EVALUATING NOVEL APPROACHES FOR SAMPLING AND ASSESSING CHANGES IN RESERVOIR FISH ASSEMBLAGES

by

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(Under the Direction of Cecil A. Jennings)

ABSTRACT

Quantifying changes in any ecological assemblage is a difficult, but reservoir fish assemblages are particularly challenging. Reservoir sampling data are highly variable temporally and spatially because of variation in fish distribution and behavior (especially schooling), differential sampling efficiency across different habitats, and gear selectivity. The affect these different sources of variation have on the strength of inferences regarding total fish abundance is poorly understood, especially for passive gears such as gill-netting. Consequently, I used a series of novel approaches evaluate reservoir fish assemblages and the utility of those approaches to make strong inferences. In the first approach, I model the relationship between gill-net catch and acoustic-derived densities and a variety of covariates that could reasonably be expected to affect encounter rates with gill-nets. The modelling approach did not elicit specific time periods or sampling conditions that would result in more reliable estimates of relative abundance. However, additional avenues of pursuit for reconciling discrepancies were provided. In the second approach, I evaluated whether reduced sampling effort could adequately characterize the reservoir fish assemblage as compared to results obtained from monthly sampling. Results showed that characterizing the assemblage with gill-nets can be performed with 3 or 4 months of sampling per year, provided the sampling is carried out across seasons. In the third approach, I evaluated Mean Rank Shift, a new “species rank” approach, that has been proposed as offering promise for detecting changes in assemblages derived from long-term monitoring studies. MRS has been used in a fisheries context in a few published studies, but the approach has not been critically evaluated. Through simulation, I evaluated the sensitivity of MRS (as proposed) and several formulations I developed, for detecting directional changes in a reservoir fish assemblage. Results indicate that two novel formulations of MRS show promise for assessing changes in a community over time, especially in the face of perturbations that result in directional changes. Though challenges still exist, my results show that reservoir fish managers can characterize fish assemblages with a reduced amount of effort and that MRS shows promise for assessing changes in a community over time.

INDEX WORDS: Reservoir, Fisheries, Sampling Methods, Gill-nets, Community, Assemblage, Mixed Models, Mean Rank Shift

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DEDICATION

In memory of my parents, James and Louise Dennerline, for their love and support, and for encouraging me to pursue my fascination with nature and my chosen profession.

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TABLE OF CONTENTS

Page

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

BACKGROUND AND CHAPTER ORGANIZATION

Fisheries managers are frequently asked to assess the how management actions or other human perturbations (such as predator or prey stockings, water level manipulations, water releases, or pumped storage operation of a dam) affects reservoir fish communities. Though this task may seem reasonable, meaningful, quantitative assessments are rare in the scientific literature. Many factors directly or indirectly inhibit quantitative community assessments in reservoirs, but several important issues include: 1) difficulty generating accurate and unbiased estimates of abundance for many of the species of interest; 2) uncertainty in the sampling effort required to adequately characterize reservoir fish communities; and 3) confusion over selecting and interpreting results from the complex indices and analytical techniques used to compare communities before and after an anthropogenic perturbation.

In this dissertation, I develop and present meaningful approaches for assessing changes in reservoir fish assemblages based on information obtained from standard sampling protocols typical of reservoir fisheries monitoring programs. In Chapter 2, I evaluate the strength of inferences regarding total fish abundance based on gill-net sampling. The underlying hypothesis is that the encounter rate of fishes with gillnets varies over time, but that it can be modeled by incorporating the biology and life-history of the fishes sampled. Consequently, the specific objective was to develop predictive models relating acoustic-derived abundance with gill-net catch, environmental variables, and time. In Chapter 3, I characterize the fish assemblage as captured by gill-net sampling in a southeastern reservoir to determine if similar inferences regarding assemblage structure can be made with reduced levels of sampling effort. The specific objectives were to: 1) characterize spatial and temporal patterns in catch (numbers and species) from the long-term dataset; and 2) evaluate similarity of inferences about the entire fish assemblage between three temporal subsets of the data and the full data record. In Chapter 4, I use ranking metrics to assess the sensitivity of a recently proposed identity-dependent diversity index called Mean Rank Shift (MRS) for detecting changes in a reservoir fish assemblage over time. In addition to the original MRS, I create and evaluate new formulations that change the context from evaluating changes in consecutive years to evaluating changes relative to the baseline assemblage. The specific objective was to compare results from five different formulations of MRS based on four ranking metrics (number, weight, %IRI, %PSIRI) to assess their ability to detect known, directional changes in a simulated reservoir fish assemblage. Chapter 5 provides a synthetic summary of key findings and implications for sampling protocols for reservoir fish assemblages and inferences that can be made with these new approaches.

The following narratives are brief introductions and justifications for chapters 2, 3, and 4 as well as the datasets on which these various analyses are based. For the dissertation proper, these three research chapters are presented as stand-alone manuscripts.

Chapter 2- Estimating abundance of reservoir fishes

Directly estimating population sizes of most reservoir fishes is extremely difficult and cost-prohibitive. As a result, researchers use traditional sampling methods (such as gill-nets) to obtain data with which to make inferences about the relative abundance of various species. Counts from samples are purported to be an index of “relative” abundance and are subsequently used to make inferences about the spatial and temporal distribution of fish populations.

However, these indices only reflect abundance if detectability is constant over space and time; these assumptions are rarely true when sampling reservoir fishes (Wilde and Fisher 1996)

The relationship between catch and abundance varies because of numerous biotic, abiotic and gear-specific factors. First, fish vary in abundance over space and time within in a lake or reservoir (Tonn and Magnuson 1982, Gido et al. 2000, Pierce et al. 2001, Matthews et al. 2004) related to behavioral or life history characteristics of the fishes. Second, sampling efficiency of gears differs across habitat types, and many gears are both species and size selective (Weaver et al. 1993, Van Den Avyle et al. 1995, Jackson and Harvey 1997). Changes in the environment also affect the relationship between gill-net catch and abundance. For example, because fish are ectothermic, their activity is temperature-dependent. At cold temperatures, many reservoir fishes are inactive, so encounter rates with gill-nets and resulting catch would be expected to be low, regardless of the absolute abundance of fish. Similarly, many riverine species exhibit predictable upstream movements related to spawning in the spring, so detectability could be extremely ephemeral as large numbers of fish concentrate in a specific area for a very brief time and subsequently disperse. For all of these reasons, Hamley (1975) cautioned that the selectivity of the same net fished in the same way may vary between different seasons or locations because of differences in distribution, behavior or condition of the fish. A large and growing body of literature support's Hamley's (1975) initial concern and suggests that indices based on counts likely are poor indicators of abundance because of imperfect detectability and a poor understanding of how detectability might vary over time and space (Anderson 2001, Bayley and Peterson 2001, Pollock et al. 2002).

However, a better understanding of detectability might be achieved by modeling catch as a function of these behavioral and environmental variables. Consequently, the objective of

Chapter 2 is to determine if gill-net catch can be related to acoustic derived abundance with biotic, environmental, and temporal covariates to make stronger inferences on the actual abundance of reservoir fishes. The underlying hypothesis is that catchability varies over time, but can be explained by the biology, activity and life-history of the fishes sampled.

Chapter 3 - Sampling regimes to characterize reservoir fish assemblages

Monitoring programs have expanded in scope over the past decade, with emphasis on monitoring the entire fish assemblage, especially in the context of documenting and tracking changes in biodiversity (Magurran and Henderson 2010, Fischer and Quist 2014). The increased scope presents additional challenges, as monitoring fish assemblages in large lentic systems such as reservoirs is a complex and difficult task given the issues identified for Chapter 2 above (Fischer and Quist 2014). As a result, timing of sampling and the total sampling effort required to obtain an accurate representation of the reservoir fish community are often unknown (Bonvechio et al. 2009). Given the seasonal variability in the catchability of species, sampling regimes to characterize the entire fish assemblage will likely require broad temporal coverage.

Fishery managers have limited resources available for monitoring (Noble et al. 2007); therefore, sampling regimes need to achieve some parsimony between cost-effectiveness and adequate representation of all species in the fish assemblage. Because many sampling programs show a pattern of diminishing information with increased sampling, there may be an identifiable threshold that achieves adequate sample representativeness a reasonable cost. For example, the number of species captured is often asymptotically related to effort, with the number of species increasing rapidly initially but tapering off rather quickly (Gotelli and Colwell 2001, Ugland et al. 2003). This phenomenon of diminishing returns presents an opportunity and need to assess the level of effort that minimizes cost while accurately characterizing the majority of the reservoir fish assemblage.

Studies on a variety of terrestrial and aquatic taxa have evaluated the effort required for estimating total diversity or sample completeness based on species accumulation curves (Moreno and Halffter 2000, Thompson and Thompson 2007, Thompson et al. 2007, Antonio Gomez-Anaya et al. 2014, Azevedo et al. 2014, Hyde et al. 2014). Because the primary focus of these authors was sampling sufficiency for estimating total species richness as part of biodiversity monitoring, other metrics or attributes of the communities were not evaluated. For reservoir fisheries monitoring programs, evaluating metrics such as relative abundance or comparable rankings of species would likely be as important to managers as diversity. The objective of chapter 3 is to characterize spatial and temporal patterns in catch (numbers and species) from a long-term dataset and evaluate similarity of inferences about the entire fish assemblage between the full data record and reduced temporal subsets (three, four, and six months).

Chapter 4 - Mean Rank Shift for assessing community change

A plethora of diversity measures or indices are available for describing diversity and comparing assemblages of animals, and several excellent reviews of the general methods exist (Krebs 1999, Magurran 2004, Kwak and Peterson 2007). Diversity and the indices used to characterize it have received extensive criticism in the literature over the years. Hurlbert (1971) referred to diversity as a “non-concept” because of the ambiguity and lack of consistency among the various diversity indices in practice and essentially encouraged ecologists not to pursue diversity indices. Similarly, (Krebs 1999) warns that similarity indices should be used with caution and that a diversity index should only be used based on solid a priori grounds because the outcome will likely depend on the index selected. Despite these criticisms, similarity indices are still routinely used, and approaches for deriving new indices are still an active area of research (Guiasu and Guiasu 2003, Buckland et al. 2005, Chao et al. 2006, Jost 2006).

Numerous non-parametric and multivariate techniques (e.g., cluster classification, multidimensional scaling, ordination techniques) have also been widely used to assess the effects of anthropogenic perturbation on changes in communities in various environments and across various taxa (Clarke and Warwick 1994, Harkantra and Rodrigues 2004). These methods are primarily descriptive in nature, but can provide confirmatory evidence when specific techniques are chosen a priori based on solid theoretical grounds. However, the results are vulnerable to subjective, post-hoc decisions such as which data transformations to apply, appropriate clustering algorithms, and which variables to include (Hruby 1987, Krebs 1999). For these reasons, Krebs (1999) concludes that “cluster analysis and measurement of ecological similarity are two parts art and one part science”.

Despite the recent advancements and continued development of new indices for defining and comparing community structure as well as the many non-parametric, multivariate, and ordination techniques, these methods have not been widely adopted and used by reservoir fishery managers. Potential reasons for not adopting these methods likely include confusion over the plethora of diversity indices and their meaning in general (see Jost 2006), a lack of conceptual understanding of the complex multivariate analyses, and an inability to explain these methods and results to non-scientific constituents and stake-holders. Consequently, pursuing more intuitive and easier-to-understand methods are warranted.

Mean Rank Shift (Collins et al. 2008) is a “species rank” approach that has been specifically suggested by several researchers as offering promise for detecting changes in assemblages derived from long-term monitoring studies (Magurran and Henderson 2010, Magurran and Queiroz 2010, Meyer et al. 2015). MRS summarizes complex temporal dynamics in assemblages by (very simply) quantifying relative changes in species rank abundances over time. MRS is calculated as the average of the rank differences of individual species from one time to the next. Though MRS was developed using abundance-based ranks, other individual or composite metrics could be used to rank species. Evaluation of composite indices is warranted by the diverse size ranges of fish captured in reservoir sampling. For example, if species ranks are based solely on numbers, a few small, highly fecund reservoir species such as blueback herring *Alosa aestivalis* and threadfin shad *Dorosoma petenense* will be ranked highest because they are caught in numbers that are orders of magnitude higher than the other fishes captured. A similar problem could result from using weight alone. Composite indices that include the frequency of occurrence also seem logical as that is the most relevant measure of how ubiquitous a species is across samples.

MRS is an appealing approach because it is intuitive, easy to calculate and easily understood by non-scientific audiences. Consequently, the goal of chapter 4 is to use different ranking metrics to assess the sensitivity of MRS-based approaches for detecting changes in a reservoir fish assemblage over time. The specific objective is to compare results from five different formulations of MRS based on four different ranking metrics (number, weight, %IRI, %PSIRI) to assess their ability to detect known, directional changes in a simulated reservoir fish assemblage.

Project dataset

All chapters/objectives for this project rely on a long-term database from fisheries sampling conducted by the Georgia Cooperative Fish and Wildlife Research Unit on J. Strom

Thurmond (JST) and Richard B. Russell (RBR) Reservoirs, Georgia-South Carolina over the period from 1986 to 2009. The purpose of the sampling was to describe the fish assemblages upstream (RBR) and downstream (JST) of the Richard B. Russell Dam prior to, and in the presence of, pumped-storage operation of the dam. The geographic distribution of sampling and gears used have varied over the duration of the project. However, the specific data included in this dissertation include: 1) Monthly sampling of four stations in JST with experimental gill-nets for approximately 19 years over the period 1986 to 2008; and 2) Monthly paired samples of gillnetting and hydroacoustics that were conducted monthly immediately below Russell dam, for approximately 15 years.

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CHAPTER 2

RELATIONSHIPS BETWEEN HYDROACOUSTIC DERIVED DENSITY AND GILL NET CATCH: IMPLICATIONS FOR FISH ASSESSMENTS[1]

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[1] Dennerline, D. E., Jennings, C. A. and Degan, D. J. 2012. Relationships between hydroacoustic derived density and gill net catch: Implications for fish assessments." Fisheries Research, 123–124: 78-89. ISSN 0165-7836, http://dx.doi.org/10.1016/j.fishres.2011.11.012. Reprinted here with permission of the publisher.

ABSTRACT

In this paper, we describe our assessment of whether gill nets and hydroacoustics provided similar inferences on the local abundance of fishes and whether gill net catch could be used to predict acoustic-derived abundances. We collected hydroacoustic and gill netting samples from a restricted area of large hydropower reservoir in the southeastern United States. We used mixed linear models in an information theoretic framework to model acoustic-derived abundances as a function of gill net catch and a variety of biological and environmental covariates. Overall, gill net catch was a poor predictor of acoustic-derived abundance and the best model only accounted for 39.6% of the within year variation. In fact, a gill net catch (e.g., 100 fish/net) was approximately equally likely across several orders of magnitude in fish abundance. This result suggests that gill net catch was unable to reliably discern substantive changes in fish abundance. Consequently, the most appropriate role for gill nets in fisheries research assessments may be to: 1) supplement hydroacoustic data by providing information on species composition and fish sizes, and 2) provide information on metrics other than fish abundance, such as fish growth and condition.

Keywords

hydroacoustics, gill nets, sampling, mixed models, AIC

INTRODUCTION

Active and passive gears have been used widely in reservoir fisheries assessments to make inferences regarding the abundance of fishes. Though a seemingly common goal, the approaches often differ in that active gears such as hydroacoustics attempt to directly estimate fish density or abundance whereas passive gears typically provide an indirect estimate of relative abundance (Ney 1999; Hubert and Fabrizio 2007). Both approaches suffer from biases related to the gears used and the gears have their own positive and negative attributes in terms of costs and ease of use. Given these differences and trade-offs, a fundamental question for fisheries managers is whether these gears provide similar inferences on the abundance of fishes over time and space.

Indices of abundance based on any gear will only reflect abundance when the probability of capturing fishes is constant over space and time, and this assumption is rarely the case when sampling fishes (Guy and Willis 1991; Neumann and Willis 1995; Pope and Willis 1996). Changes in capture probability can result from changes in fish activity, gear selectivity (Hamley 1975; Spangler and Collins 1992; Van Den Avyle et al. 1995a; Finstad and Berg 2004), or changes in the environment. For example, because fish activity is temperature-dependent, encounter rates with and the resulting catch of gill nets would be expected to be very low at cold temperatures regardless of absolute fish abundance. For these reasons, Hamley (1975) cautioned that the selectivity of the same net fished in the same way may vary between different seasons or locations because of differences in distribution, behavior or condition of the fish. A large and growing body of aquatic and terrestrial literature support’s Hamley’s (1975) concern and suggests that indices based on counts, from most sampling gears, likely are poor indicators of abundance (Anderson 2001; Yoccoz *et al.* 2001; Rosenstock et al. 2002; Thompson 2002; Peterson et al. 2004).

Because of the problems associated with passive gears and associated indices, hydroacoustics has become a widely used and accepted method for estimating total fish abundance in lake and reservoir fisheries assessments (Simmonds and MacLennon 2002; Kubecka et al. 2009; Yule et al. 2009). In fact, recent sampling protocols developed to meet European initiatives mandating lake and fisheries assessments rely on hydroacoustics for deriving abundance of pelagic fishes (Winfield et al. 2009). Similarly, as part of an on-going research project, we concurrently collected hydroacoustic and gill net samples from a small area immediately adjacent to a hydropower dam to estimate the number of fishes that might be vulnerable to entrainment during pumped storage operation of the dam. A fundamental question of interest was to assess how similar inferences regarding total abundance were between hydroacoustics and gill nets.

The specific objective of this study was to develop predictive models relating acoustic-derived abundance with gill-net catch, environmental variables, and time. The underlying hypothesis is that the encounter rate of fishes with gill nets varies over time, but that it can be modeled by incorporating the biology and life-history of the fishes sampled. If successful, the models developed would provide managers with the flexibility to choose which gear to use at specific times based on costs, ease of use, or desire to minimize fish mortality and handling. A secondary objective was to determine if month-to-month variability in hydroacoustic-derived abundances and gill net catch were repeatable and predictable among years. If predictable temporal patterns are identified, the information could be used to allocate future sampling efforts or modify operational guidelines to minimize abundance-based entrainment risk.

MATERIALS AND METHODS

Site Description

Gill-netting and hydroacoustic sampling were conducted immediately below Richard B. Russell Dam (RBR, Figure 1) on the Savannah River (GA-SC). Because RBR Dam is pumped-storage project, the sampling area is unique in many ways. The habitat is generally lacustrine because water impounded by the J. Strom Thurmond (JST) Dam backs all the way to the RBR Dam to facilitate pumped storage. However, appreciable flow exists during conventional hydropower generation and pumped-storage operation. A relatively deep pool (8-10 m when JST is at full pool) that was created during construction of the dam is another unique feature of this site. This pool starts at the dam and extends 300 m downstream, but quickly rises to just several meters in depth. The morphology creates an artificial 10-hectare “pool” that captures and retains cold water from conventional hydropower releases. Unlike hypolimnetic releases from most southeastern reservoirs, the water coming through RBR Dam is well oxygenated because of an oxygen injection system in the RBR forebay. As a result, several cool-water species such as striped bass *Morone saxatilis* and blueback herring *Alsoa aestivalis* inhabit this general area throughout the summer.

