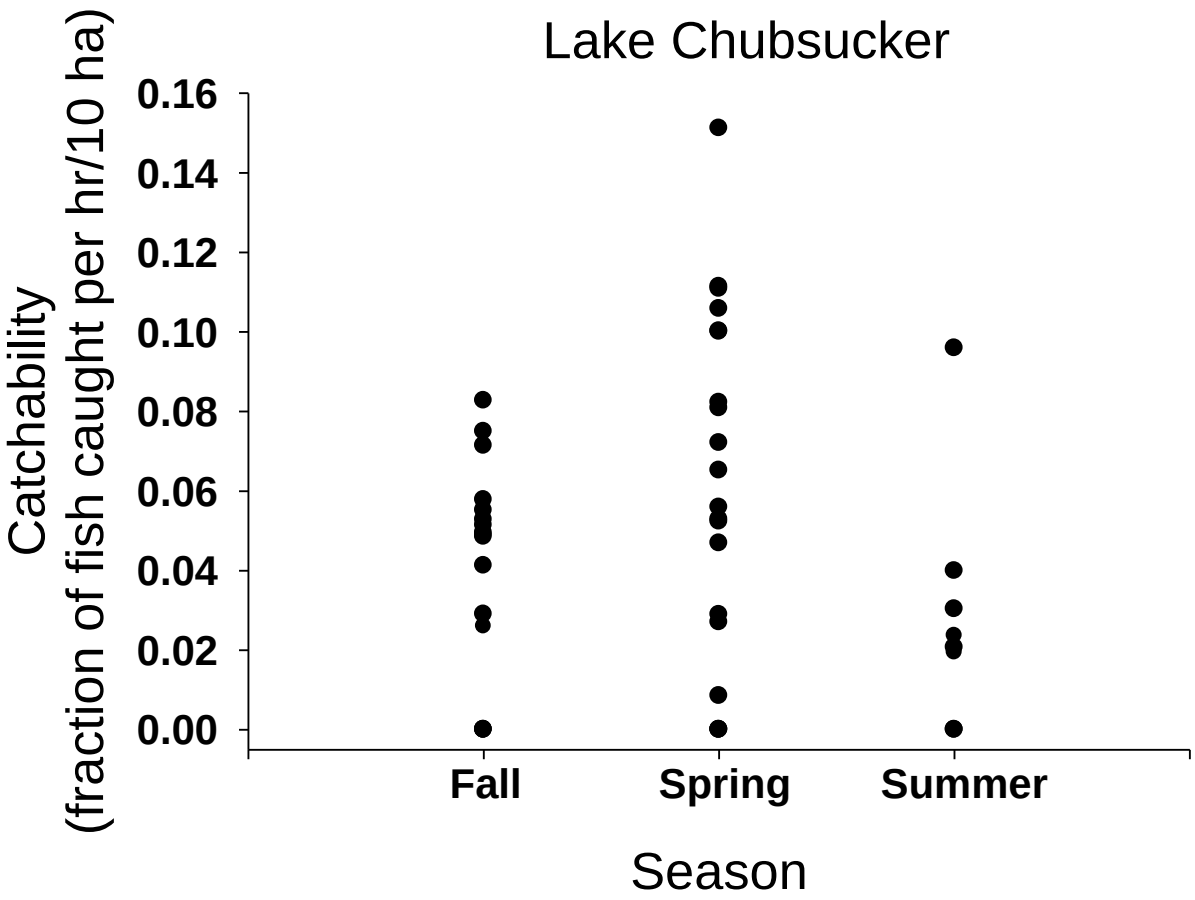

Figure 3-2. Observed catchability (fraction of fish caught per unit effort) for lake chubsucker during the fall, spring and summer recapture events.