Sampling

Gill-netting and hydroacoustic sampling were both conducted during (48 hr.) generation moratoria. A BioSonics®[2] 200-kHz DTX system with a 6° circular split-beam transducer mounted on a pole 0.5 m below the water surface was used to conduct acoustic sampling during

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[2] The use of trade names or products does not constitute endorsement by the U.S. Government.

night-time hours. Data were collected from 1.5 m below the water surface to bottom and stored in digital format on a laptop PC. A total of 23 fixed, cross-channel transects were sampled in the two areas of interest: the immediate “tailrace” area consisted of 8 transects starting from the base of Russell Dam and extending approximately 250 m downstream (~10 ha); and the entire “tailwater” area that included the tailrace and 15 additional transects that extended ~5 km downstream (534 ha, Figure 1). During each survey, a calibration sphere with known target strength (TS) of -42.0 dB was used for an *in-situ* calibration. For all surveys, the echo amplitude threshold, pulse rate and pulse duration were set as −60 dB, 10 pulses s^{-1}, and 0.4 ms, respectively. The hydroacoustic data were processed using Echoview® software (up to V3.5) with the target threshold set at -60 db to provide mean acoustic size of the fish targets, total acoustic energy reflected for geo-referenced cells 1m deep by 200 m distance, and geo-referenced total lake depths along the transect lines. Scaling the total reflected acoustic energy within a cell by the mean acoustic size for a fish provided fish density estimates by cell. The areal fish density was then derived by summing the densities for all depth strata. Fish densities were extrapolated to the total area for each 1 m depth strata over the sample area to calculate the overall abundance.

Gill net sampling was conducted immediately below Russell Dam (tailrace) during monthly generation moratoria concurrent with the acoustic sampling. Tailrace samples were overnight sets with durations ranging from 14 to 22 hours and were fishing during acoustic sampling. A sample consisted of two sinking and two floating nets. Bottom depth for sinking nets depended on the pool level and placement and typically ranged from 6-10 m. The nets were 76.20 m X 2.44 m and consisted of 10 panels. Mesh sizes (bar measure, mm) across the panels were 9.5, 12.7, 19.1, 25.4, 38.1, 50.8, 63.5, 76.2, 88.9, and 101.6 mm. Captured fishes were identified to species, measured (total length in mm), weighed (g), and the mesh size of capture was recorded. When more than 30 fish of the same species were captured within a mesh panel, the first 30 individuals from the panel were individually measured and weighed, and the remaining individuals were counted and weighed in bulk. Catch from all four nets was summed to generate total catch from gill nets. Vertical profiles of temperature and dissolved oxygen were measured using a Yellow Springs Instruments® temperature and dissolved oxygen meters (several models) during deployment or retrieval of the gill nets in most months.

Analysis and Modeling

A total of 97 acoustic samples and 145 gill netting samples were available to address the two objectives. For objective one, a total of 58 paired samples over seven sampling years had the needed temperature information to be included in the analysis (Table 1).

Pearson correlation coefficients were used to assess the relatedness of the response variables and to assess the strength of the individual models for predicting acoustic-derived abundances. Correlation coefficients were generated for the three possible pairings of the response variables (gill net catch and tailwater abundance; gill net catch and tailrace abundance; tailwater and tailrace abundance). Coefficients were calculated using the untransformed data and were used primarily to compare the current study with results from previously published studies.

Relationships between gill net catch (independent variable) and acoustic-derived abundances (dependent variables) were evaluated with random effects models implemented with the SAS® mixed procedure (SAS 9.13). Random effects models were used because we expected monthly samples to be spatially correlated over time. The resultant data structure is analogous to a repeated measures design, but mixed modeling allows more flexibility for specifying random effects in the models of interest (Bryk and Raudenbush 1992).

Mixed models were used to account for year-to-year variation that was not accounted for by the covariates. Consequently, the repeated measures were placed within a temporal or longitudinal construct with monthly samples as repeated observations of the same site within years. Using a random intercept model for year also allowed us to extend inferences to non-sampled years if we considered the years that were sampled as a random sample of years.

A "season" variable was created to incorporate both temperature and time because we hypothesized that the effect of temperature might vary at different times of the year. For example, fish activity and corresponding encounter rates with gill nets may vary between the spring and fall because of seasonal or spawning movements of fishes, availability of prey resources, or other factors even if surface temperatures are equal. Therefore, we expected the relationship between gill net catch and acoustic-derived abundances to be most similar for samples collected from temporally proximal months with closely related temperatures. We used hierarchical cluster analysis to examine relationships among different months based on surface temperature at time of sampling. Pairwise relationships were estimated using Euclidean distances and were clustered with unweighted pair group arithmetic averaging method (Romesburg 1990). The resulting dendrograms were visually inspected to identify logical "seasons".

An information theoretic approach (Burnham and Anderson 2002) was used to develop and assess models that related acoustic-derived abundances to a variety of predictor variables (Table 2). The global model included all of the variables, then a limited set of *a priori* candidate models were added to incorporate combinations of variables corresponding to different biological hypotheses about the relationship between gill net catch and acoustic-derived abundances. For example, water temperature at the time of sampling was expected to have a direct effect on fish behavior and physiology and was predicted to influence catchability through encounter rates with nets. At low temperatures, fish activity is low so encounter rates and subsequent catch are hypothesized to be weakly related to abundance. Conversely, increased temperatures result in increased fish activity, increased encounter rates and higher catch (relative) which is hypothesized to be more strongly related to abundance. Variables that expressed the same effect at different scales or combinations were not included in the same models because of concerns regarding multicolinearity.

Akaike's Information Criterion corrected for small sample size (AIC_c; Burnham and Anderson 2002) was used to assess the relative fit of the candidate models, and the model with the lowest AIC_c score was deemed the best fitting model. The relative belief in each model was assessed using Akaike model weights, where weight (w_i) corresponds to belief in a given model. Model averaging of parameter estimates based on the Akaike weights is commonly used with information theoretic approaches to account for model selection uncertainty. However, model averaging is not appropriate for mixed models, so we adopted the approach of Rieman et al. (2006) and used the AIC_c-derived model weights to develop a confidence set of models for each response variable (tailrace abundance or tailwater abundance) and provided fixed and random parameter estimates for all of the models in the confidence set. Models with an Akaike weight within 10% of the best model were included in the confidence set (Royall 1997). Intra-class correlation coefficients (ICC) were used to estimate the percent of total variance that was among and within the level-2 units (years) for the models in the confidence set. Lastly, goodness of fit for each candidate model was assessed prior to model selection by examining normal probability plots of the lower (within year) level residuals (Bryk and Radenbush 1992).

The relative importance of individual variables across the set of candidate models was evaluated using importance weights derived from the Akaike model weights. The importance weight for each variable is obtained by summing the Akaike model weights across all models containing the variable (Burnham and Anderson 2002). Because our primary interest was relating acoustic derived abundances to gill net catch, most of the models in the candidate set included gill net catch. However, models without gill net catch were also included to assess the relative effects of the other factors in the absence of gill net catch and as a way to assess the importance of gill net catch.

To determine if the month-to-month variation in catch and acoustic-derived abundances were predictable and repeatable among years, we fit three unconditional, random effects models for each response variable and used Akaike weights to determine which model form was most plausible given the data. The three models were: 1) an additive model (Y = year + month) indicating that month-to-month variability was the same among years in direction and magnitude (repeatable and predictable); 2) an additive model with interaction (Y = year + month + year*month) indicating that month-to-month variability was the same among years in direction, but not in magnitude (repeatable but not predictable); and 3) a nested model (Y = year + month(year)) indicating that month-to-month variability differed among years in direction and magnitude (neither repeatable nor predictable). Conceptual representations of these three model forms are provided in Figure 2-2.

RESULTS

A total of 24,823 fish from 33 species were captured in the 58 gill net samples (232 nets) that were used for modeling. Despite the large number of species captured, few species made up the bulk of the catch. Two species, blueback herring and threadfin shad *Dorosoma petenense*, accounted for over 86% of the total catch by number and seven species accounted for over 95% of total catch (Table 2-3). The months of May, June and July accounted for approximately 64% of the total catch when temperatures in the top four meters were similar and ranged, on average, from the low to upper 20's (Figure 2-3). Overall, 83% of the fish were captured in the floating gill nets with the remaining 17% captured in the sinking gill nets.

Gill net catch was not correlated to acoustic-derived abundances in the tailwater (r=0.1030) or the tailrace (r=0.1022), and the tailwater and tailrace abundances were only weakly correlated (r=0.28). Cursory examination of plots between gill net catch and acoustic-derived abundances revealed generally weak and inconsistent relationships among years (Figure 2-4) and that the proportion of fish occurring in the tailrace (relative to the tailwater) varied widely among samples. In some samples, tailrace abundance accounted for a major portion of the entire tailwater abundance (Figure 2-4, two rightmost points in 1996 panel). In other cases, the tailrace abundance was a small portion of the tailwater abundance (Figure 2-4, three rightmost points in 2005 panel).

Hierarchical cluster analysis of months by temperature showed two very distinct, but continuous seasons: November to April and May to October (Figure 2-5; Table 2-4). Mean surface temperatures from November to April ranged from approximately 9 to 16 °C, whereas mean temperatures from May to October were considerably warmer and ranged from approximately 21 to 30 °C (Table 2-4). Temperature differences between the two seasons were approximately 5-6 °C during the transitions periods (April to May and October to November). Consequently, we created a binary coded variable by using the "warm" months as the baseline to allow the modeled relationships to vary among the two identified seasons.

The lower-level residuals of the normal probability plots were non-linear and indicated a departure from normality. A Log_{10} transformation of the gill net catch and hydroacoustic-derived abundances for the tailrace and tailwater was used to normalize the data, and subsequent examination of the residual plots of the log transformed data suggested the data fit adequately. Consequently, all of the models presented below are based on the log-transformed gill net catch and acoustic derived abundances.

Tailwater Acoustic Abundance

The intra-class correlation coefficient from the random effects ANOVA for the tailwater abundance model revealed that most (96%) of the variation occurred within (versus among) years. For tailwater abundance, three models were included in the confidence set of models, and all were based primarily on surface temperature, which had an overall importance weight of 99.1% (Table 2-5). The best approximating model was the surface temperature only model, which explained 68.0% of the within year variance and had an Akaike weight (w_i) of 0.499 (Table 2-5). This model was only 1.35 times more likely than the second model, which included the variables surface temperature and gill net catch. Plots of fish abundance in the tailwater versus gill net catch by individual years and years pooled (Figure 2-6) reveal that the random intercept model with a common slope for surface temperature fit the data reasonably well. All parameter estimates for surface temperature were positively related to tailwater abundance (Table 2-6), and 95% confidence intervals were all strongly positive. Gill net catch appeared in two of the three models in the confidence set, even though gill net catch was itself a poor predictor of tailwater abundance. Parameter estimates for gill net catch from both models were relatively imprecise and inconsistent; the estimate was positive in one model but negative in the other. In both cases, the 95% confidence intervals spanned zero (Table 2-6). Not surprisingly, the inclusion of gill net catch and the interaction term only accounted for an additional 1% of the within year variance beyond that accounted for by surface temperature alone (68.1%). Furthermore, the model including gill net catch as the only predictor variable only explained approximately 15% of the within year variance in tailwater abundance.

Tailrace Acoustic Abundance

The intra-class correlation coefficient from the random effects ANOVA for the tailrace model revealed that most (88%) of the variation of fish abundance in the tailrace also occurred within years. Six models were included in the confidence set of models (Table 2-7). The dispersed nature of the w_i scores indicates model selection uncertainty was fairly high for this confidence set of models. However, the best approximating model included gill net catch and season, explained 39.6% of the within year variance, and had an Akaike weight (w_i) of 0.419. This model was 2.12 times more plausible than the next best model, which contained gill net catch and surface temperature. Despite being the best model, fish abundance in the tailrace was predicted very poorly in some years and seasons (for example, the cold season in 1997; Figure 2-7). Gill net catch had the highest overall importance weight (83%) of any of the variables in the tailrace models, but this might be expected as gill net catch occurred in a disproportionately high number of the models. Surface temperature and season were also represented in the confidence set and had overall importance weights of 34.8% and 62.0%, respectively (Table 2-7).

3.3 Temporal Patterns in Catch and Abundance

The additive random effects model was the only plausible model (w_i = 1.00) for both the tailwater and tailrace abundances. This finding indicated that the predictable portion of the month-to-month variance was similar among years. The additive random effects model was also the most plausible model for gill net catch (w_i = 0.78) and was 3.3 times more likely than the model that included the interaction term.

DISCUSSION

The area immediately below Richard B. Russell Dam (i.e., tailrace) is well defined, constrained, relatively small (10 ha.), and has a hard (bedrock) substrate. These attributes make the tailrace an ideal place to explore the relationship between gill net catch to acoustic-derived abundance. Consequently, the absence of a meaningful relationship between gill net catch and hydroacoustic derived abundances in the tailrace is problematic and does not bode well for developing meaningful relationships between the catch of these two gears under “normal” reservoir sampling conditions.

The utility of gill net catch for predicting acoustic-derived abundances was somewhat ambiguous when it co-occurred with surface temperature. These results were likely indicative of an unanticipated correlation between surface temperature and gill net catch (r=0.55). The parameter estimates for gill net catch in all models, from both confidence sets, were relatively imprecise and confidence intervals spanned zero in five of the six models (Tables 2-6 and 2-8). Plots based on the best-fitting tailwater abundance model (Figure 2-6) showed high among year variability in the relationship between gill net catch and tailwater abundance and poor predictive ability for some years (for example, cold months in 1997 and warm months in 2005) when only a random intercept term was used. In some years, there was a limited amount of data for developing relationships for some combinations of years and month groups (Figure 2-7; note warm months in 2006), which suggests caution be used when interpreting model predictions, especially for individual years.

Using year as the basis of the repeated measure (level-2 unit) in the models relating abundance and gill-net catch seemed prudent and logical. Biologically, expecting certain effects to vary among years based on annual attributes or characteristics of the system is reasonable. For example, turbidity may be higher during a wet year than a dry year, and less visible nets in turbid water could possibly increase gill net catch rates (Hansson and Rudstam 1995). Similarly, the periodic production of strong year classes of fish that are highly vulnerable to the gear would also lead to high variation among years.

A few other studies have compared gill net catch with acoustic-derived abundances in marine and freshwater environments, and all found similar results regarding a general lack of concurrence, low correlation, and poor predictive ability between the methods. For example, shad *Dorosoma spp.* density from acoustics was not correlated with catch from surface gill nets at three sites in Lake Texoma, Texas-Oklahoma (Van Den Avyle *et al.* 1995b). A significant correlation (r = 0.47) was reported only after pooling sites, and this was probably caused by differences in mean density among sites (based on visual assessment of their plots) as opposed to improving resolution of the relationship by pooling the data. Likewise, acoustic-derived abundance of vendance *Coregonus albula* in a small oligotrophic lake in Germany was not correlated with either total vendance catch or with catch by individual, size-inferred age groups when all ages were included (Mehner and Schulz 2002). Acoustic-derived abundance of herring *Clupea harengus* and sprat *Sprattus sprattus* in the north Baltic Sea was significantly correlated with gill net catch corrected for selectivity and fish swimming speed, but explained only 28% of the variance in catch per unit effort (Hansson and Rudstam 1995).

There are several reasons why gill net catch may not be strongly or consistently related to true or hydroacoustic estimated abundance. A better understanding of some of the factors is gained by thinking of gill net catch as the result of two processes: encountering a net and being retained by a net. In the current study, we attempted to include factors (temperature, julian day, season) that we hypothesized would influence the encounter process through increases or decreases in fish activity or fish abundance. We did not include retention because a review of the literature raised concerns about the validity and efficacy of the approaches most commonly used (e.g., Millar 2000).

Selectivity of gill nets has a long and extensive history of study that began almost a century ago (Baranov 1914, per Hamley 1975) and is still ongoing in the contemporary literature (Helser et al. 1998, Millar 2000). Numerous researchers have used indirectly derived selectivity curves to expand gill net catches to presumably make more accurate inferences on the relative abundance of fishes or to make "better" comparisons to other gears, including hydroacoustics (Spangler and Collins 1992; Hansson and Rudstam 1995; Helser *et al.* 1998; Mehner and Schulz 2002). However, catch data used to derive indirect selectivity curves cannot be appropriately expanded because selectivity is confounded with the size distribution of fish "at large" during the time of sampling (Millar 2000). Consequently, catch data from multiple meshes can only be used to indirectly estimate a relative population size structure (Millar 2000; Moth-Poulsen 2003). Because of the confounding issue, we did not see solid theoretical grounds for expanding gill net catch prior to developing the relationships. Furthermore, we suspect relatively minor benefits would be gained because when catch has been "corrected" for selectivity, the relative patterns in catch changed little, if any. For example, the relative length distributions of smelt *Osmerus eperlanus* were essentially the same whether based on corrected or uncorrected catch (Figure 3a *in* Kurkilahti et al. 1998). In a study where both uncorrected and corrected catches were reported, neither explained a large portion of the observed variability in abundance and selectivity corrected catch only explained 10% more (R^2=0.13 to R^2=0.23) of the variability than uncorrected catch (Hansson and Rudstam 1995).

Predictable temporal patterns occurred within acoustic-derived tailwater abundances and gill net catch, but the patterns were disparate and unrelated to one another. The summer peak in the overall tailwater abundance is likely the result of recruitment of young-of-year (YOY) fishes, primarily threadfin shad. Summertime peaks in acoustic-derived abundances have been observed in marine (Hansson 1993) and freshwater environments (Cyterski 1999). The absence of a summertime peak in abundance in the immediate tailrace is likely the result dam operations. Previous hydroacoustic analysis suggests that YOY shad rarely occur in the immediate tailrace area presumably due to flushing flows and the cold temperature regime associated with hypolimnetic releases from Russell Dam.

We were unable to re-process the acoustic data to facilitate size-specific analyses, but limiting analyses to specific sizes of fishes may result in better correlations between gill net catch and acoustics because of differential sampling of fish sizes. This is especially true for small fishes because there is a lower limit on the size of fishes sampled by gill nets. For example, threadfin shad typically aren’t captured by gill nets until they are 60-70 mm long (Van Den Avyle *et al.* 1995a; our own unpublished data). Consequently, if fishes smaller than this length (YOY in summer) constitute a large portion of the overall abundance estimated by hydroacoustics, then a poor relationship would be expected with gill net catch. In these situations, stronger relationships might be obtained by eliminating specific ages or sizes, particularly YOY fish, from the analyses (Mehner and Schulz 2002). In the present study, stronger relationships might have been obtained for the lower tailwater area had we eliminated YOY fishes (based on target strength) from the hydroacoustic estimates. However, as noted, this was unlikely a problem (or a much smaller problem) in the immediate tailrace as YOY are infrequently found there in substantial numbers.

Hydroacoustics has several desirable attributes for reservoir fisheries assessments. First, recent advancements in technology have made sophisticated acoustic equipment and software available to virtually anyone at a reasonable cost. As a result, the use of acoustics has become widespread and widely accepted over the past decade. Another important consideration is the sources of error and variation have been extensively studied and documented for acoustic methods (Simmonds and MacLennon 2002). The precision of hydroacoustics samples is as at least as precise as other commonly used sampling methods (Hansson 1993; Van Den Avyle *et al.* 1995b). Hydroacoustics is also very efficient in terms cost and effort (time to collect and process) compared to other sampling gears (Van Den Avyle *et al.* 1995b; Simmonds and MacLennon 2002). Lastly, because hydroacoustic sampling is an active process, “capture” is not dependent on fish activity and is not as confounded by issues of selectivity as compared to gill nets. In contrast to the known properties of acoustics, fish activity patterns may be neither intuitive nor obvious. For example, in one study, the catchability of brown trout *Salmo trutta* in experimental gill nets was inversely related to fish density and was a biased estimator of trout density (Borgstrøm 1992). Presumably, low densities of trout resulted in increased fish activity; and thus, higher encounter rates with the gill nets.

Hydroacoustics is not a panacea for all reservoir fisheries assessments. A substantial limitation for reservoir fisheries assessments is the inability to directly differentiate species. Species composition can only be inferred based on information on the size, depth or location of fishes collected with secondary sampling gears such as gill nets. However, in cases such as the current study, this was not a limitation as we were concerned with estimating the total number of fish vulnerable to entrainment without regard to species. Differentiating fish from the bottom can also be problematic depending on the substrate and fish size, so acoustics may not provide good estimates for some benthic species. Counting fishes in the surface layer can also be problematic because of fish avoidance of the vessel, wind related noise in the surface layers that mask fish echoes, and inability to sample the top few meters using only down-looking transducers (Kubecka and Wittingerova 1998; Knudsen and Sægrov 2002).

The present study used only down-looking acoustics, which did not sample the top few meters of the water column. Thus, we undoubtedly underestimated total fish abundance, but the extent is unknown. Total fish abundance can be underestimated when horizontal beaming is not used in conjunction with vertical beaming, but the range is extremely variable (Kubecka and Wittingerova 1998; Knudsen and Sægrov 2002). Because most of the fish in the present study were captured in the floating gill nets, the lack of horizontal beaming data is a concern. However, given the wide variation (2-3 orders of magnitude) in total abundance across the range of gill net catches (see “All Years” in Figure 2-5), the bias in total abundance caused by the lack of horizontal beaming would have to be both extremely large and directly proportional to gill net catch to meaningfully alter the relationship. Essentially, all abundance estimates associated with gill net catches exceeding 2.0 (on the $\log_{10}$ scale) would need to be increased by two to three orders of magnitude from 10^5 to 10^7 or 10^8 while those less than 2.0 would be expanded very little, if any. Accordingly, we do not envision that the total abundance estimates for the 10 ha. tailrace area would be so biased as to affect our interpretation of the data we present.

A major assumption of the approach we took in modeling gill net catch with hydroacoustic abundance was that the hydroacoustic estimates represented a measure of “truth”. Admittedly, truth is unknown, and we readily acknowledge that acoustics estimates are also estimates based on samples. However, hydroacoustic sampling in the immediate tailrace was conducted at a fine scale compared to typical lake-wide sampling regimes. Distances between the tailrace transects ranged from only 20-50 m (see inset in Figure 1), whereas distances between transects in whole-lake assessments are often hundreds of meters apart (lower tailwater transects in this study; Godlewska et al. 2009). The degree of coverage (km of survey transect/square root of area in km^2) for the tailrace was approximately 9.5; whereas, a general rule of thumb for acoustic surveys is to achieve a degree of coverage ranging from three to six. Given the morphometry and small size of the area, the hard bottom, and the intensive level of effort relative to the area, we believe the acoustic estimates, though underestimates related the lack of horizontal beaming, are useful indicators of true abundance in the immediate tailrace area.

CONCLUSIONS

Though our results were generally similar to previous published studies, our approach was different from most in that we tried to model the relationship between the two sampling methods by using a variety of covariates expected to affect encounter rates with gill nets. We expected that certain conditions or factors would result in poor correspondence between the methods. However, we hoped the approach would also identify particular times or factors that produced strong positive relationships between the methods. If so, then gill net catch could be used to make meaningful inferences regarding abundance under those specific times or conditions and researchers could choose to use either method based on costs or other constraints. Unfortunately, this was not the case, as gill net catch by itself never explained more than 20% of the within year variation in acoustic-derived abundances which we believe better represented “truth”.

Our results and those we reviewed support the prevailing consensus to use hydroacoustics for estimating abundance in reservoir fisheries assessments. In most cases, passive gears such as gill nets will likely have limited utility for making reliable inferences on total fish abundance over space or time unless species and/or size-specific relationships can be demonstrated using appropriate modeling and calibration. Consequently, we view the utility of gill nets in reservoir fisheries research assessments is that of supplementing hydroacoustic data by providing information on species composition and fish sizes and to provide information on population metrics other than abundance. For example, condition indices derived from netted fish can be an important component of fisheries assessments (Pope and Kruse 2007), are readily attainable, and may provide more direct interpretation of the effects of management actions or other anthropogenic perturbations than abundance, which may be infeasible to estimate.

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Table 2-1. Fifty-eight samples included in the final data set for modeling gill net catch and acoustic-derived abundances. Cells with an “X” indicate that acoustic and gill nets samples were collected along with water temperature data during that month and year.

Month	1995	1996	1997	1998	2004	2005	2006
January	X	X	X	X			X
February			X	X			X
March	X	X	X	X			X
April		X		X			X
May		X	X	X	X		X
June			X	X	X	X	X
July	X		X	X	X	X	
August	X	X	X	X	X	X	
September	X	X	X	X	X	X	
October	X		X	X	X	X	
November	X	X	X	X		X	
December	X	X	X	X		X	

Table 2-2. Predictor variables used in candidate models to predict acoustic-derived abundances in the tailwater and tailrace.

Predictor variables	Interpretation
Gill net catch	Used as a covariate to model variation in acoustic derived abundances.
Temperature	Temperature has a direct effect on behavior and physiology of fishes which influences encounter rate with gill nets.
Season	Incorporates time of year along with temperature to include other factors that may affect encounter rates with nets. For example, fish activity and corresponding encounter rates, may vary between the spring and fall due to seasonal or spawning movements of fishes, seasonal availability of prey, or other factors even if surface temperatures are equal.
Julian day	Date as a continuous variable to account for seasonal or cyclical behavior that might affect relationship between gill net catch and acoustic-derived abundance.
Gill net catch × Season	Indicates that relationship between gill net catch and acoustic estimates varies between different temperature groupings.
Gill net catch × Temperature	Indicates that relationship between gill net catch and acoustic abundance varies with temperature.
Gill net catch × Julian day	Indicates that relationship between gill net catch and acoustic abundance varies with time.

Table 2-3. Number, percentage and cumulative percentage of gill net catch by species and the proportion of each species captured in floating and sinking nets.

		Total Catch		Net Type	
Species	N	%	Cumul. %	Floating %	Sinking %
Alosa aestivalis (Blueback herring)	14700	0.592	0.592	0.923	0.077
Dorosoma petenense (Threadfin shad)	6549	0.264	0.856	0.996	0.004
Dorosoma cepedianum (Gizzard shad)	571	0.023	0.879	0.779	0.221
Morone americana (White perch)	558	0.022	0.902	0.081	0.919
Morone saxatilis X Morone chrysops (Hybrid bass)	511	0.021	0.922	0.429	0.571
Notropis hudsonius (Spottail shiner)	438	0.018	0.940	0.112	0.888
Pomoxis nigromaculatus (Black crappie)	404	0.016	0.956	0.609	0.391
26 other species	1092	0.044	1.000	0.268	0.732

Table 2-4. Number of measurements (*N*) and mean (standard error) surface temperatures by month for the modeled set of data. The dashed line separates the two “seasons” identified by hierarchical cluster analysis in Figure 2.

Month	*N*	Average surface temperature (°C)
November	5	15.6 (0.99)
December	5	12.9 (0.88)
January	5	9.3 (0.77)
February	3	8.9 (0.34)
March	5	11.5 (0.49)
April	3	15.7 (2.64)
May	5	22.3 (1.93)
June	5	27.0 (0.69)
July	5	29.8 (0.78)
August	6	27.1 (0.94)
September	6	23.7 (1.36)
October	5	21.1 (0.73)

Table 2-5. Results of random intercept models relating acoustic-derived abundance for the entire tailwater with gill net catch and other predictor variables as defined in Table 2. The confidence set of models includes the first three models listed.

Model	K	Log$L$	AIC$_c$	ΔAIC$_c$	w_i
Temperature	4	-31.60	72.0	0.0	0.499
Gill net catch, Temperature	5	-30.70	72.6	0.6	0.370
Gill net catch, Temperature, Gill net catch × Temperature	6	-30.70	75.0	3.0	0.111
Gill net catch, Temperature, Julian day, Season, Gill net catch × Temperature, Gill net catch × Julian day, Gill net catch × Season	10	-27.50	79.7	7.7	0.011
Season	4	-36.05	80.8	8.8	0.006
Gill net catch, Season	5	-36.05	83.2	11.2	0.002
Gill net catch, Season, Gill net catch × Season	6	-35.95	85.6	13.6	0.001
Gill net catch, Julian day, Gill net catch × Julian day	6	-46.00	105.6	33.6	0.000
Gill net catch, Julian day	5	-51.50	114.2	42.2	0.000
Gill net catch	4	-56.05	120.9	48.9	0.000
Julian day	4	-56.50	121.7	49.7	0.000

Table 2-6. Estimates (standard errors) and 95% confidence intervals of fixed and random effects for the confidence set models of acoustic-derived abundance for the entire tailwater. Note that the random intercept effect is an estimate of the variance component.

Model Estimated parameters	Estimate	95% confidence interval Lower	 Upper
Temperature			
Fixed effect			
Intercept	4.6267 (0.1840)	4.1765	5.0769
Temperature	0.0736 (0.0071)	0.0593	0.0879
Random effect			
Intercept	0.0839 (0.0545)	0.0321	0.5410
Residual	0.1408		
Gill net catch, Temperature			
Fixed effect			
Intercept	4.7866 (0.2171)	4.2552	5.3179
Gill net catch	-0.1301 (0.0958)	-0.3225	0.0623
Temperature	0.0803 (0.0086)	0.0631	0.0975
Random effect			
Intercept	0.0840 (0.0544)	0.0322	0.5364
Residual	0.1360		
Gill net catch, Temperature, Gill net catch × Temperature			
Fixed effect			
Intercept	4.7708 (0.5301)	3.4738	6.0678
Gill net catch	-0.1230 (0.2375)	-0.6006	0.3546
Temperature	0.0812 (0.0292)	0.0225	0.1399
Gill net catch × Temperature	-0.0004 (0.0118)	-0.0242	0.0234
Random effect			
Intercept	0.0839 (0.0544)	0.0321	0.5376
Residual	0.1360		

Table 2-7. Results of random intercept models relating acoustic abundance from the immediate tailrace with gill net catch and other predictor variables as defined in Table 2. The final confidence set includes the first six models listed.

Model	K	Log$L$	AIC$_c$	ΔAIC$_c$	w_i
Gill net catch, Season	5	-52.75	116.6	0.0	0.419
Gill net catch, Temperature	5	-53.45	118.1	1.5	0.198
Gill net catch, Season, Gill net catch × Season	6	-54.25	119.0	2.4	0.126
Temperature	4	-55.40	119.6	3.0	0.094
Season	4	-57.65	120.1	3.5	0.073
Gill net catch, Temperature, Gill net catch × Temperature	6	-53.45	120.6	4.0	0.057
Gill net catch	4	-57.25	123.2	6.6	0.015
Gill net catch, Julian day	5	-56.30	123.7	7.1	0.012
Gill net catch, Julian day, Gill net catch × Julian day	6	-56.10	125.8	9.2	0.004
Gill net catch, Temperature, Julian day, Season, Gill net catch × Temperature, Gill net catch × Julian day, Gill net catch × Season	10	-51.60	127.9	11.3	0.001
Julian day	4	-64.00	136.8	20.2	0.000

Table 2-8. Estimates (standard errors) and 95% confidence intervals of fixed and random effects for the confidence set models of acoustic derived abundance for the immediate tailrace. Note that the random intercept effect is a variance component.

Model Estimated parameters	Estimate	95% confidence interval Lower	 Upper
Gill net catch, Month group			
Fixed effect			
Intercept	3.9457 (0.3095)	3.1883	4.7030
Gill net catch	0.3262 (0.1315)	0.0619	0.5904
Month group	0.5555 (0.1730)	0.2079	0.9032
Random effect			
Intercept	0.1507 (0.1030)	0.0555	1.1235
Residual	0.2964		
Gill net catch, Temperature			
Fixed effect			
Intercept	3.6136 (0.3183)	2.8346	4.3925
Gill net catch	0.2858 (0.1426)	-0.0008	0.5723
Temperature	0.0377 (0.0127)	0.0121	0.0632
Random effect			
Intercept	0.1634 (0.1103)	0.0607	1.1729
Residual	0.3021		
Gill net catch, Month group, Gill net catch × Month group			
Fixed effect			
Intercept	3.8660 (0.4071)	2.8699	4.8621
Gill net catch	0.3668 (0.1885)	-0.0122	0.7458
Month group	0.7323 (0.6126)	-0.4994	1.9641
Gill net catch × Month group	-0.0792 (0.2632)	-0.6085	0.4500
Random effect			
Intercept	0.1502 (0.1028)	0.0552	1.1241
Residual	0.2960		
Temperature			
Fixed effect			

Intercept	3.9673 (0.2740)	3.2968	4.6378
Temperature	0.0524 (0.0108)	0.0307	0.0740
Random effect			
Intercept	0.1755 (0.1186)	0.0652	1.2634
Residual	0.3228		
Month Group			
Fixed effect			
Intercept	4.5642 (0.1895)	4.1006	5.0278
Month group	0.7562 (0.1604)	0.4341	1.0783
Random effect			
Intercept	0.1521 (0.1073)	0.0547	1.2473
Residual	0.3309		
Gill net catch, Temperature, Gill net catch × Temperature			
Fixed effect			
Intercept	3.5702 (0.7868)	1.6449	5.4954
Gill net catch	0.3053 (0.3537)	-0.4059	1.0165
Temperature	0.0402 (0.0434)	-0.0471	0.1274
Gill net catch × Temperature	-0.0011 (0.0176)	-0.0365	0.0344
Random effect			
Intercept	0.1633 (0.1103)	0.0607	1.1734
Residual	0.3021		

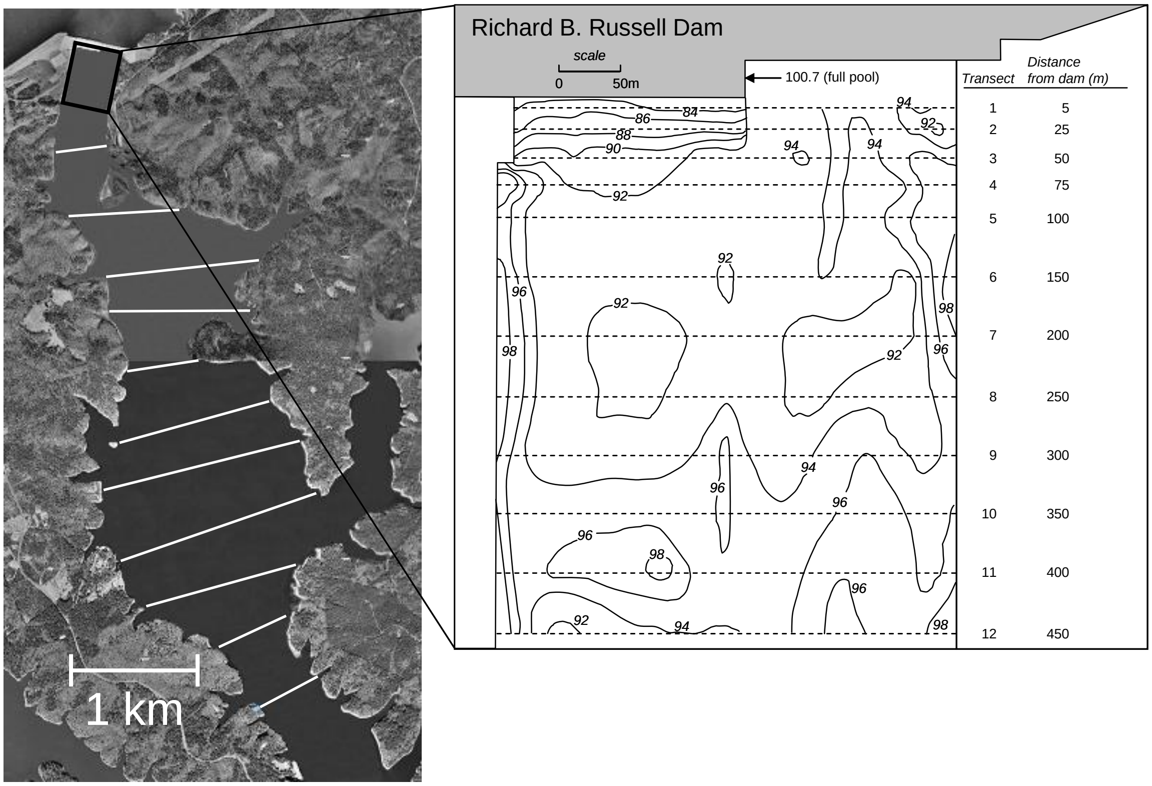

Figure 2-1. Picture showing the Richard B. Russell (RBR) Dam tailrace and tailwater, hydroacoustic transects 1 thru 12 (in inset) and transects 13 thru 23 (white lines). The inset shows the area immediately below RBR dam including the first 12 transects, the distances (in meters) of each transect from the dam, and the bottom contour of the area. The tailrace extends from the dam to transect number 8 and the tailwater extends from the dam to the last transect (number 23).

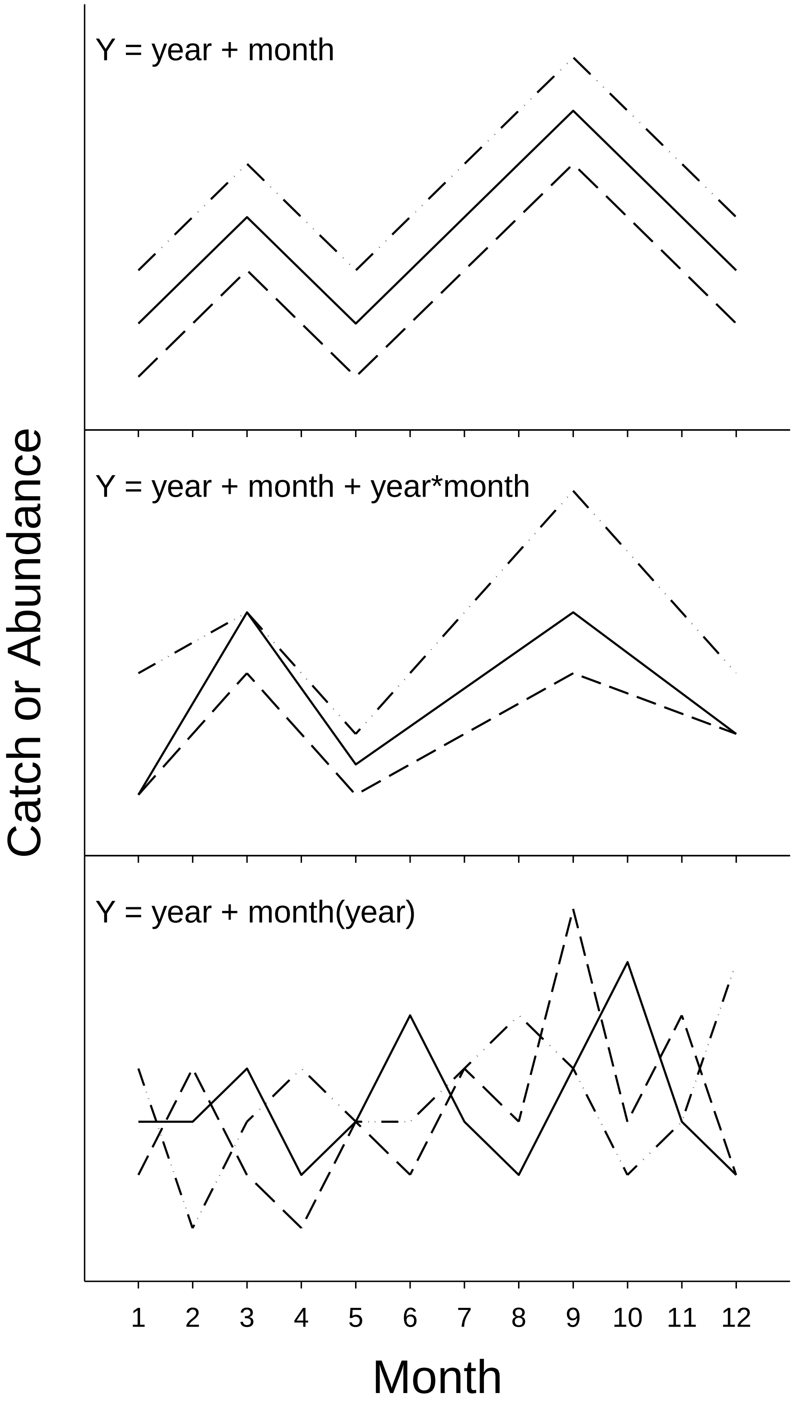

Figure 2-2. Hypothetical examples to illustrate additive (top panel), interaction (middle panel), and nested (bottom panel) models. In each panel, catch or abundance is plotted by month for three years (lines).