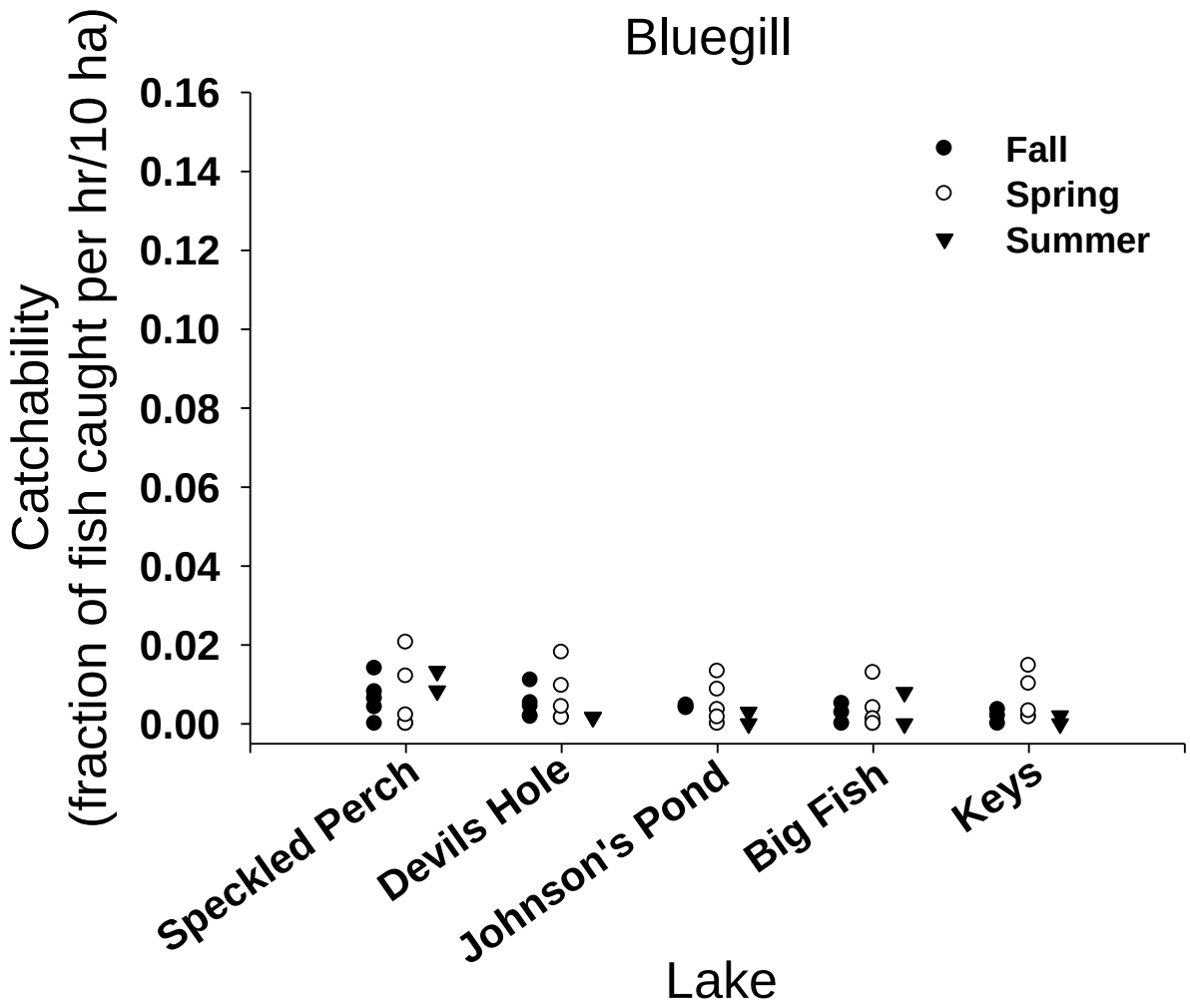

Figure 3-3. Observed catchability (fraction of fish caught per unit effort) for bluegill in each lake during fall, spring, and summer recapture events.

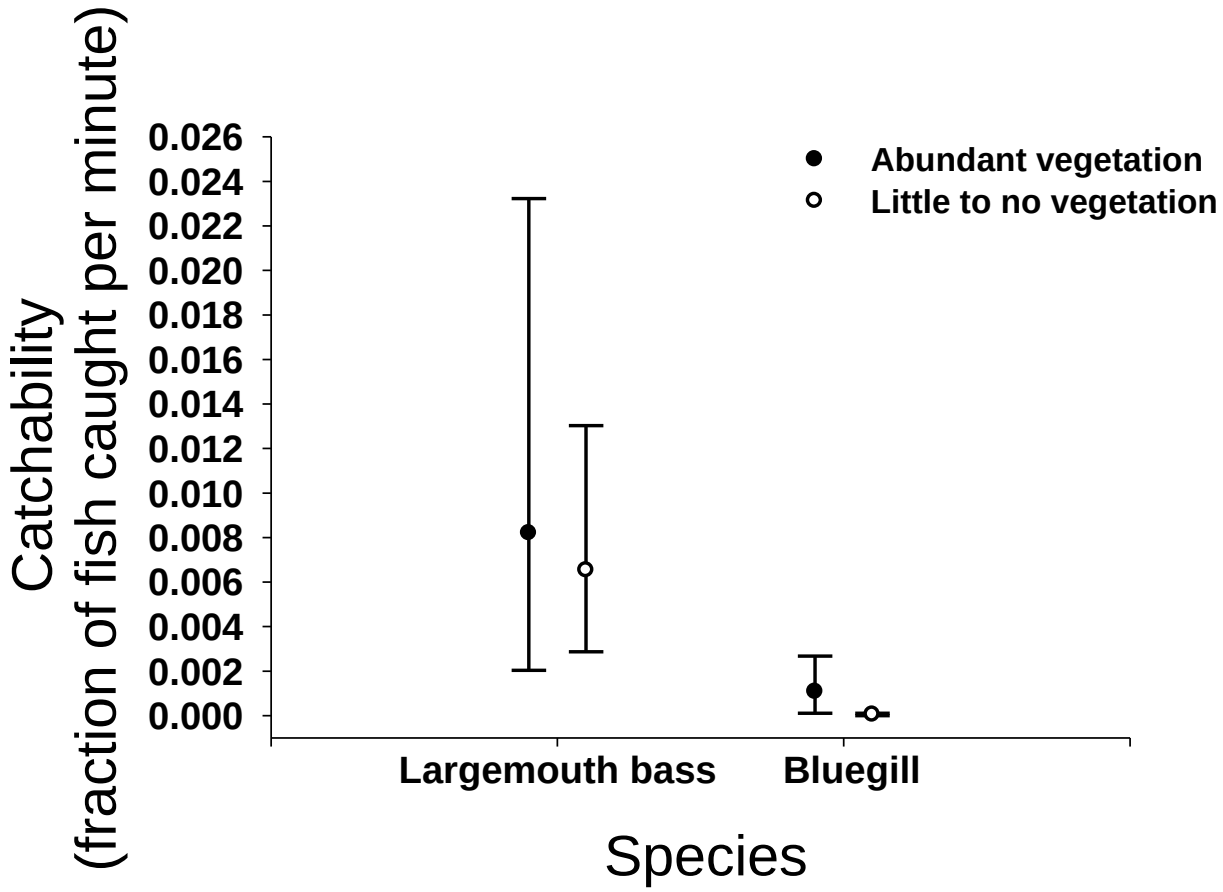

Figure 3-4. Catchability (fraction of fish caught per unit effort) for largemouth bass and bluegill in ponds with abundant vegetation and ponds with little to no vegetation.