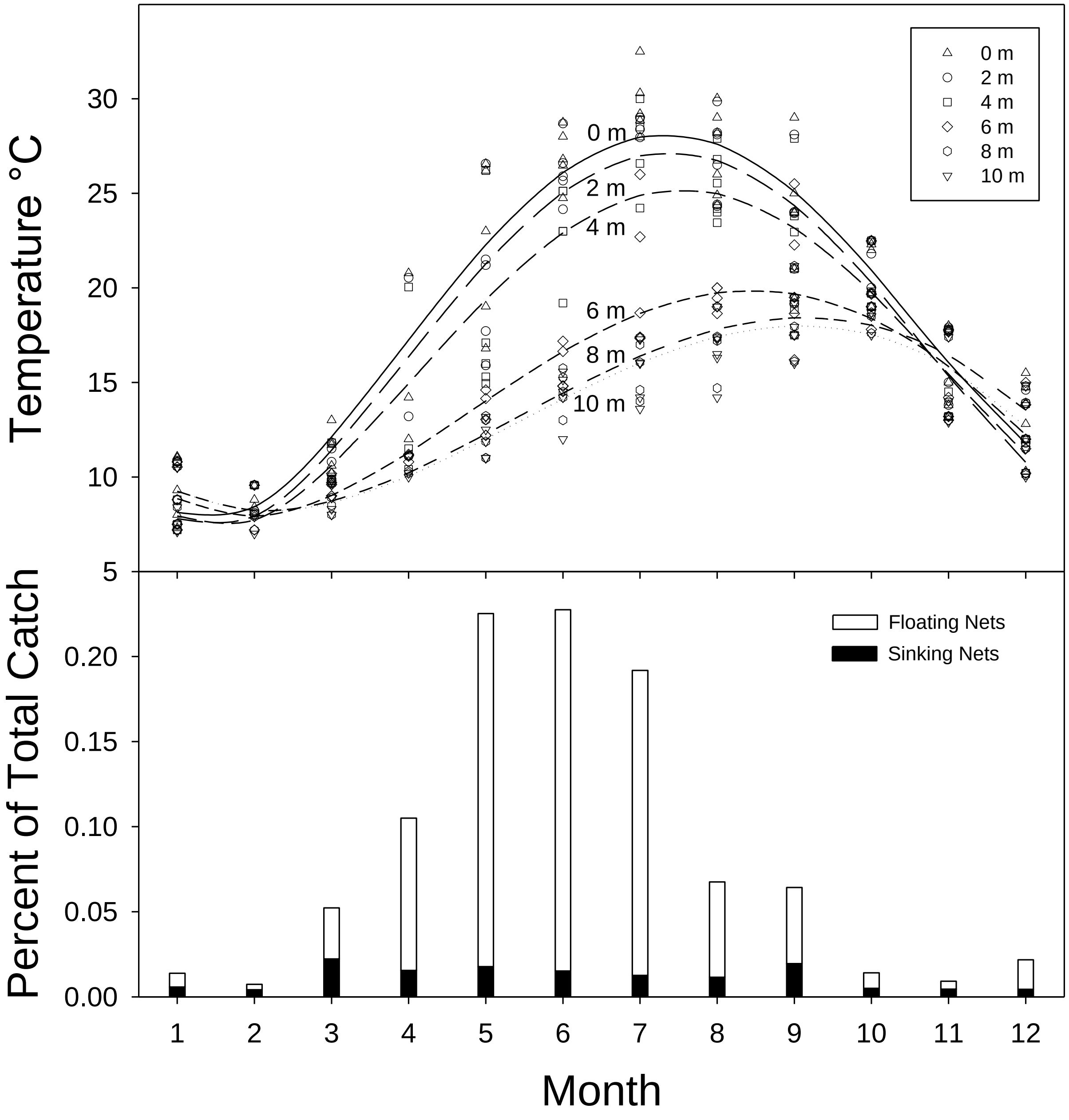

Figure 2-3. Temperature (top panel) and percent of total gill net catch (bottom panel) by month. In the top panel, points are temperatures by depth for the different sample years and the lines are derived by fitting a fourth-order polynomial to the mean temperature by month for each depth (Adj. $R^2 \geq 0.96$ for all depths).

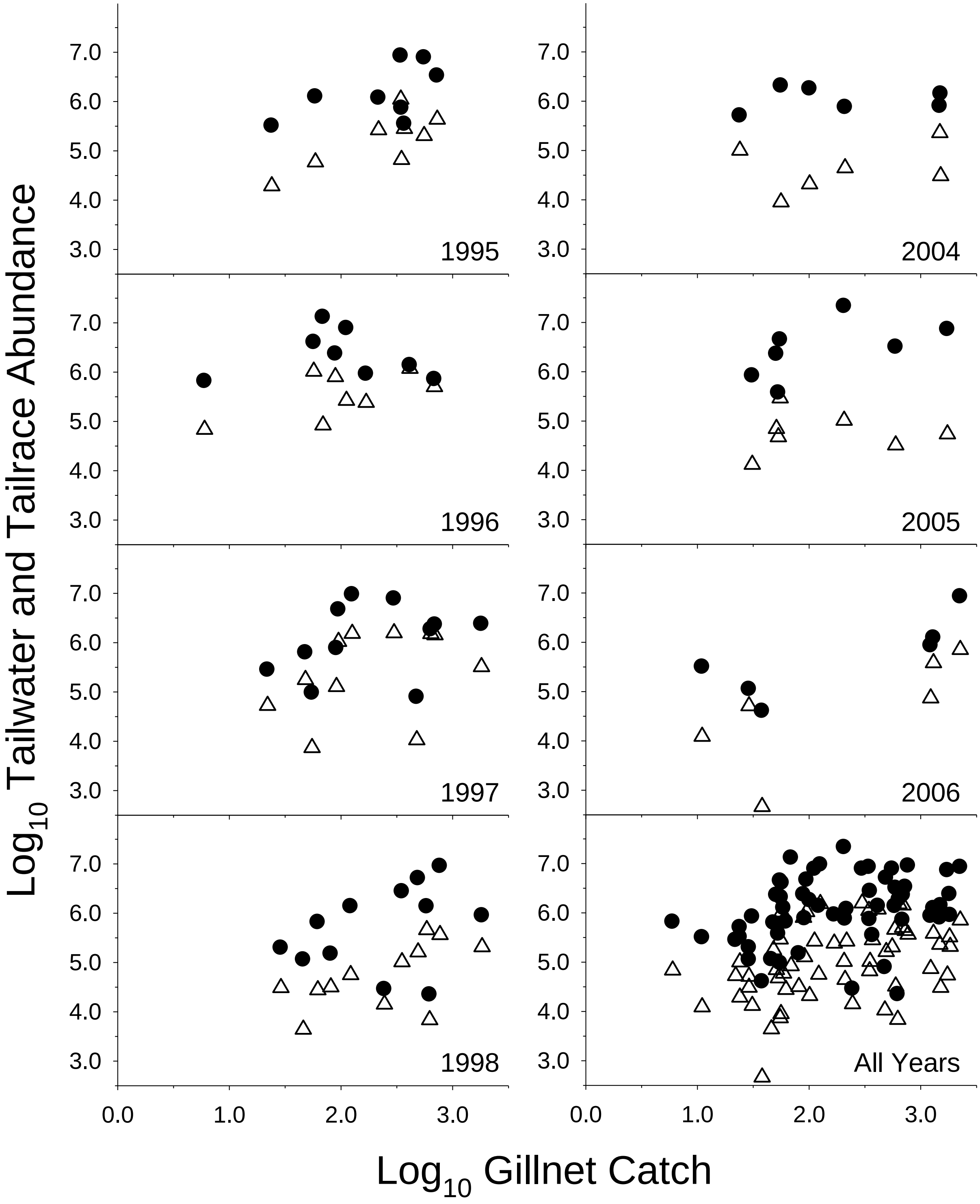

Figure 2-4. Plot of acoustic-derived tailwater (solid circles) and tailrace (open triangles) abundances versus gill net catch each month by year and all years combined.

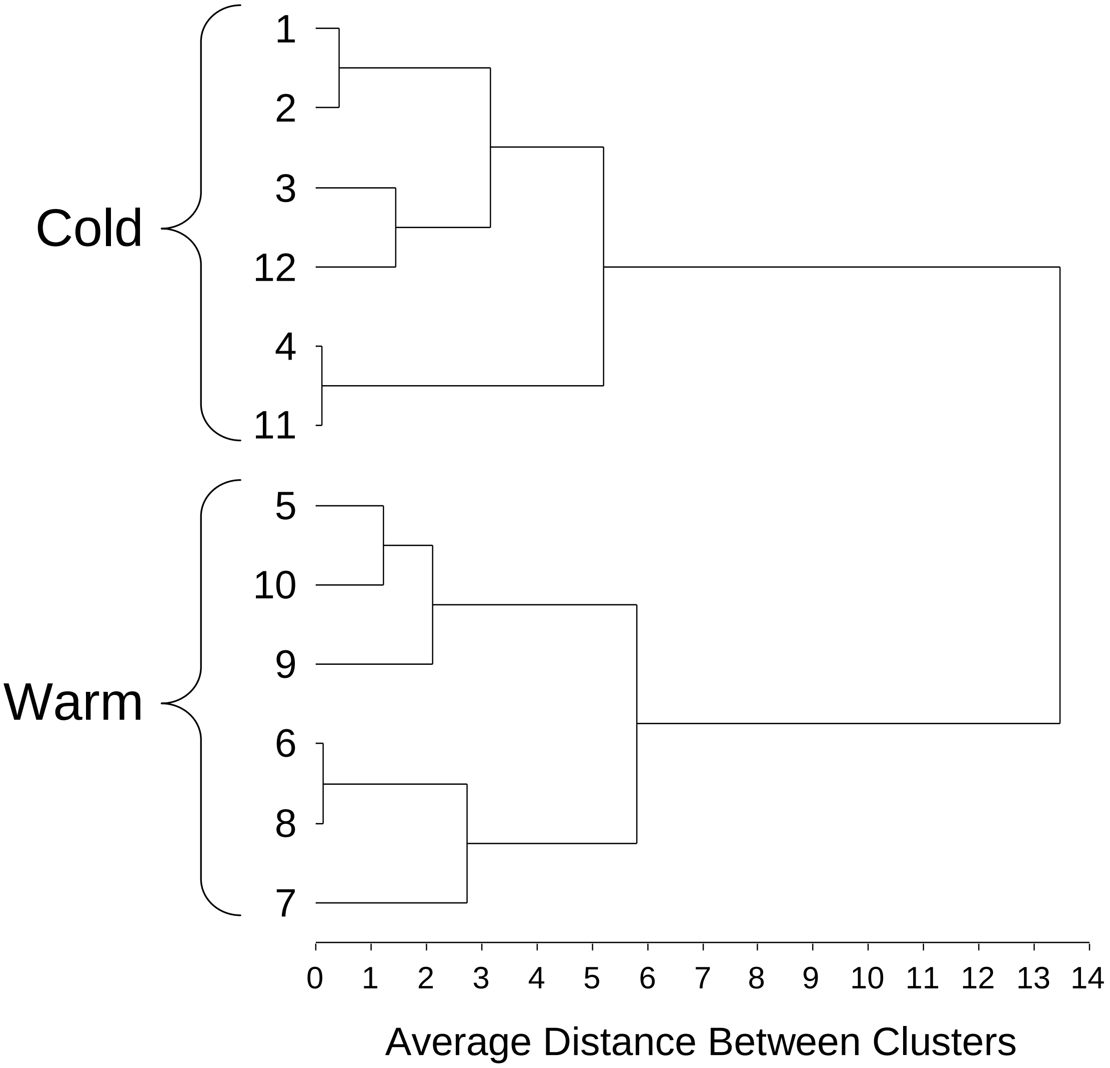

Figure 2-5. Dendrogram of the relationships among months from a hierarchical cluster analysis based on surface temperature. Brackets show the two groupings used for the season variable.

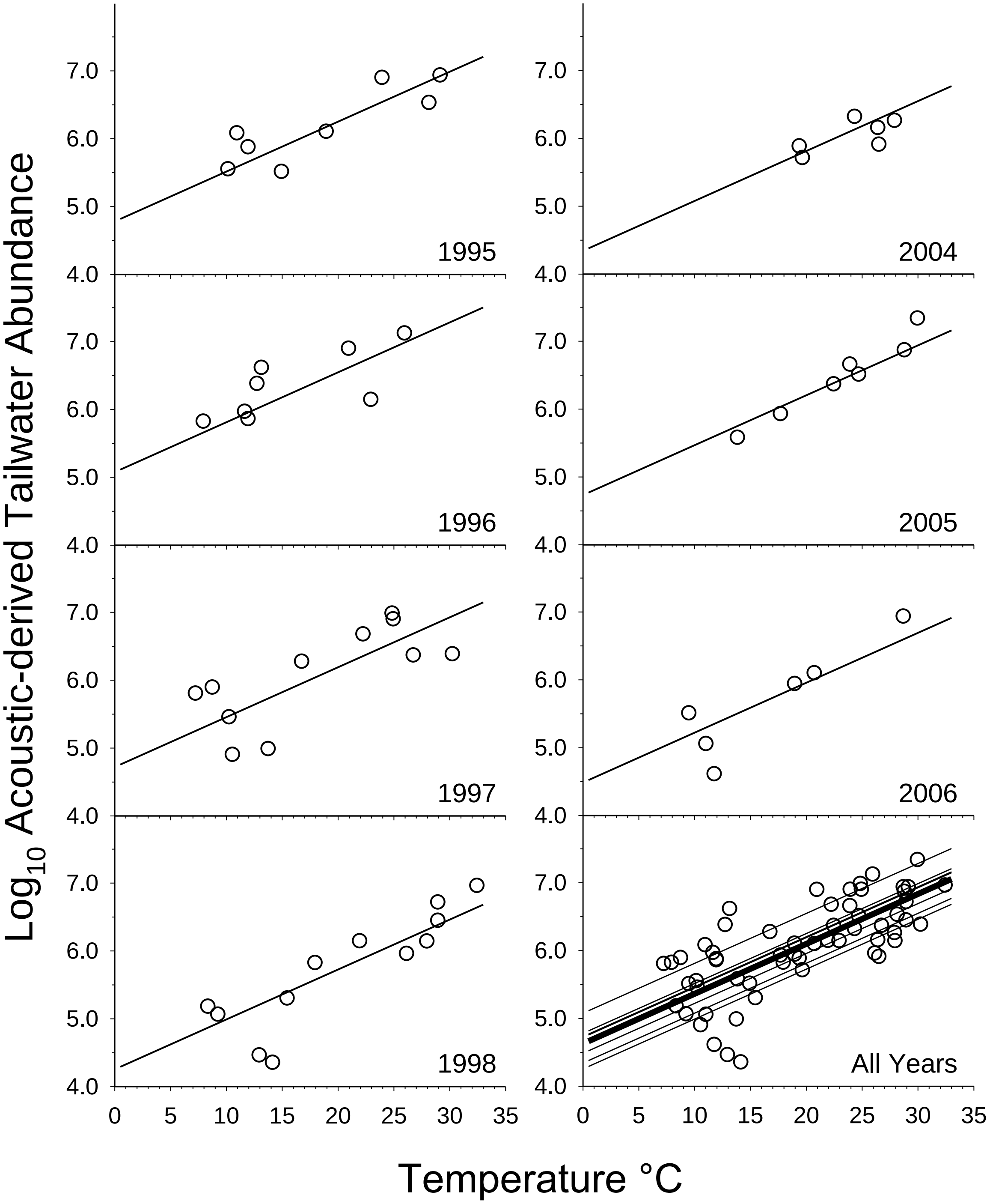

Figure 2-6. Plot of $\log_{10}$ total acoustic abundance by temperature for each year. Regression lines are from the best fitting linear mixed model with a random intercept and common slope. Regression lines were extended beyond the observed data to show the year specific intercepts. The bottom right graph includes all data, individual year regressions and the overall mean relationship (thick line) between tailwater abundance and surface temperature.

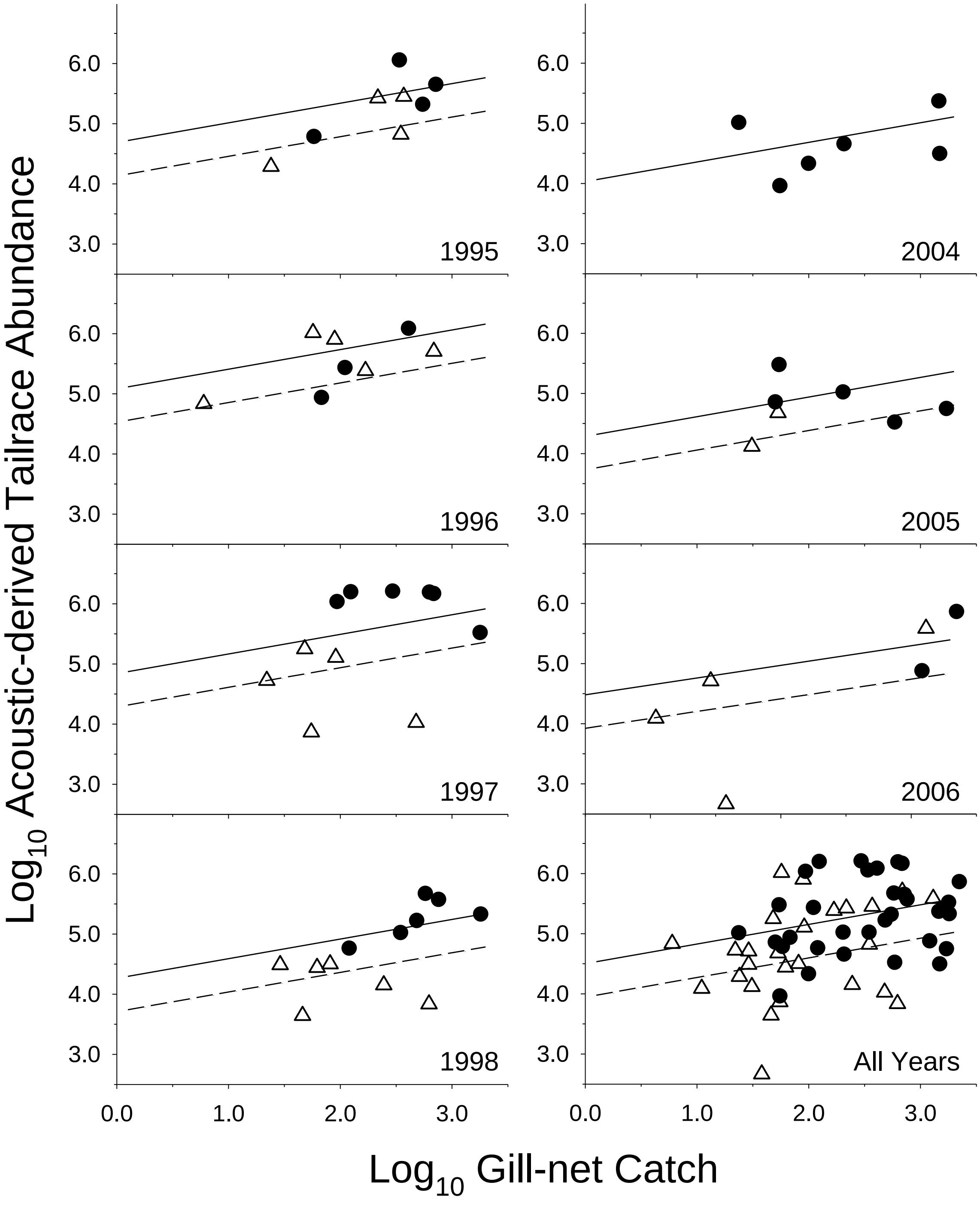

Figure 2-7. Plot of $\log_{10}$ tailrace acoustic abundance against gill net catch. Fitted lines are from the best fitting mixed linear model (tailrace abundance = gill net catch + season) with a random intercept and common slope for warm (filled circles, solid line) and cold (open triangles, dashed line) seasons. Fitted lines were extended beyond the observed data to convey the random, year-specific intercepts. The bottom right graph includes all data and the overall mean relationships by season.

CHAPTER 3

CHARACTERIZING RESERVOIR FISH ASSEMBLAGES WITH GILLNETS: HOW MUCH SAMPLING IS ENOUGH? [3]

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[3] Dennerline, D. E. and C. A. Jennings. To be submitted to North American Journal of Fisheries Management

ABSTRACT

We analyzed 20+ years of monthly gill-netting data collected from 1986 to 2009 to describe the fish assemblage and to determine if a reduced level of sampling effort could accurately characterize the fish assemblage as derived from the full data record. Our focus on the entire assemblage differed from most previous studies that developed sampling regimes based primarily on one or two species of interest. Monthly sampling data were combined to generate 3-, 4- and 6-month sampling regimes (representing 25%, 33% and 50% of the sampling effort), and three metrics were used to compare the temporal subsets with the full record: the sum of the differences in ranks of the top 10 species; Percent Similarity Index (PSI); and percent of total species captured. The species abundance distribution we observed was typical of other fish assemblages consisting of a few abundant species, 10-12 common species, and many rare species. Species accumulation curves were asymptotic, and a large number of species were captured with relatively little effort (80% of species were captured after 10% of the effort on average). Based on our results, gill-nets fished over several seasons and years seemingly provide meaningful inferential value on the relative abundances of species despite potential issues associated with encounter and retention probabilities for any given sample. Gill-nets were also effective at detecting colonization and extinction of species over the course of the study based on anecdotal evidence and known stocking records. Sampling for three, four or six months, especially scenarios that sampled across seasons, all reasonably characterized the fish assemblage as derived from gill-net sampling in terms of the species rankings, PSI scroes and proportion of species sampled, . Increasing effort from three to six months generally improved metric scores and reduced variability, so the decision to sample three, four or six months will depend on the desired accuracy, financial and logistical constraints, and acceptable level of fish

mortality. Importantly, these findings suggest that sampling effort can be reduced by 50-75%, substantially reducing costs as well as fish mortality and free up additional resources for addressing other common reservoir research objectives such as age and growth or condition.

INTRODUCTION

Monitoring programs are common throughout state and federal agencies responsible for manging fishery resources. Traditionally, monitoring efforts focused on one or two recreationally important species and the sampling regimes were designed around those species. For example, numerous studies identified and recommended specific times of the year to sample for a specific target species such as bluegill *Lepomis macrochirus* (Schultz and Haines 2005), largemouth bass *Micropterus salmoides* (Bettross and Willis 1988), sauger *Sander canadensis*, and walleye *Sander vitreous* (Mero and Willis 1992); such sampling regimes have been advocated for several other recreational sport fishes (Guy and Willis 1991).

Monitoring programs have expanded in scope over the past decade, with emphasis on monitoring the entire fish assemblage, especially in the context of documenting and tracking changes in biodiversity (Magurran and Henderson 2010, Fischer and Quist 2014). The increased scope presents new challenges, as monitoring fish assemblages is a complex and difficult task because of many sources of sampling bias and variation in abundance over space and time (Kwak and Peterson 2007). Large lentic systems such as reservoirs are especially problematic (Fischer and Quist 2014). As a result, how to sample, when to sample, where to sample, and the total sampling effort required to obtain an accurate representation of the reservoir fish community are often unknown (Bonvechio et al. 2009). Unlike species-specific sampling regimes that can target a specific month or season, a sampling regime to characterize the entire fish assemblage requires a broader temporal coverage to account for seasonal variability in the catchability of species.

Fishery managers have limited resources available for fisheries monitoring (Noble et al. 2007), so intensive sampling regimes (e.g., monthly) designed to incorporate seasonal changes in the catchability of all species in a fish assemblage can be cost-prohibitive. However, a reduced sampling effort might be sufficient for characterizing a reservoir fish assemblge when there is a pattern of diminishing information returns with increased sampling. For example, the number of species captured is often asymptotically related to effort, with the number of species increasing rapidly initially but tapering off rather quickly (Gotelli and Colwell 2001, Ugland et al. 2003). The phenomena of dimishing returns presents an opportunity and need to assess whether and how well a reduced, temporal sampling regime can represent most of the assemblage and an estimate of the relative abundances of species.

Studies on a variety of terrestrial and aquatic taxa have evaluated the effort required for estimating total diversity or sample completeness based on species accumulation curves (Moreno and Halffter 2000, Thompson and Thompson 2007, Thompson et al. 2007, Antonio Gomez-Anaya et al. 2014, Azevedo et al. 2014, Hyde et al. 2014). Because the primary focus of these authors was sampling sufficiency for estimating total species richness as part of biodiversity monitoring, other metrics or attributes of the communities were not evaluated. For reservoir fisheries monitoring programs, metrics such as relative abundance or rankings of species would likely be as important to managers as diversity.

As part of a long-term study related to pumped-storage operation of Richard B. Russell Dam, we conducted an intensive, monthly, gill-net sampling regime over an approximately 20-year period immediately below Russell Dam. The sampling regime used would be cost-prohibitive in most cases, but provides an opportunity to empirically evaluate trade-offs between metrics used to characterize a reservoir fish assemblage based on continuous monthly sampling records with those from temporal subsets of the data. The goal of this research was to characterize the fish assemblage captured by gill-net sampling in a southeastern reservoir to determine if similar inferences regarding assemblage sturucture can be made with a reduced level of sampling effort. Specific objectives were to: 1) characterize spatial and temporal patterns in catch (numbers and species) from the long-term dataset; and 2) evaluate similarity of inferences about the entire fish assemblage between three temporal subsets (three, four, and six months) of the data and the full data record.

METHODS

Study Site

J. Strom Thurmond Reservoir (JST; Figure 1) is a U.S. Army Corps of Engineers impoundment on the Savannah River, Georgia and South Carolina. Originally authorized for hydropower, flood control, and downstream navigation, the multi-purpose project now includes water supply, water quality, recreation, and fish and wildlife management. At full pool, the reservoir has a surface area of 28,773 hectares and extends 63.4 kilometers to the base of Richard B. Russell Dam, which is important because Russell Dam is a pumped-storage facility consisting of four 75-MW conventional hydropower generators and four 75-MW pumpback units. For this manuscript, the study area was restricted to just the upper portion of J. Strom Thurmond Reservoir (Figure 3-1).

Fish sampling

Standardized gill-net sampling was conducted monthly at four stations (1-4) in J. Strom Thurmond Reservoir from July 1986 to November 1999 and from November 2002 to April 2009. One of the stations was located in the tailrace immediately below the Richard B. Russell (RBR) Dam and sampling was restricted initially because of strong flows during conventional hydropower operations. Consequently, a scheduled, weekend generation moratorium was initiated in October 1987 to facilitate sampling with the complete compliment of nets. As a result, only the moratorium samples from that station were used in this analysis. The other three stations were all within 5.9 river kilometers of the Russell Dam. Sampling effort consisted of four experimental gill nets (combinations of floating/sinking and nearshore/offshore) at each station. All gill net samples were overnight sets with duration ranging from 14 to 22 hours.

Two net configurations were used during the course of the study. From July 1986 to February 1992, the experimental nets used were 45.72 m x 2.44 m and consisted of six 7.62 m x 2.44 m panels. Mesh sizes (bar measure, mm) across the panels were 25.4, 38.1, 50.8, 63.5, 76.2 and 88.9. Starting in March 1992, additional meshes were added, primarily to obtain better information on the spatial and temporal distribution of clupeids. The experimental nets were 76.20 m x 2.44 m and consisted of 10 7.62 m x 2.44 m panels. Mesh sizes (bar measure, mm) across the panels were 9.5, 12.7, 19.1, 25.4, 38.1, 50.8, 63.5, 76.2, 88.9, and 101.6. The new net configuration was implemented in March 1992; and beginning with this implementation, the mesh size was recorded for each fish sampled.

Data Analysis

Data analyses were performed on two sets of the available data. Because the first 6 years of data were collected using the six panel nets, the analyses of the entire long-term data record for JST was accomplished by only including catch from the same six meshes from both the six panel and 10 panel nets (JST-6). The second data group (JST-10) included catch only from the 10 panel nets and included catch from all of the meshes.

Boxplots were used to characterize spatial and temporal patterns in the median number of individuals and median number of species caught. Statements regarding the statistical significance of differences in catch were based on whether the notches of the plots overlapped (Chambers et al. 1983, R Core Team 2014).

A variety of techniques was used to characterize the fish assemblages and to evaluate the similarity of inferences between the entire sampling frame and reduced temporal sampling frames for both data groups. The temporal subsets consisted of 3-, 4- and 6-month periods to represent 25%, 33% and 50% of the annual gill-netting effort. Species accumulation curves were generated for each dataset (i.e., JST-6 and JST-10) to compare the number of species collected for a given level of sampling effort and included the overall curves for each dataset as well as curves for individual months and stations. Species accumulation curves were initially generated for each dataset by using sample-based and individual fish-based approaches to determine whether species were randomly distributed over stations (Kindt and Coe 2005). Because the sample-based and individual-based curves were very similar when scaled to the same x-axis and because samples were collected at fixed sites (e.g., stations), the results presented are the sampled-based accumulation curves. The resultant mean number of species caught by month and station were used to assess the temporal and spatial variability in the number of species collected. Four incidence-based richness estimators (Chao, Jackknife1, Jacknife2, Bootstrap) were calculated using the Vegan package in R (Oksanen et al. 2013) to estimate total species richness and assess the proportion of the total species sampled for each dataset. Rank accumulation curves were used to evaluate the distribution of species collected for each gear and station. Lastly, boxplots of catch by month were generated for the top 10 species sampled by each gear to characterize seasonality of catch and to identify important time frames for defining and evaluating sampling strategies.

Three metrics were used for evaluating the comparability of inferences between the full sampling record and the temporal subsets from the two datasets. The first metric was the sum of the absolute difference in rankings of the top 10 species from the complete data record with those same species in each temporal subset (Rank-10). For example, if a species was ranked 2nd overall but 5th in the temporal subset, the species was assigned a score of 3 (absolute value of 2-5). These values were summed across the top 10 species for each temporal subset. This metric was created to focus on getting the top 10 species correct (e.g., a score of zero indicates the same 10 species in the same rank order) as we expected the top 10 species to comprise the bulk of the catch by both number and weight. The percent similarity index (PSI; Renkonen 1938) was used to assess similarity of the entire fish assemblage. PSI is a robust measure that is not influenced by the number of individuals in a sample and unaffected by proportional changes in abundance (Krebs 1999, Kwak and Peterson 2007). The third metric was the percent of total species collected.

All three performance metrics were derived for every possible combination of the data subsets, and the resultant frequency distributions and 95th percentiles were plotted to evaluate tradeoffs among the different levels of effort for each metric. There were 220 combinations for the 3-month scenario, 495 cominations for the 4-month scenario, and 924 combinations for the 6-month scenarios. Because all possible combinations of the data included many scenarios that did not include sampling across seasons (for example, January, February and March scenario), we also evaluated a reduced number of sampling scenarios that explicitly incorporated seasonality. For example, one 3-month sampling strategy included all combinations that sampled one month between January to April, one month between May to August and one month between September and December. Similarly, a 4-month sampling scenario only used combinations of four months where one month was sampled between January and March, one month was sampled between April and June, one month was sampled between July and September, and one month was sampled between October and December.

All analyses and graphics were generated using the statistical programming language R (R Core Team 2014). Species accumulation curves and rank abundance curves were calculated using the BiodiversityR package (version 2.4-4; Kindt and Coe 2005).

RESULTS

For the JST-6 dataset, a total of 908 samples (3,635 nets) collected 46,139 fishes from 44 species (Table 3-1). For the JST-10 dataset, a total of 651 samples (2,603 nets) collected 152,035 fishes from 44 species. The number of species captured at each station within each dataset ranged from 37 to 39 for JST-6 and 36 to 38 for JST-10. The top 10 species from JST-6 accounted for 93% of the total catch and nine of those species were captured frequently, occurring in ≥45% of the samples (Table 3-2). Similarly, the top 10 species from JST-10 accounted for 96% of the total catch and all 10 species were captured frequently, occurring in ≥50% of the samples (Table 3-2).

The amount of spatial disparity (differences in catch among stations) differed between the JST-6 and JST-10 datasets. JST-6 showed the most spatial disparity as median catch at Station 1 was lower than the other stations (Figure 3-2). Median catch was similar but highly variable among stations for JST-10 (Figure 3-2). Seasonality of catch was much more pronounced in the 10-panel nets as opposed to the 6-panel netsbecause of the seasonally high catches of blueback herring *Alosa aestivalis* and threadfin shad *Dorosoma petenense* in the 10-panel nets. These two species were rarely captured in the 6-panel nets. For JST-6, catch was lowest for the four coldest months (November to February) but was similar from March to October (Figure 3-2). Median catch for JST-10 peaked in May or June, decreased throughout the summer, and remained at low levels until the next April or May (Figure 3-2). Spatially and temporally, the highest catches for both sets of nets typically also had the widest range and highest variance (i.e., widest box width).

For both datasets, the number of species collected was much less variable (relative to the median) spatially and temporally than than number of fishes collected (Figure 3-3). The spatial pattern in catch of species was similar for JST-6 and JST-10. In both instances, there was a significantly lower number of species collected at Station 1, but the median numbers of species collected at stations 2 - 4 were similar to one another (Figure 3-3 top row). The 10-panel nets collected four more species on average than the 6-panel nets at all stations (range 10-12 vs 6-8) and months (range 10-13 vs 6-9). Temporally, both datasets showed a 1- or 2-species increase in the median number of species collected from September to December (Figure 3-3).

The overall species accumulation curves were similar between the two datasets, with 22 species (50%) caught in 12 or fewer samples and greater than 30 species in 50 samples (32 for JST-6 and 34 for JST-10; Figure 3-4). At 200 samples, both datasets had acquired 39 species, which represented 89% of the total species collected from JST-6 and JST-10. Both nets captured a total of 44 species (42 shared species). The four incidence-based richness estimators ranged from 46 to 52 species for JST-6 and 46 to 49 species for JST-10 indicating we captured a high percentage of the species (85%-96%) vulnerable to gill-nets. Species accumulation curves were similar among stations (Figure 3-4 second row) but varied among months. For example, a range of 10 species was observed among months at JST-6 over the total number of samples (Figure 3-4, third row). The highest curves were for the cooler weather months (Figure 3-3). Lastly, the species accumulation curves for individual years (Figure 3-4, bottom row) reveal that the total number of species captured within a typical sampling year ranged from 25 to 33 for JST-6 (48 samples) and 28-34 for JST-10 (48 samples).

Patterns in species compostion were similar between data sets, with relatively few species comprising the bulk of the catch. The top-10 ranked species, based on number, accounted for

93% of the total catch for JST-6 and 96% of the total catch JST-10 (Figure 3-5). The species comprising the top-10 ranked species varied between JST-6 and JST-10, as expected, because of the additional meshes used in the 10-panel nets caught large numbers of small fishes, especially clupeids, which were not effectively sampled with the six-panel nets. For JST-6, three species (gizzard shad *Dorosoma cepedianum*, hybrid bass *Morone saxatilis X M. chrysops,* and white perch *Morone americana*) were in the top five species at all four stations and accounted for about 70% of the total catch. Gizzard shad was the highest ranked species at all stations and accounted for 30-60% of the total catch across all stations, with the percentage increasing with distance from RBR dam. Three *Morone* species (white perch, striped bass *Morone saxatilis*, and hybrid bass) were in the top-5 species at all stations for the JST-6 data set, but decreased in relative importance with distance from RBR dam. For JST-10, three clupeids (blueback herring, threadfin shad, and gizzard shad) numerically dominated the catch and accounted for greater than 82% of the toal catch. Blueback hering and threadfin shad alone accounted for greater than 70% of the catch by number.

Though the most important species were similar spatially among stations, importance varied temporally for many top-10 species because of seasonality in catch (Figure 3-6). For example, catch varied substantially among months from JST-10 for species like threadfin shad and longnose gar *Lepisosteous osseus*, with peak catch occurring during the summer and low to absent catches during cold weather months, especially January and February (Figure 3-6). Conversely, peak catch of a few species such as spottail shiner *Notropis hudsonius* and yellow perch *Perca flavescens* occurred during January to March when they achieved their highest relative ranking (Figure 3-6).

Median scores for the three metrics we evaluated (Rank-10, PSI, and percent of species) showed good concordance (low Rank-10 scores and relatively high values for PSI, and percent of species) between the three temporal subsets and the full data record (Figures 3-7 and 3-8). Increasing effort from 3 months to 6 months generally improved all three metric scores as well as reduced variability in both datasets (Figures 3-7 and 3-8). For example, using all possible combinations for JST-6 (Figure 3-7; grey bars and boxplots), median values for Rank-10 (left column) improved from eight to four (lower is better) going from three months of sampling to six months of sampling. Likewise, median PSI score (middle column) went from 91% to 95%, and median percent of species caught (right column) went from 86% to 96% as sampling increased from three to six months (Figure 3-7; grey bars and boxplots). A similar pattern in the median scores for all three metrics was observed for JST-10 when all possible combinations were used (Figure 3-8; grey bars and boxplots). Rank-10 went from eight to four, PSI went from 85% to 93%, and percent of species caught 86% to 93% as effort increased from three to six months of sampling.

The reduced, season-specific sampling scenarios improved metric scores and reduced the variability compared to all possible combinations of the data for both datasets. For example, the white histograms and boxplots in Figures 3-7 and 3-8 show metric scores based on combinations of samples from specific month groups that included multiple seasons. The months included in the five best sampling scenarios (those with the lowest Rank-10 score and highest PSI score) varied between the two datasets (Tables 3-3 and 3-4). For example, sampling in January and February was important for the larger meshes (6-panel nets) across all levels of sampling effort (Table 3-3). However, for the 10-panel nets with the smaller meshes, March and April were more prevalent in the best temporal subsets (Table 3-4). Despite these differences between the datasets, the reduced seasonal scenarios that sampled across "seasons" showed a high degree of concordance with the full data record based on the relatively low median Rank-10 scores and high PSI and high percentage of of species captured.

DISCUSSION

For this study, we characterized a reservoir fish assemblage collected by gill-net sampling and evaluated the similarity in composition between the full data set and temporal subsets of the data. We focused on gill-net derived data for this manuscript because the species of most interest to reservoir and project managers were open-water predators (striped bass and hybrid bass) and forage fishes (primarily blueback herring and threadfin shad) that are susceptible to gill-net sampling. These groups were also expected to be the most directly affected by pump-storage operation of Russell Dam.

The species abundance distributions (SAD) characterizing our fish assemblage based on the full data records are consistent with those from other long-term ecological studies and a general rule of community ecology where there are a few common species and many rare species (McGill et al. 2007, Henderson and Magurran 2010). For example, Magurran and Henderson (2003) analyzed a 21-year fisheries data set and similarly found that three species accounted for greater than 70% of the catch by number (and weight), 28 additional "core species" accounted for another 29% of the catch, and 49 "occasional and typically non-abundant species" (transient species) constituted the remaining 1%.