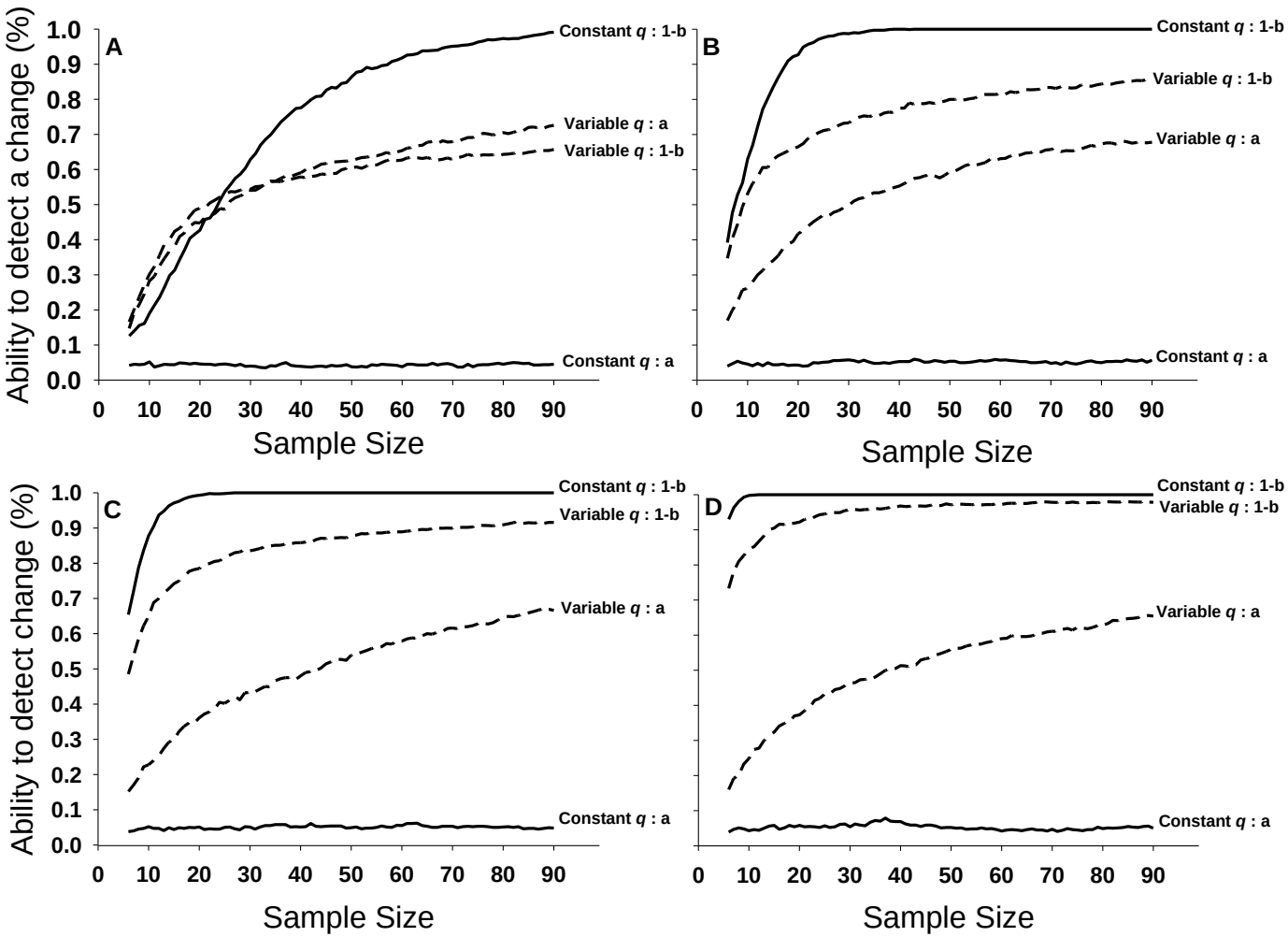

Figure 3-5. Simulated ability to detect a change in largemouth bass abundance using electrofishing CPUE data with variable and constant catchability: (A) comparing one year to one year; (B) comparing three years to three years; (C) comparing five years to five years; (D) comparing 10 years to 10 years.