Spatially, the top five ranked species were similar among stations but the relative rankings varied with distance from the dam. The similarity in the top five species among the four stations was likely caused by the limited geographic extent of the study area, which was designed to focus on near-field effects of Richard B. Russell Dam operations. Had we sampled a larger portion of the reservoir, the top-ranked species likely would have changed as we encountered longitudinal gradients typical in southern reservoirs (Siler et al. 1986, Kennedy and Walker 1990). Differences in the relative contributions of the top five species in our study are believed to result from pronounced, local thermal differences caused by oxygenated, hypolimnetic releases from Russell Dam. Coolwater species such as striped bass and blueback herring were more prominant immediately below the dam where water temperatures were cooler, especially during the summer). Conversely, warmwater species such as gizzard and threadfin shad increased in importance farther from the dam where temperature of the upper water column wasaffected less by hyplolimnetic releases.

Seasonality in catch was pronounced for many of the top 10 species in this study and varied among species and dataset. Specific sampling time frames to maximize catch of specific species were readily identifiable as with previous studies that focused on individual species (see introduction). However, the variability among the top 10 species increased the difficulty of easily discerning a specific, reduced sampling time frame that would account for the variability and result in relative abundances and species rankings consistent with the full data record. Our empirical results indicate that sampling across seasonal time blocks will, on the average, produce results similar to the full data record.

We did not directly investigate the annual variability in species rankings or species turnover (extinction/colonization) over the period of study. Our logic was that most long-term monitoring programs would be designed to provde a general description of the fish assemblage over a broad period of time. This logic also accepted that there would be annual variation in relative abundances as species periodically experience strong or weak year classes over the longer duration. With respect to turnover, gill-nets at all sampling levels seemingly were effective at detecting the presence of new species as they arose and the loss of species as they disappeared. Numerous species disappeared or thrived over the duration of our study, and their relative contributions to the assemblage were well represented by the temporal subsets of the data. For example, sauger, a riverine-dependent species, was predictably extirpated after RBR Dam was built and the riverine habitat between JST reservoir and Hartwell Dam was lost. Seventy-six sauger were captured in the 6-panel nets early in the study, but catch rate decreased very rapidly, which was consistent with expectations. Sauger were ranked 23rd overall and the mean rank for sauger across all 220, 3-month sampling scenarios was 23.08 (SE = 0.33). Similarly, several species such as blueback herring, spotted bass *Micropterus punctulatus*, and white perch were not present or present in very low numbers at the beginning of the study, but were introduced or flourished over the course of the study. These species were also represented well in the temporal susbsets, with mean ranks being similar to the overall rankings. For example, white perch were essentially non-existent the first few years of the study, but became a dominant species over the 20 years with a rank of 3rd overall and a mean rank of 2.57 (SE = 0.04) across all three months scenarios. Lastly, robust redhorse *Moxostoma robustum* were stocked in the Broad River upstream of the reservoir to re-establish a population of the species within its historical range (Straight and Freeman 2013). The gill-net data included as part of our analysis indicated we were effective at sampling this species; 112 individuals were captured over the course of the study. Given the number of fish stocked, unknown survival rate, and large geographic area, the number of fish captured suggests gillnets were effective at both initially detecting the species (once they achieved a vulnerable size) and continuing to capture the species once established.

We do not suggest that gill-nets adequately sampled the entire fish assemblage, but suggest that gill-nets adequately sampled the species of most interest to managers. Given the diversity of habitats and complexity of the assemblages in large impoundments, a single sampling method will not adequately represent the entire reservoir fish assemblage (Jackson and Harvey 1997, Fago 1998, Olin and Malinen 2003). However, the species accumulation curves from this study showed our gill-net sampling collected many species at a relatively low level of effort. Our results are similar to those of Fischer and Quist (2014) who found in a multi-gear comparison that gill-nets collected a relatively high number of species and reached an asymptote much quicker than other gears. The accumulation curve for our JST-10 dataset was slightly steeper at the onset than JST-6 because of the collection of numerous, small-bodied species not readily or frequently sampled by the larger meshes used in JST-6. The more rapid accumulation of species in the JST-10 data set resulted in slight differences in the total richness estimators, but a high percentage of species were captured in both data sets. Most of the species were collected with relatively little effort initially and additional species came at a high cost (e.g., both real and opportunity costs). Similar results have been noted across a wide variety of individual taxa (Moreno and Halffter 2000, Thompson and Thompson 2007, Thompson et al. 2007).

Though no single gear will collect all species in an assemblage, information from a single gear is useful if it accurately describes the relative abundances of the fishes vulnerable to the gear. Knowing whether the SAD observed in this or any study is the true distribution or an artifact of sampling is difficult (McGill 2003). This is especially true when sampling with a single gear as there is no basis for discerning whether species that are rarely caught are truly rare in the environment being sampled, 'transient' species that infrequently and sporadically stray into an area, or are present but not captured efficiently with the gear used (Thompson et al.

2007). For example, a single gill-net sample has unknown utility for evaluating species composition or relative abundance because catch is dependent on many species-specific factors that influence encounter rates with nets and capture and retention probabilities once a net is encountered (Spangler and Collins 1992, Dennerline et al. 2012). Thus, an individual sample has unknown inferential value and might not be representative. For example, this may be true when the modal size of a core species is a size not effectively captured by the gear. Despite potential inconsistencies in individual samples in a long-term monitoring program, we suggest that seasonal gillnet samples over several years provide useful inferences on the relative abundance of species vulnerable to gill nets. This assertion is corroborated by the observed SADs being consistent with ecological theory, sampling of new species after known stocking events, increased number and frequency of newly expanding species over time, and the temporal subsets accurately describing the relative contribution of most of the species.

To assess similarities between the full data record and temporal subsets, we used three metrics to combine attributes that would be of interest in long-term monitoring of a reservoir fish assemblage for management purposes. The Rank-10 metric we used was consistent with the notion of "core species" from gill-net sampling and focused on identifying the species that accounted for most of the catch. The decision to evaluate the top-10 species was an arbitrary cut-off, but seemed reasonable as the top-10 species accounted for more than 93% of the catch by number in both data sets. The ability to discern changes in the assemblage over time will likely be limited to a subset of core species that are captured often enough and in large enough numbers to have some inferential value. PSI was initially chosen as a metric to assess robustness of the subsets to include all species captured. However, the typical, skewed species abundance distribution noted above suggests that PSI is not a very robust metric for evaluating changes in a large reservoir fish assemblage, unless the change is to one of the “core” species captured by the gear. By definition, if 50% of the species only account for 1% of the catch, then not catching any of those species would only result in a 1% change in the PSI score. With respect to the percent of species sampled, results from the temporal subsets were consistent with expectations based on the accumulation curves and showed that a median of 86% of the species captured in the full data record could be expected to be caught in just three months of sampling (e.g., 25% of effort). Increasing effort from three to six months generally resulted in improved metric scores for all three metrics relative to those derived from the full data record and reduced the variance (i.e., range of the distributions). Sampling beyond six months on an odd or even month schedule is unlikely to provide additional meaningful information.

Our results suggest that sampling three, four or six months per year year across seasons will all reasonably characterize the fish assemblage as derived from gill-net sampling for the entire year. Consequently, the decision to sample for three, four or six months will depend on the level of accuracy and precision desired given financial and logistical constraints and acceptable levels of fish mortality. Regardless, the sampling regimes evaluated represent a 50 to 75% reduction in total effort so the benefits and savings will be substantial in terms of both real and opportunity costs. The real costs of labor, equipment and supplies, as well as fish mortality can be reduced by 50 to75% without compromising the value of the information obtained. Furthermore, reducing the gillnetting effort by 50 to 75% frees resources and provides opportunities to address additional research needs of reservoir fishery managers.

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Table 3-1. The number of samples, number of fishes, and number of species collected, by station, for each net configuration from J. Strom Thurmond Reservoir from July 1986 to April 2009.

Net Configuration	Station	Number of samples	Number of fish	Number of Species
JST-6				
	1	200	7,475	37
	2	238	14,425	39
	3	235	11,291	37
	4	235	12,948	38
	Total	908	46,139	44
JST-10				
	1	153	59,653	38
	2	168	32,827	37
	3	165	25,157	36
	4	165	34,398	38
	Total	651	152,035	44

Table 3-2. Number of individuals caught and the number of samples catching at least one individual (in parentheses) for each species from JST-6 (908 samples) and JST-10 (651 samples). Numbers are the combined catch from stations 1 through 4 in J. Strom Thurmond Reservoir from July 1986 to April 2009.

Common Name	Species	JST-6		JST-10	
Blueback herring	*Alosa aestivalis*	195	(88)	60,387	(600)
Gizzard shad	*Dorosoma cepedianum*	21,556	(844)	17,019	(603)
Threadfin shad	*Dorosoma petenense*	9	(6)	46,882	(461)
Chain pickerel	*Esox niger*	51	(49)	44	(42)
Blue catifish	*Ictalurus furcatus*	21	(15)	21	(14)
White catfish	*Ameiurus catus*	79	(68)	40	(37)
Yellow bullhead	*A. natalis*	5	(5)	3	(3)
Brown bullhead	*A. nebulosus*	9	(7)	4	(2)
Channel catfish	*Ictalurus punctatus*	1,322	(465)	1,264	(389)
Flathead catfish	*Pylodictis olivaris*	57	(47)	42	(40)
Longnose gar	*Lepisosteus osseus*	1,351	(430)	1,566	(381)
White perch	*Morone. americana*	5,062	(579)	7,675	(546)
White bass	*M. chrysops*	230	(155)	121	(90)
Striped bass	*M. saxatilis*	2,560	(667)	2,392	(517)
Hybrid bass	*M. saxatilis x M. chrysops*	5,469	(657)	4,451	(496)
River carpsucker	*Carpiodes carpio*	801	(189)	207	(90)
Quillback carpsucker	*C. cyprinus*	139	(50)	67	(39)
White sucker	*Catostomus commersoni*	2	(2)	1	(1)
Northern hogsucker	*Hypentelium nigricans*	21	(17)	12	(11)
Spotted sucker	*Minytrema melanops*	1,375	(485)	1,198	(391)
Robust redhose	*Moxostoma robustus*	112	(61)	112	(61)
Silver redhorse	*M. anisurum*	1,808	(505)	1,033	(350)
Golden redhorse	*M. erythrurum*	11	(5)	-	(-)
Brassy jumprock	*M. rupiscartes*	1	(1)	1	(1)
Warmouth sunfish	*Lepomis gulosus*	32	(30)	84	(68)
Redbreast sunfish	*L. auritis*	19	(12)	24	(18)
Green sunfish	*L. cyanellus*	3	(3)	6	(6)
Bluegill sunfish	*L. macrochirus*	97	(82)	493	(252)
Redear sunfish	*L. microlophus*	454	(259)	422	(218)
Redeye bass	*Micropterus coosae*	48	(31)	46	(30)
Spotted bass	*M. punctatus*	51	(30)	67	(38)
Largemouth bass	*M. salmoides*	446	(268)	311	(191)
White crappie	*Pomoxis annularis*	88	(51)	82	(46)
Black crappie	*P. nigromaculatus*	1,679	(459)	2,065	(410)
Carp	*Cyprinus carpio*	547	(279)	358	(175)
Grass carp	*Ctenopharyngodon idella*	1	(1)	-	(-)
Bluehead chub	*Nocomis leptocephalus*	1	(1)	2	(2)
Golden shiner	*Notemigonus crysoleucas*	111	(59)	174	(89)
Spottail shiner	*Notropis hudsonius*	23	(7)	1,831	(329)
Whitefin shiner	*Cyprinella nivea*	1	(1)	96	(43)

Spotfin shiner	*C. spiloptera*	-	(-)	2	(2)
Banded killifish	*Fundulus diaphanus*	-	(-)	9	(7)
Yellow perch	*Perca flavescens*	184	(123)	1,414	(392)
Sauger	*Sander canadense*	76	(45)	1	(1)
Walleye	*S. vitreum*	18	(18)	1	(1)
Rainbow trout	*Oncorhyncus mykiss*	14	(10)	5	(3)

Table 3-3. Mean and standard error (in parentheses) for Rank-10, PSI and the percent of species captured for the different sampling effort scenarios including: all possible combinations, seasonal scenarios where the combinations included one month from each hyphenated group, and the top 5 combinations that resulted in the best metric scores for each level of sampling effort (3, 4 or 6 months), as determined by the lowest Rank-10 score coupled with the highest PSI score. Data are for the six panel nets (JST-6) from J. Strom Thurmond stations 1 through 4 collected from July 1986 through April 2009.

Month group or months sampled	Number of combinations	Rank-10	PSI	% spp
3 months				
All combinations	220	8.20 (0.24)	0.91 (0.00)	0.88 (0.00)
1-4, 5-8, 9-12	64	7.20 (0.32)	0.93 (0.00)	0.89 (0.00)
3-6, 7-10, 11-2	64	6.42 (0.31)	0.92 (0.00)	0.88 (0.00)
1, 4, 7	1	2	0.96	0.86
2, 4, 6	1	2	0.94	0.80
2, 5, 11	1	2	0.94	0.93
1, 4, 8	1	2	0.93	0.89
1, 4, 9	1	2	0.92	0.89
4 months				
All combinations	495	6.68 (0.14)	0.93 (0.00)	0.91 (0.00)
1-3, 4-6, 7-9,10-12	81	4.94 (0.25)	0.94 (0.00)	0.91 (0.00)
3-5, 6-8, 9-11, 12-2	81	5.54 (0.28)	0.95 (0.00)	0.91 (0.00)
2, 4, 6, 11	1	0	0.97	0.86
2, 4, 6, 12	1	0	0.95	0.84
1, 2, 4, 6	1	0	0.95	0.84
1, 4, 7, 10	1	2	0.97	0.91
1, 4, 7, 11	1	2	0.97	0.91
6 months				
All Combinations	924	5.16 (0.09)	0.95 (0.00)	0.95 (0.00)
1-2, 3-4, 5-6, 7-8, 9-10, 11-12	64	4.05 (0.23)	0.97 (0.00)	0.95 (0.00)
Odd months	1	2	0.98	1.00
Even months	1	2	0.99	0.89
1, 2, 4, 7, 8, 10	1	0	0.98	0.91
1, 3, 5, 6, 9, 12	1	0	0.98	0.98
1, 2, 4, 5, 7, 11	1	0	0.98	0.95
1, 2, 4, 5, 7, 12	1	0	0.97	0.91
1, 2, 4, 5, 8, 11	1	0	0.96	0.95

Table 3-4. Mean and standard error (in parentheses) for Rank-10, PSI and the percent of species captured for the different sampling effort scenarios including: all possible combinations, seasonal scenarios where the combinations included one month from each hyphenated group, and the top 5 combinations that resulted in the best metric scores for each level of sampling effort (3, 4 or 6 months), as determined by the lowest Rank-10 score coupled with the highest PSI score. Data are for the ten panel nets (JST-10) from J. Strom Thurmond stations 1 through 4 collected from March 1992 through April 2009.

Month group or months sampled	Number of combinations	Rank-10	PSI	% spp
3 months				
All combinations	220	8.66 (0.32)	0.84 (0.016)	0.87 (0.00)
1-4, 5-8, 9-12	64	5.80 (0.42)	0.86 (0.018)	0.87 (0.00)
3-6, 7-10, 11-2	64	7.23 (0.49)	0.89 (0.019)	0.88 (0.01)
4, 7, 12	1	0	0.98	0.89
4, 7, 11	1	0	0.97	0.84
3, 6, 9	1	0	0.96	0.91
3, 5, 7	1	0	0.95	0.89
4, 8, 12	1	0	0.92	0.86
4 months				
All combinations	495	6.92 (0.17)	0.88 (0.00)	0.90 (0.00)
1-3, 4-6, 7-9,10-12	81	3.75 (0.26)	0.94 (0.00)	0.90 (0.00)
3-5, 6-8, 9-11, 12-2	81	5.82 (0.33)	0.91 (0.01)	0.90 (0.00)
3, 5, 7, 12	1	0	0.98	0.93
1, 4, 8, 9	1	0	0.98	0.93
3, 5, 7, 11	1	0	0.98	0.91
3, 5, 8, 11	1	0	0.96	0.89
2, 5, 9, 11	1	0	0.95	0.84
6 months				
All combinations	924	4.90 (0.10)	0.92 (0.00)	0.94 (0.00)
1-2, 3-4, 5-6, 7-8, 9-10, 11-12	64	2.14 (0.26)	0.95 (0.00)	0.93 (0.01)
Odd months	1	2	0.98	1.00
Even months	1	2	0.99	0.89
1, 3, 5, 8, 9, 12	1	0	0.98	0.98
2, 4, 6, 7, 10, 12	1	0	0.98	0.89
1, 3, 5, 8, 9, 10	1	0	0.98	1.00
1, 3, 5, 8, 9, 11	1	0	0.98	0.98
3, 4, 6, 8, 9, 11	1	0	0.98	0.91

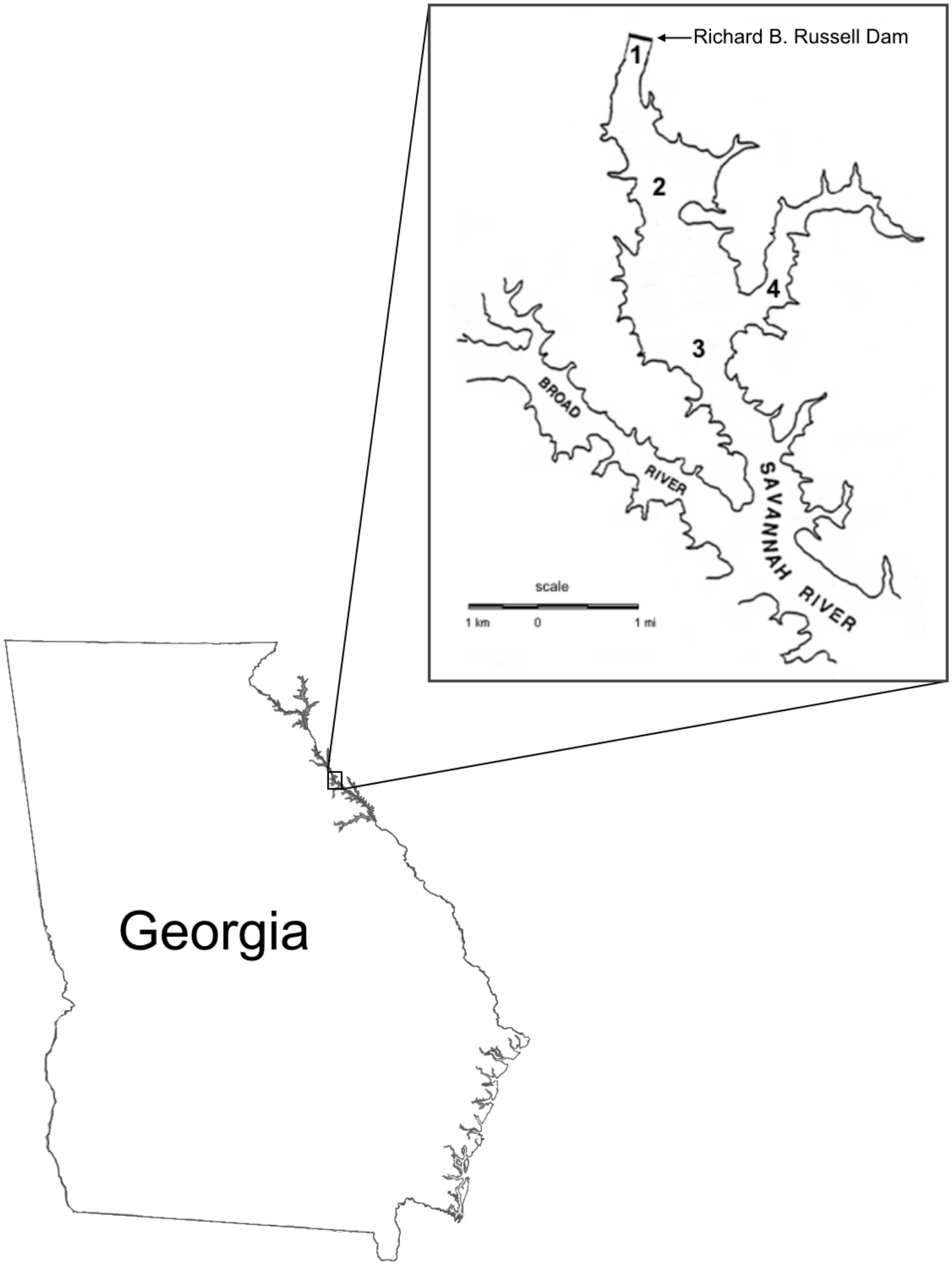

Figure 3-1. Map showing location of J. Strom Thurmond Reservoir on the Savannah River, GA/SC and the location of stations 1, 2, 3 and 4 sampled from July 1986 to April 2009.

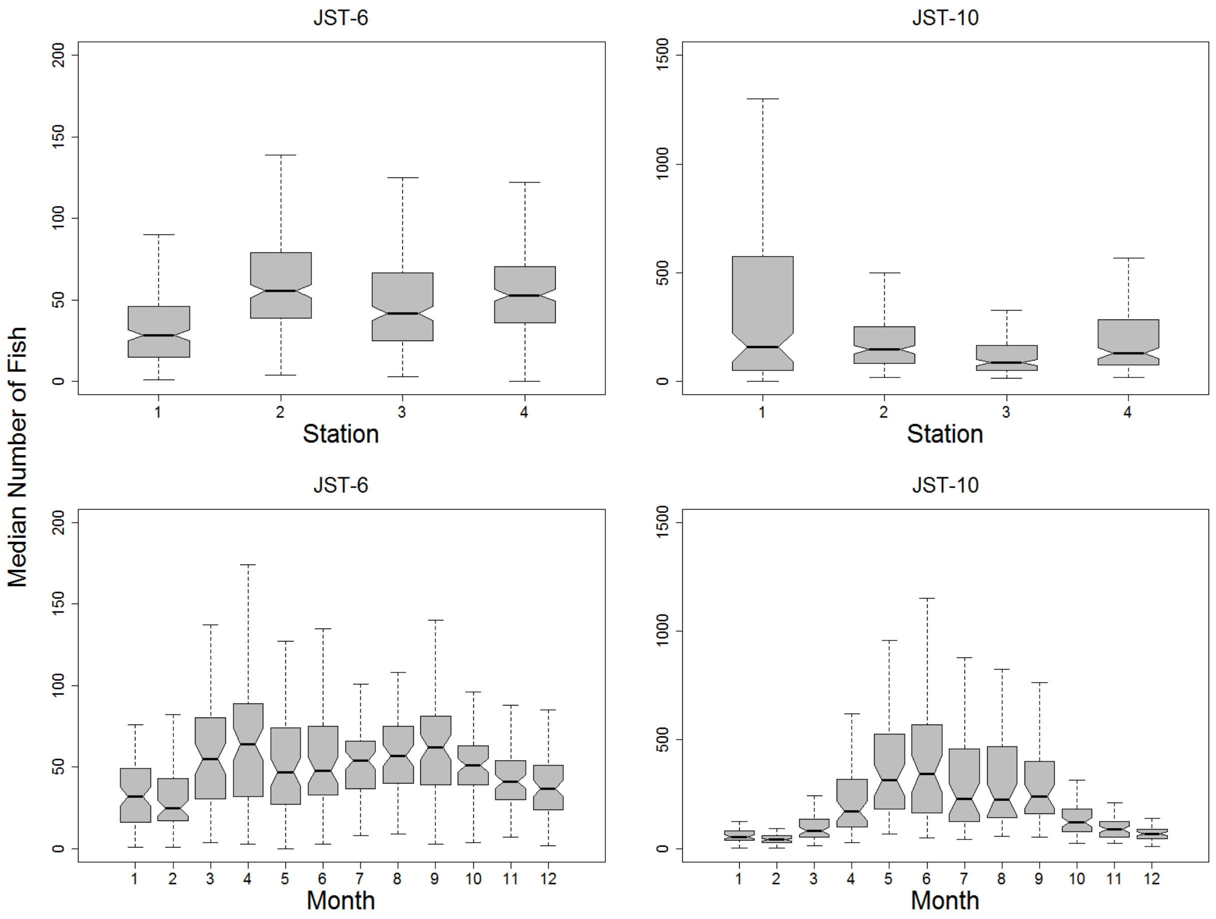

Figure 3-2. Box and whisker plots of the number of fish per sample for each station (top row) and month (bottom row) from JST-6 (left column) and JST-10 (right column) sampled in J. Strom Thurmond Reservoir from July 1986 to April 2009. Note the Y axes are scaled differently to highlight the variation within each panel.

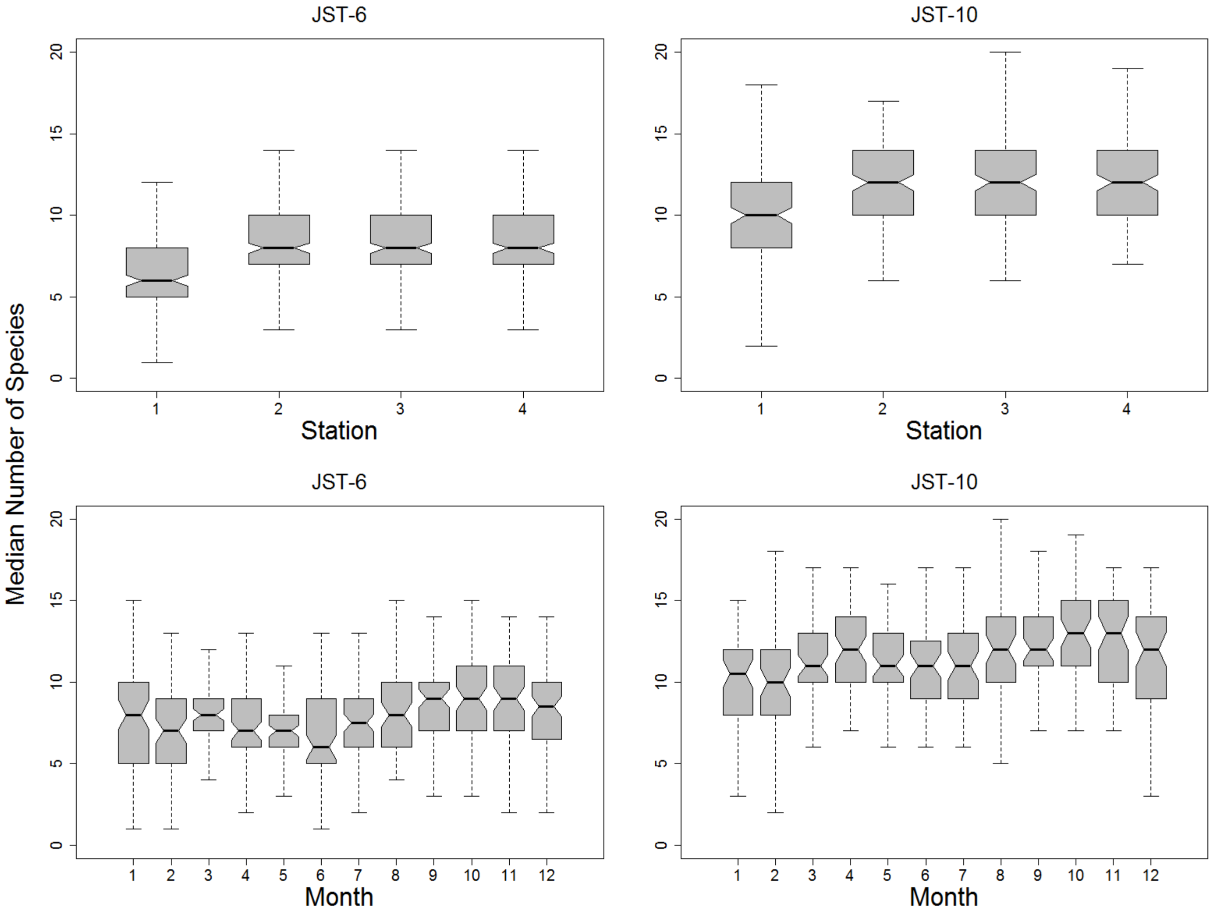

Figure 3-3. Box and whisker plots of the median number of species per sample for each station (top row) and month (bottom row) from the six panel (JST-6; left column) and ten panel (JST-10; right column) nets used in sampling J. Strom Thurmond Reservoir from July 1986 to April 2009.

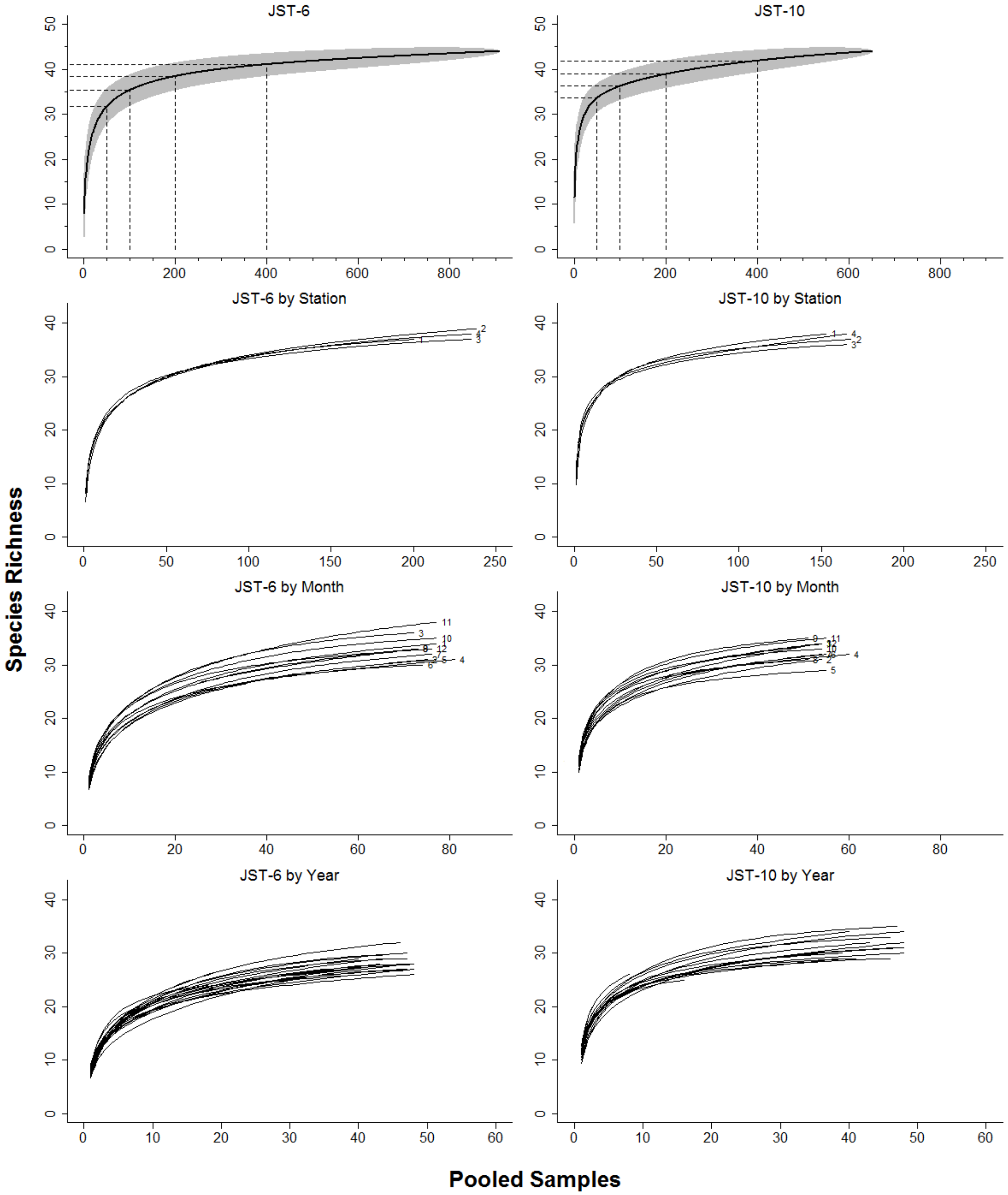

Figure 3-4. Species accumulation curves for JST-6 and JST-10. The top row of plots are the fitted (heavy line) to the observed number of species and includes 95% confidence interval (shaded area) based on 1000 permutations. The dashed lines show the number of species accumulated at 50, 100, 200, and 400 samples. The second, third, and four rows show accumulation curves by individual stations, months, and years, respectively.

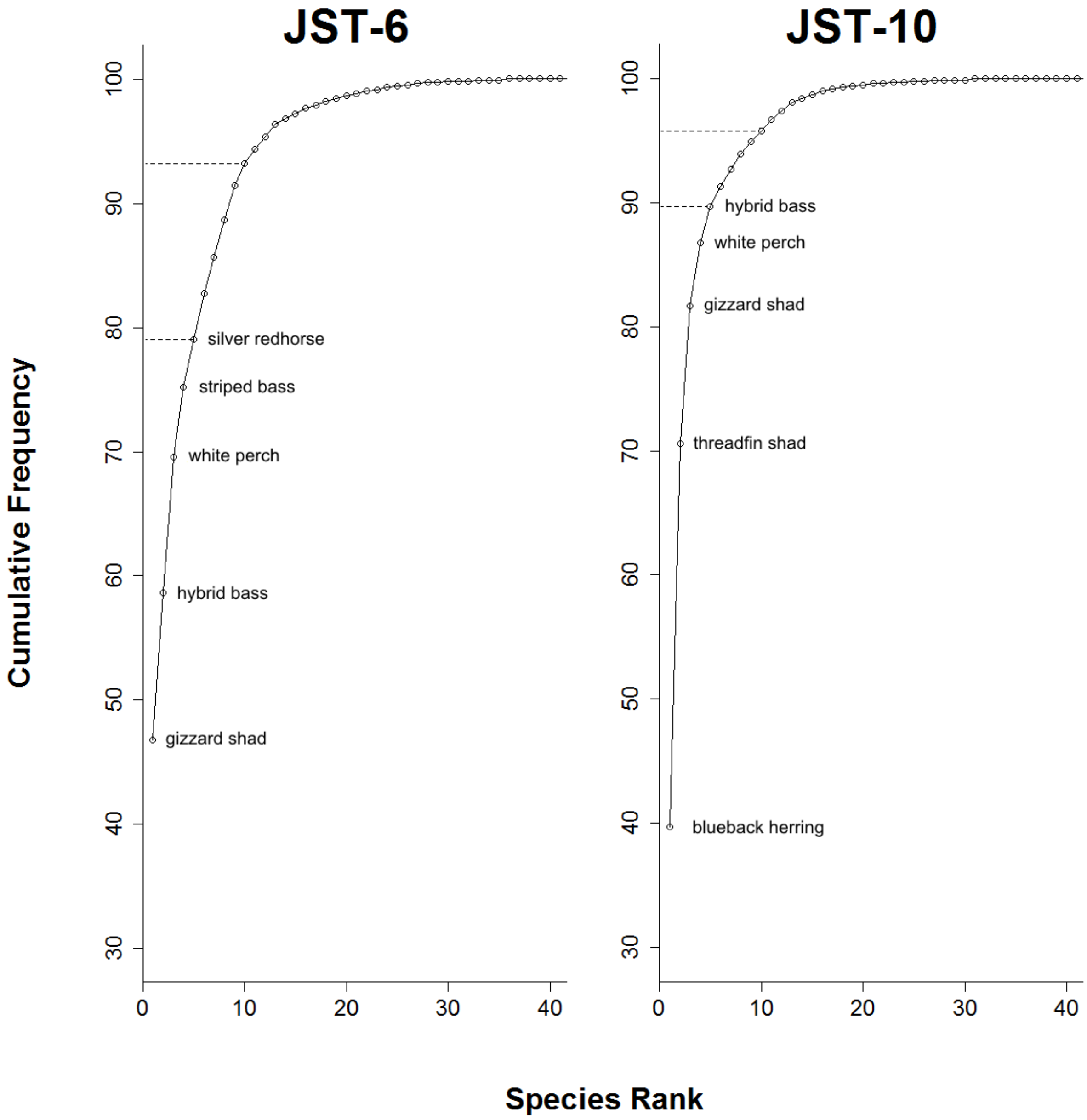

Figure 3-5. Rank accumulation curves showing the top five ranked species for the entire data record for JST-6 and JST-10 datasets. The dashed lines show the accumulated frequency represented by the top 5 and top 10 ranked species from July 1986 to April 2009.

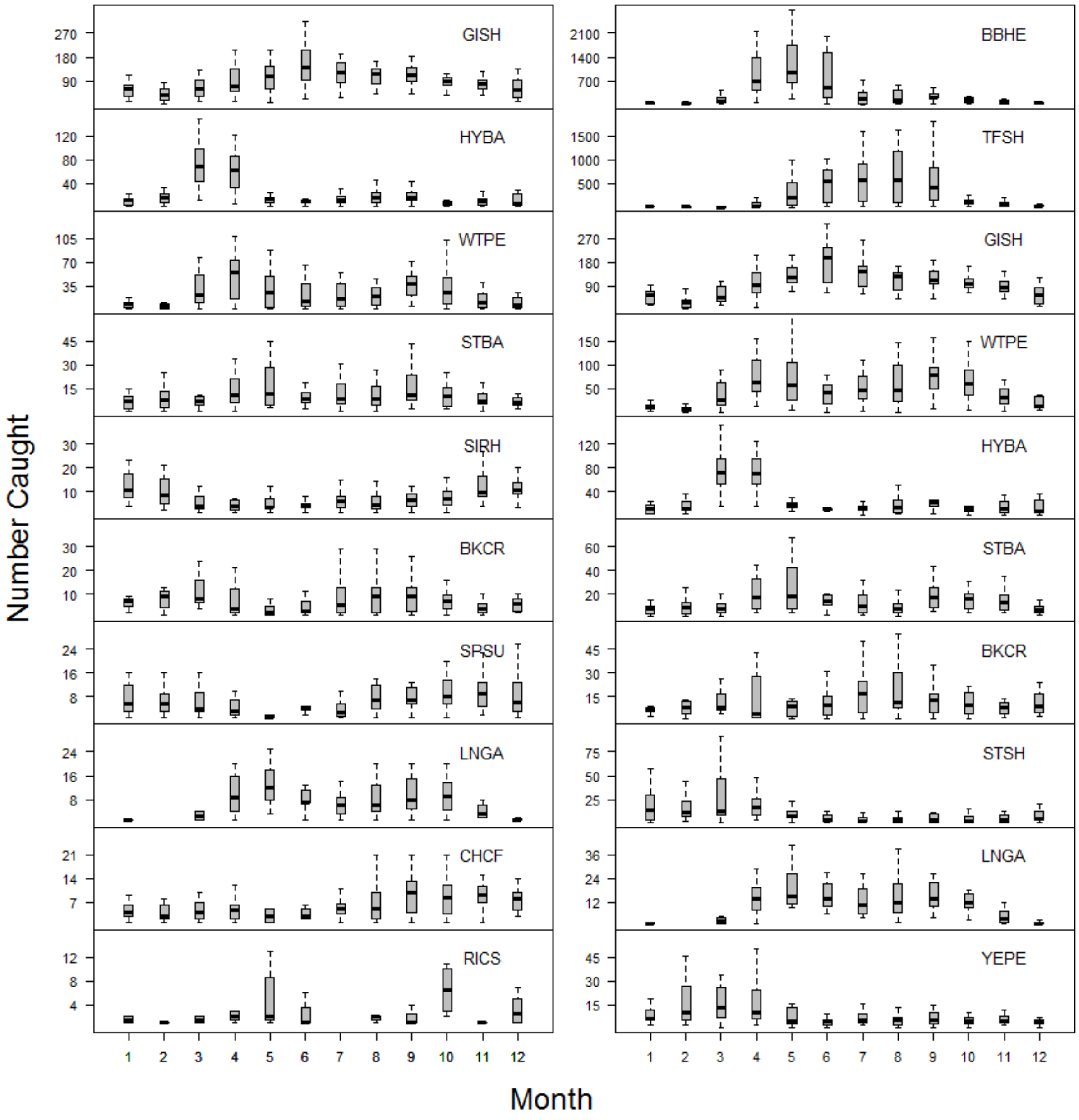

Figure 3-6. Boxplots of catch by month for each of the Top-10 ranked species for JST-6 (left panels) and JST-10 (right panels) nets from J. Strom Thurmond Reservoir sampled from July 1986 to April 2009. Boxplots contain the median, first and third quartiles, and whiskers (≤1.5*interquartile range). Outliers have been omitted for clarity and scaling.