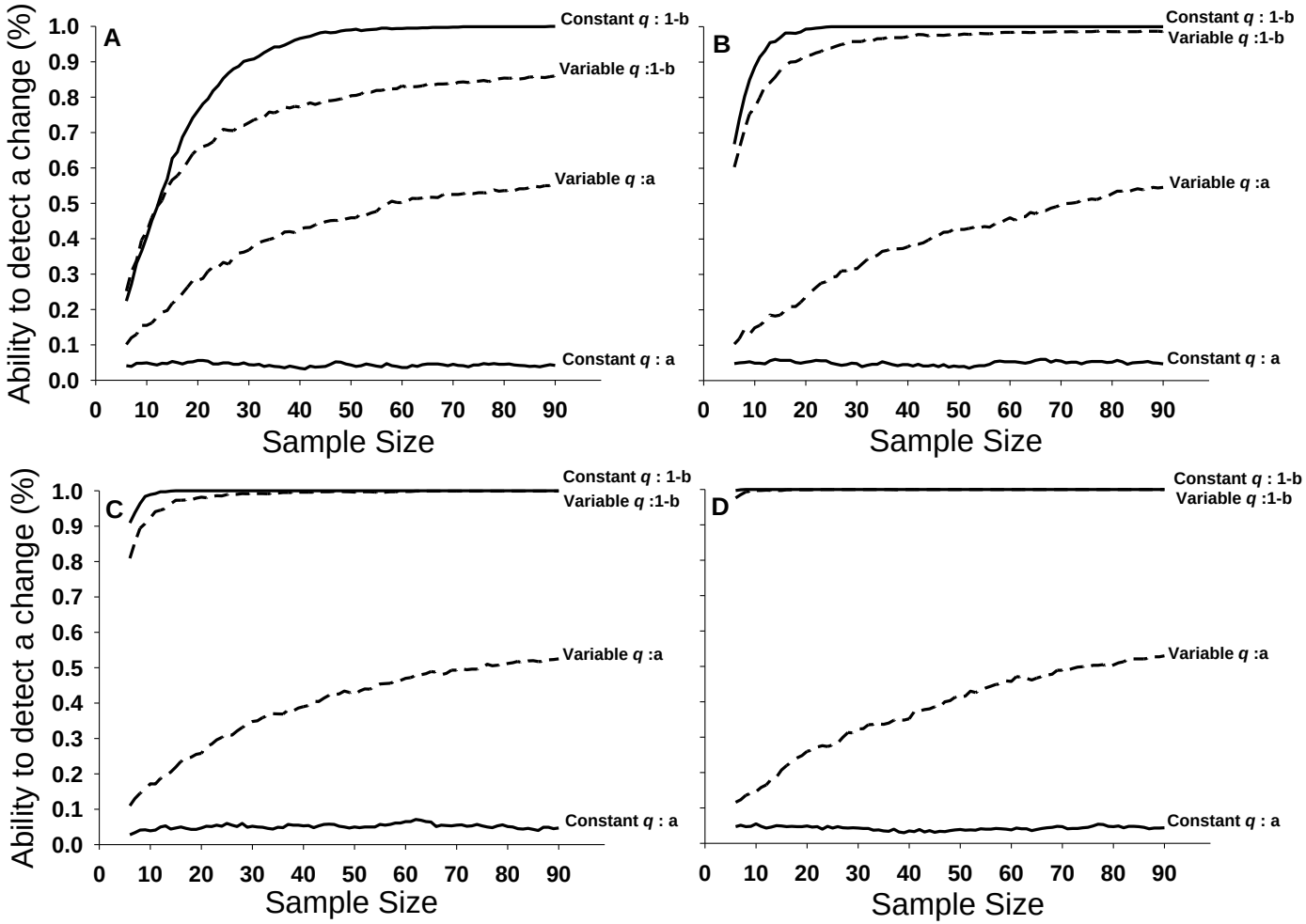

Figure 3-6. Simulated ability to detect a change in lake chubsucker abundance using electrofishing CPUE data with variable and constant catchability: (A) comparing one year to one year; (B) comparing three years to three years; (C) comparing five years to five years; (D) comparing 10 years to 10 years.

CHAPTER 4
DISCUSSION

My results provided evidence that electrofishing catchability can be quite variable for Florida lakes and demonstrate how variable catchability can reduce the usefulness of CPUE indices for evaluating changes in fish abundance. Electrofishing catchability varied by species, season, and lake. Constant catchability for bluegill suggests that electrofishing CPUE data may be used to index abundance of bluegill, and thus electrofishing would be a viable method for measuring bluegill abundance in Florida lakes. Alternately, my simulation showed that the variability in catchability observed for largemouth bass and lake chubsucker substantially increased the Type-I error rates and decreased the ability to detect a real change in abundance. These results highlight the inherent problems in applying existing conventions, such as constant catchability, without first confirming their validity.

Many researchers have argued that electrofishing CPUE data can be used to index abundance under certain conditions (Hall 1986; Coble 1992; Hill and Willis 1994; Bayley and Austen 2002; Schoenebeck and Hansen 2005). Schoenebeck and Hansen (2005) showed that population density can be estimated from electrofishing CPUE data for walleye *Sander vitreus*, largemouth bass, smallmouth bass *Micropterus dolomieu*, northern pike *Esox lucius*, and muskellunge *E. masquinongy* during specific seasons in Wisconsin lakes, assuming that catchability is density independent and that the effects of relevant environmental variables are known. However, they only evaluated the possibilities of hyperstability, hyperdepletion, or proportional relationships between CPUE and abundance (Hilborn and Walters 1992) and did not consider the possibility that q could vary substantially across sequential sampling events. My results showed

high variation in *q* across lakes for largemouth bass, and thus indicated that electrofishing CPUE could misrepresent changes in abundance in many instances.

Bayley and Austen (2002) argued that CPUE data can be corrected to produce unbiased estimates of density, but only with a standardized protocol and constant environmental and target fish conditions. They proposed a linear regression model that predicts mean *q* from mean fish length, mean lake depth and macrophyte coverage. Using their model to predict mean *q* in my five study lakes produced close estimates to the measure mean *q* for four out of the five lakes. However, like Schoenebeck and Hansen (2005), Bayley and Austen (2002) did not account for the possibility that *q* can vary substantially across sequential sampling events. Evaluating how *q* varies temporally is critical in understanding whether CPUE data can be used to index trends in abundance through time in monitoring programs.

Some studies have found that macrophytes affect electrofishing CPUE (Miranda and Pugh 1997; Chick et al. 1999), while others have found no relationship (Bain and Boltz 1992). However, no studies have evaluated how *q* varies with different macrophyte coverages. My results showed that *q* is more variable in systems with higher macrophyte coverages for largemouth bass and bluegill, but that there is no difference in the mean *q* between systems with abundant plants and those devoid of macrophytes. Conversely, Bayley and Austen's (2002) catchability model predicted that *q* will decrease for largemouth bass as macrophyte cover increases from 0% to 50%. Further research needs to focus on how electrofishing *q* varies with different macrophytes coverages, but my results indicated little difference in mean *q* between my submersed vegetation treatments.

A key assumption of my simulation was that the variability in *q* observed among lakes and seasons would approximate within-lake trends through time for a monitoring program. I assert that this approximation was valid because the variation in vegetation abundance, depth, and water clarity in my lakes could represent the changes in depth, water clarity, and littoral habitat complexity that would occur in a single lake through time due to changes in water level and water chemistry. There are substantial temporal changes in vegetation abundance, water clarity, and water level in Florida lakes (Bowes et al. 1979; Nagid et al. 2001; Hoyer et al. 2005). Bowes et al. (1979) found that hydrilla abundance and water chemistry changed substantially through time in three Florida lakes. Nagid et al. (2001) and Hoyer et al. (2005) documented that water level in some Florida lakes varies temporally and can affect water chemistry and macrophyte abundance. My assumption may not be valid for systems that have very little fluctuations in depth, water clarity, and vegetation abundance. However, I believe that the variability I observed among lakes would represent temporal habitat changes within some lakes, and thus changes in *q* that could be observed.

An example of where this assumption may not be valid is Lake Carlton, Florida. Brandon Thompson (Florida Fish and Wildlife Commission, personnel communication) found estimates of annual mean *q* to be more precise in the spring for largemouth bass over three years of an electrofishing mark-recapture study, when compared to the variability I observed across lakes. However, the mean *q* decreased by about two-thirds between the first two years at Lake Carlton. I saw a similar decrease in the spring mean *q* for largemouth bass at Lake Speckled Perch in my study, when comparing between two years. Conversely, at Johnson's Pond the mean *q* values were very

similar between years in the spring. Thus, I saw evidence in some cases of large variation in *q* between sampling years, even when standardizing all other fish collection methods. Even using the more precise Lake Carlton *q* estimates for largemouth bass in my simulation, the Type-I error rate was only reduced from 0.5 to 0.4 when comparing between two years with 25 samples. These examples demonstrate that CPUE data could be misleading in monitoring trends in abundance through time. Further research needs to focus on how electrofishing catchability varies temporally.

Long-term monitoring programs frequently use electrofishing CPUE data to index trends in abundance. However, many monitoring programs often neglect two sources of variability, spatial variation and detectability, which influence the use of CPUE data as an index of abundance (Yoccoz et al. 2001). Yoccoz et al. (2001) recommend that monitoring programs should incorporate estimating detection probabilities into their sampling, instead of relying on indices to draw temporal inferences. However, incorporating estimates of detection probabilities would require substantially more effort and cost. In many cases this is not feasible due to the limited resources and time many monitoring agencies are faced with.

This study evaluated one source of variation (i.e. detectability) in monitoring programs; however, spatial variation also needs to be accounted for. Mesing and Wicker (1986) showed in two Florida lakes that largemouth bass not only move to inshore areas to spawn but have considerable inshore offshore movement throughout the year. Largemouth bass also have considerable inshore offshore movement in Lake Santa Fe, Florida (B. Matthias, personal communication, University of Florida). Inshore offshore movement of fish could be a major cause of the variability I observed in

electrofishing catchability. If monitoring programs seek to index abundance of fish species using electrofishing CPUE data spatial variation and detectability need to be accounted for.

CHAPTER 5
FURTHER STUDY

My results indicate that if electrofishing catchability is highly variable then CPUE data should not be used to index abundance. However, a major assumption of my analysis was that the variability I observed in electrofishing catchability among lakes and seasons would approximate the temporal variability in one lake over a large number of years. Therefore, I recommend multiple years of sampling on a few systems similar to this study are needed to further evaluate the temporal variability in electrofishing catchability.

I showed how variable catchability would influence the ability of CPUE data to index fish abundance, but the analysis didn't explore how variable catchability affects other fisheries metrics. Other fisheries metrics have assumptions like constant vulnerability that that could be violated if catchability is highly variable. Therefore, further analysis could explore how variation in *q* could influence other fisheries metrics, such as estimation of size/age structure from electrofishing.

If electrofishing catchability varies substantially through time causing unacceptable levels of statistical power and Type-I error rate, then CPUE data should not be used to index fish abundance. However, monitoring trends in abundance is not the only way to understand how fish populations change through time. I recommend that alternate sampling methods and data sources (e.g., creel surveys, age sampling, etc.) be explored for their reliability for monitoring trends in abundance or the rates that affect abundance (e.g. recruitment, mortality, and growth) . A simulation model would be helpful to explore the utility of alternate data sources to monitor fish stocks.

APPENDIX
PLANT FREQUENCY OCCURANCE IN LAKES

Devils Hole Lake

Aquatic plant data collected on July 27, 2010

Frequency that plant species occur in 8 evenly spaced transect around the lake.

Common Name	**Scientific Name**	**Frequency (%)**
spatterdock	*Nuphar lutea*	100
maidencane	*Panicum hemitomon*	100
pickerelweed	*Pontederia cordata*	100
lemon bacopa	*Bacopa caroliniana*	100
willow	*Salix spp.*	87.5
leafy bladderwort	*Utricularia foliosa*	87.5
road grass	*Eleocharis baldwinii*	75
St. John's wort	*Triadenum virginicum*	75
buttonbush	*Cephalanthus occidentalis*	62.5
green algae	*Chlorphyta*	62.5
yellow-eyed grass	*Xyris spp.*	50
St. John's wort	*Hypericum spp.*	37.5
unidentified #8	Family: Lamiaceae	37.5
banana lily	*Hymphoides aquatica*	25
unidentified #7		25
water moss	*Fontinalis spp*	25
water-pennywort	*Hydrocotyle umbellata*	12.5

redroot	*Lachnanthes caroliniana*	12.5
unidentified #9		12.5
unidentified #10	Family: Poaceae	12.5

Speckled Perch Lake

Aquatic plant data collected on July 28, 2010

Frequency that plant species occur in 8 evenly spaced transect around the lake.

Common Name	**Scientific Name**	**Frequency(%)**
road grass	*Eleocharis baldwinii*	100
St. John's wort	*Hypericum spp.*	100
spatterdock	*Nuphar lutea*	100
banana-lily	*Nymphoides aquatic*	100
maidencane	*Panicum hemitomon*	100
leafy bladderwort	*Utricularia foliosa*	87.5
unidentified #27		50
buttonbush	*Cephalanthus occidentalis*	37.5
fascicled beaksedge	*Rhynchospora fascicularis*	37.5
rush fuirena	*Fuirena scirpoidea*	25
torpedograss	*Panicum repens*	25
knotweed	*Polygonum spp.*	25
pickerelweed	*Pontederia cordata*	25
St. John's wort	*Triadenum virginicum*	25
giant spikerush	*Eleocharis interstincta*	12.5
willow	*Salix spp.*	12.5
yellow-eyed grass	*Xyris spp*.	12.5
green algae	*Chlorphyta*	12.5

unidentified 8	Family: Lamiaceae	12.5
tape grass	*Vallisneria americana*	12.5
little bluestem	*Schizachyrium scoparium*	12.5

Johnson's Pond

Aquatic plant data collected on July 29, 2010

Frequency that plant species occur in 8 evenly spaced transect around the lake.

Common Name	**Scientific Name**	**Frequency (%)**
spatterdock	*Nuphar lutea*	100
maidencane	*Panicum hemitomon*	75
water-pennywort	*Hydrocotyle umbellate*	62.5
sawgrass	*Cladium jamaicense*	50
small duckweed	*Lemma valdiviana*	50
giant cut-grass	*Zizaniopsis miliacea*	50
big-floating bladderwort	*Utricularia inflata*	37.5
southern naiad	*Najas guadalupensis*	25
duck-potato	*Sagittaria lancifolia*	25
cattail	*Typha spp.*	25
buttonbush	*Cephalanthus occidentalis*	12.5
flat sedge	*Cyperus odoratus*	12.5
common waterweed	*Egeria densa*	12.5
knotweed	*Polygonum spp.*	12.5
unidentified #27		12.5
tangled bladderwort	*Utricularia biflora*	12.5

Big Fish Lake

Aquatic plant data collected on July 28, 2010

Frequency that plant species occur in 8 evenly spaced transect around the lake.

Common Name	**Scientific Name**	**Frequency (%)**
musk-grass	*Chara spp*	100
rush fuirena	*Fuirena scirpoidea*	100
green algae	*Chlorphyta*	100
spadeleaf	*Centella asiatica*	87.5
water-pennywort	*Hydrocotyle umbellata*	87.5
piedmont primrose	*Ludwigia arcuata*	25
frogs fruit	*Phyla nodiflora*	25
maidencane	*Panicum hemitomon*	25
sweetscent	*Pluchea odorata*	12.5
unidentified #33		12.5

Keys Lake

Aquatic plant data collected on July 28, 2010

Frequency that plant species occur in 8 evenly spaced transect around the lake.

Common Name	**Scientific Name**	**Frequency(%)**
road grass	*Eleocharis baldwinii*	100
St. John's wort	*Hypericum spp.*	100
yellow-eyed grass	*Xyris spp.*	100
green algae	*Chlorphyta*	100
rush fuirena	*Fuirena scirpoidea*	100
florida bladderwort	*Utricularia floridana*	87.5
maidencane	*Panicum hemitomon*	62.5
spadeleaf	*Centella asiatica*	25
hatpin	*Eriocaulon spp.*	25
fox-tail club moss	*Lycopodium alopecuroides*	12.5

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BIOGRAPHICAL SKETCH

Matt Allen Hangsleben was born in Shawnee Mission, Kansas in 1983. His passion for the outdoors led him to seek a career in natural resources. He earned his Bachelor of Science in animal ecology in 2006, with an emphasis in fisheries and aquatic sciences at Iowa State University. He spent his summers in college working in various fisheries jobs in Iowa, Wyoming, and Arkansas. While working in western Wyoming and Arkansas, his love of the outdoors grew. After working a kids fishing clinic in Wyoming, and seeing the smiles on all the kids faces whenever they caught a fish he was certain this is what he wanted to do with his life. After graduation, he took a job working for the Idaho Game and Fish in a remote part of north central Idaho. Then, he took a job working in the Grand Canyon for the Arizona Game and Fish. Finally, he moved to Florida to join the Allen lab for a few months before starting his master's research. He started his master's research under Dr. Mike Allen in the fall of 2009 working on electrofishing catchability issues. Matt completed his master's research in 2011.