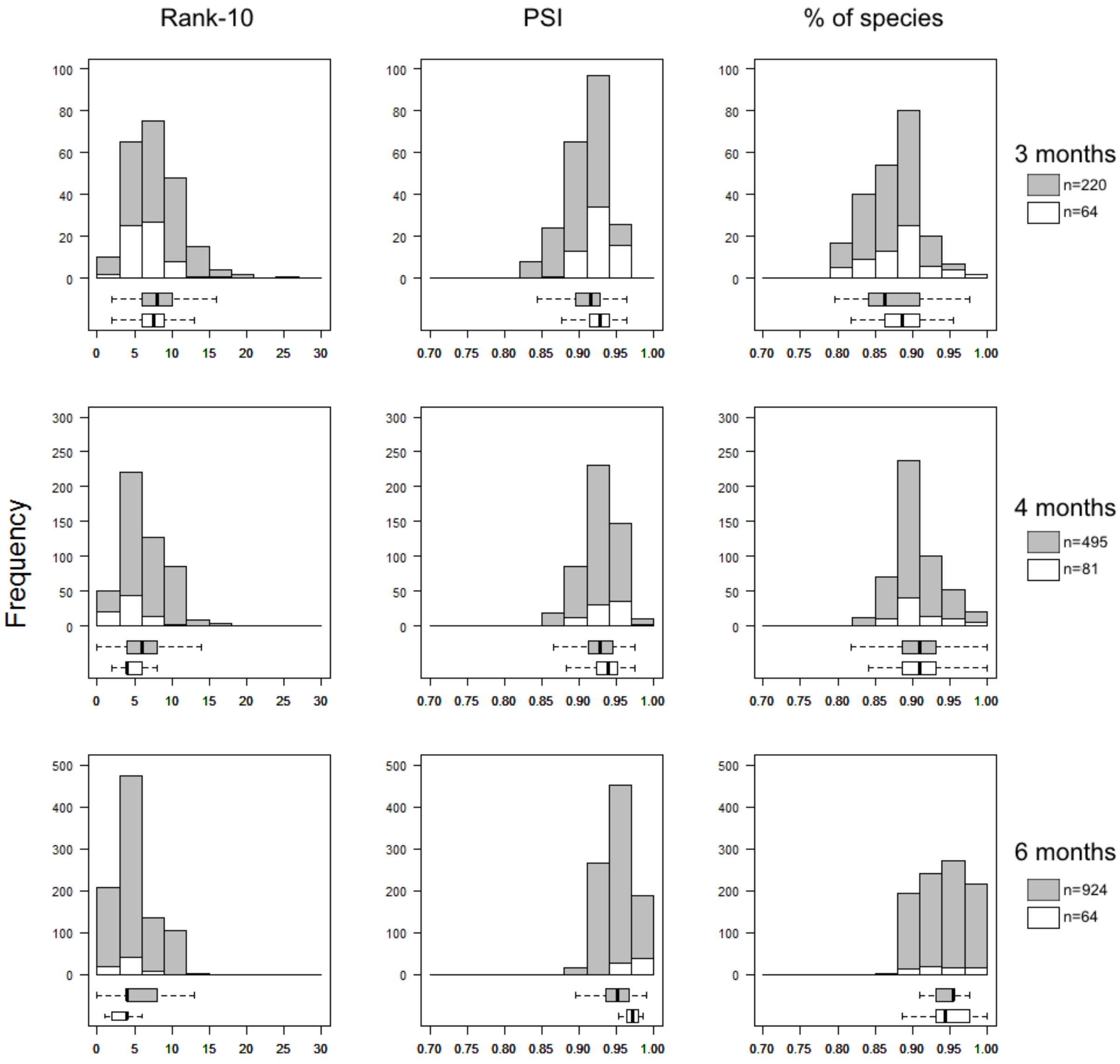

Figure 3-7. Frequency distributions of the summed absolute rank difference for the Top-10 species (left column), Percent Similarity Index (PSI; middle column) and the percent of species captured (right column) for three, four, and six months of sampling (top, middle, and bottom rows, respectively) from the JST-6 data set. The grey histograms are based on all possible combinations of 3, 4, and 6 months and the white histograms are based on the first seasonal subset listed in Table 3-3 for each level of effort. The boxplot for each distribution is provided below each graph to facilitate comparisons and show the median, first and third quartiles, and whiskers (≤1.5*interquartile range). Outliers have been omitted for clarity and scaling purposes.

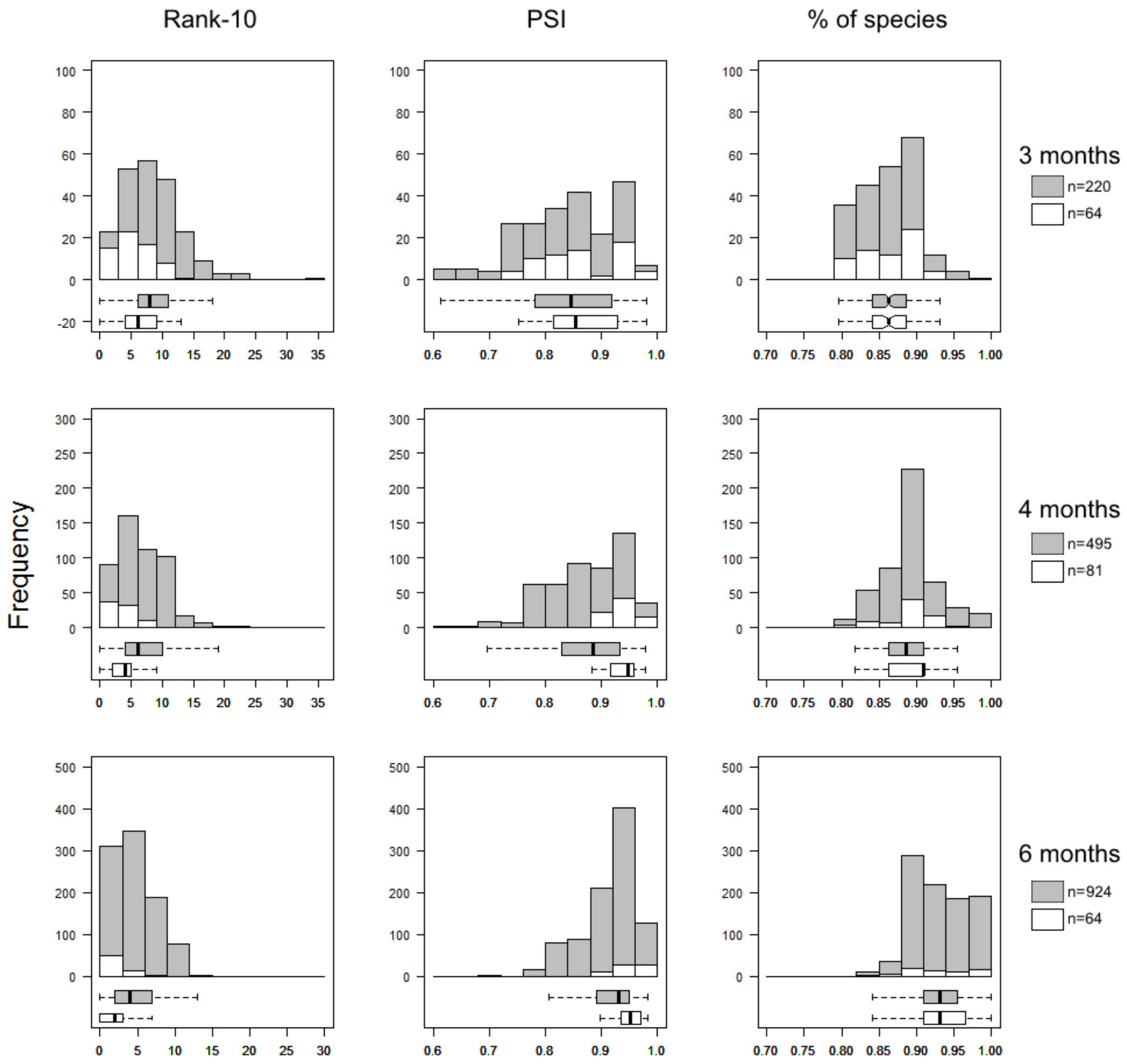

Figure 3-8. Frequency distributions of the summed absolute rank difference for the Top-10 species (left column), Percent Similarity Index (PSI; middle column) and the percent of species captured (right column) for three, four, and six months of sampling (top, middle, and bottom rows, respectively) from the JST-6 data set. The grey histograms are based on all possible combinations of 3, 4, and 6 months and the white histograms are based on the first seasonal subset listed in Table 3-4 for each level of effort. The boxplot for each distribution is provided below each graph to facilitate comparisons and show the median, first and third quartiles, and whiskers (≤1.5*interquartile range). Outliers have been omitted for clarity and scaling purposes.

CHAPTER 4

EVALUATION OF MEAN RANK SHIFT FOR DISCERNING CHANGES IN RESERVOIR FISH ASSEMBLAGES [4]

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[4] Dennerline, D. E. and C. A. Jennings. To be submitted to North American Journal of Fisheries Management

ABSTRACT

Comparing communities over time and space has long been a central topic in ecology and new approaches are continually being developed. Mean Rank Shift is a recently proposed "species rank" approach that has been specifically suggested as offering promise for detecting changes in assemblages derived from long-term monitoring studies. Though MRS has been used in a fisheries context in a few published studies, the approach has not been critically evaluated. Given the simplicity of the approach, I evaluated the sensitivity and performance of MRS for detecting temporal changes in reservoir fish assemblages. I also constructed alternative formulations to use the general approach in a before after context and restricted calculations to subsets of the data that focused on "core" species. A simulated dataset based on 14 years of gill-net sampling was used to evaluate the performance and sensitivity of the MRS formulations based on four ranking metrics including number, weight, index of relative importance (IRI) and the prey-specific index of relative importance. The original MRS was not sensitive to directional changes resulting from simulated perturbations (i.e., reductions or increases of 10%, 25%, and 50%) of subsets of species. Two formulations of MRS that used the initial assemblage as the basis for calculating differences and resultant MRS scores (MRS_{10} and MRS_{20}) were useful for detecting directional changes in a management relevant time frame of 4 to 8 years when PSIRI was used as the ranking metric. Therefore, the modified versions of MRS with PSIRI based rankings offer managers a new tool for quantifying changes in the structure of reservoir fish assemblages in response to perturbations.

INTRODUCTION

Comparing terrestrial and aquatic assemblages over time and space has been a fundamental goal many ecological assessments. As a result, a variety of methods have been developed and used by ecologists for this purpose. A plethora of similarity indices (e.g., Jaccard, Sorenson, Bray-Curtis) have been developed to determine the degree to which two or more assemblages are alike. These indices are readily available to managers and researchers (Krebs 1999, Magurran 2004, Kwak and Peterson 2007) and several new or modified indices have recently been proposed (Buckland et al. 2005, Chao et al. 2005, 2006, Jost 2006, Chao et al. 2008). Likewise, numerous non-parametric and multivariate techniques (e.g., cluster classification, multidimensional scaling, and ordination) have been widely used to assess the effects of anthropogenic perturbation(s) on changes in communities in a variety of environments and across a variety of taxa (Clarke and Warwick 1994, Harkantra and Rodrigues 2004). Unfortunately, the large number of indices and analytical techniques has also created confusion over which index or type of analysis is the most appropriate to use for a given situation. Research about changes in community composition also has suffered from a lack of understanding about the trade-offs between the various indices and analyses from which researchers have to choose (Krebs 1999, Kwak and Peterson 2007). As a result of this uncertainty, Krebs (1999) urges managers to use similarity measures and diversity indices with caution as the outcomes will depend on the index selected as well as numerous post-hoc, subjective decisions such as data transformations and deciding which transformation to use.

Despite recent advancements and continued development of new indices for defining and comparing community structure as well as the many non-parametric, multivariate, and ordination techniques, the published literature suggests that these methods have not been widely adopted and routinely used by reservoir fishery managers. The subjectivity, complexity, general lack of understanding of the methods, and an inability to explain the results and methods to non-scientific audiences have likely prevented widespread adoption of these methods among reservoir managers. Consequently, new approaches that are more intuitive, easier to calculate, and more readily understood by non-scientific audiences than the current indices are needed to assist managers with assessing changes in fish assemblages over time.

Recent long-term studies suggest that the species richness of assemblages are persistent over time; therefore, detecting changes will likely require methods that track temporal dynamics of individual species. Dornelas et al. (2014) analyzed 100 time series datasets from biomes across Earth and found that assemblages were undergoing biodiversity change but not systematic biodiversity loss. Using long-term studies on terrestrial plants, Collins et al. (2008) showed that a relatively constant species richness masked considerable temporal dynamics in relative species abundances. Similarly, Magurran and Henderson (2010) used the results of a long-term fisheries study to suggest that species diversity metrics were insensitive to change and suggested that measures that track species ranks may provide better early warning that an assemblage is being perturbed than traditional diversity indices.

Mean Rank Shift (MRS; Collins et al. 2008) is a “species rank” approach that has been specifically suggested by several researchers as offering promise for detecting changes in assemblages derived from long-term monitoring studies (Magurran and Henderson 2010, Magurran and Queiroz 2010, Meyer et al. 2015). MRS summarizes complex temporal dynamics in assemblages by quantifying relative changes in species rank abundances over time. MRS was developed using abundance-based ranks, but other individual or composite metrics could also be used to rank species for calculating MRS. For example, ranking species within a reservoir fish assemblage can be viewed as analogous to the investigation of food habits to identify and rank the important components of a predators diet (Kolding 2002). If one considers each unit of sampling effort (e.g., a gill-net, an electrofishing transect) as a surrogate predator, then the fishes captured in the sample can be viewed as "prey" items and used to calculate the component metrics and composite diet indices.

A variety of individual component metrics, such as percent by weight (%W, or volume), percent by number (%N), and frequency of occurrence (FO) can be used to describe fish diets (Hyslop 1980, Wallace 1981). However, the interpretation of what prey items are the most important to a fish's diet will be affected by the metric used, especially when a wide range of prey sizes are consumed (Liao et al. 2001). For example, reliance on weight alone may suggest that a large prey species is most important to predators even when that species is consumed relatively rarely and by just a few of the predators sampled. Conversely, reliance on numbers alone could indicate that numerous small prey items, which were readily consumed by a large number of predators, were most important even if they only accounted for a small portion of the total biomass consumed by all predators.

Diet indices that incorporate several or all of the individual components to overcome the limitations of any single component have been developed (Pinkas et al. 1971, George and Hadley 1979, Cortés 1997). Several of these composite indices exist, but the Index of Relative Importance (IRI; Pinkas et al. 1971) has withstood the most scrutiny over time, including a review by Liao et al. (2001). Continued use of IRI (albeit recently modified versions) in the contemporary literature demonstrates the robustness of the IRI as a useful index of "prey" importance. For example, a standardized version of IRI (%IRI) was proposed by Cortés (1997) to allow comparisons among prey items and is still routinely used (e.g., Bangley and Rulifson

2014, Bornatowski et al. 2014, Landaeta et al. 2014). The %IRI was further revised by Brown et al. (2012) to the Prey Specific IRI (PSIRI) which made the calculated % IRI scores additive across taxonomic levels and has recently been incorporated into diet studies (Harvey et al. 2014, Molina and Cazorla 2015, Mulas et al. 2015).

Though MRS has been suggested as an approach for detecting changes in community assemblages over time, a rigorous evaluation of the sensitivity of MRS for assessing changes in reservoir fish assemblages has not been performed. Furthermore, alternative formulations of MRS have also been suggested (Yedid and Heier 2012). To date, all applications of MRS have relied solely on abundance data for deriving ranks, so results based on composite metrics (such as %IRI and PSIRI) have not been evaluated. Thus, the use of different ranking metrics to evaluate the sensitivity of different versions of MRS for detecting changes in reservoir fish assemblages is warranted. If the ability to detect such changes can be demonstrated, MRS could be a desirable approach as it is straight-forward, easy to calculate, and easy to convey to non-scientists.

The goal of this investigation is to use different ranking metrics to assess the sensitivity of MRS-based approaches for detecting changes in a reservoir fish assemblage over time. The specific objective is to compare results from five different formulations of MRS based on four different ranking metrics (number, weight, %IRI, %PSIRI) to assess their ability to detect known, directional changes in a simulated reservoir fish assemblage. Identifying specific combinations of MRS and ranking methods that are sensitive to detecting changes would provide managers with a simple but effective method for discerning changes.

METHODS

Study Site and Fish Sampling

J. Strom Thurmond Reservoir (JST; Figure 1) is a U.S. Army Corps of Engineers impoundment on the Savannah River, Georgia and South Carolina. Originally authorized for hydropower, flood control, and downstream navigation, the multi-purpose project now includes water supply, water quality, recreation, and fish and wildlife management. At full pool, the reservoir has a surface area of 28,773 hectares and is a pumped-storage facility consisting of four 75-MW conventional hydropower generators and four 75-MW pumpback units.

Standardized gill-net sampling was conducted monthly at four stations in J. Strom Thurmond Reservoir from March 1992 to November 1999 and again from November 2002 to April 2009. Sampling effort consisted of four experimental gill nets (combinations of floating/sinking and nearshore/offshore) at each station. All gill net samples were overnight sets with duration ranging from 14 to 22 hours. Experimental gill nets were 76.20 m x 2.44 m and consisted of 10 7.62 m x 2.44 m panels. Mesh sizes (bar measure, mm) across the panels were 9.5, 12.7, 19.1, 25.4, 38.1, 50.8, 63.5, 76.2, 88.9, and 101.6 mm.

Calculations of Mean Rank Shift

We evaluated five different formulations of Mean Rank Shift ($\mathrm{MRS}_{\mathrm{orig}}$, $\mathrm{MRS}_{\mathrm{all}}$, $\mathrm{MRS}_{\mathrm{init}}$, MRS_{10}, MRS_{20}). Mean Rank Shift was calculated as originally proposed by Collins et al. (2008):

$$MRS_{orig} = \sum_{i=1}^{n} \left(\left| R_{i,t+1} - R_{i,t} \right| \right) / n$$

where n is the number of species in common in sequential years, t is year, $R_{i,t}$ is the relative rank of species i in year t.

$\mathrm{MRS}_{\mathrm{orig}}$ includes only species common in consecutive years. Because a large number of species are not caught every year and often not in consecutive years, the consequence of discarding that information is unknown. For that reason, we evaluated MRS_{all} which was calculated the same as MRS_{orig}, except that all species in the catch record were included every year. This was done by assigning a zero catch to all species that were not caught and calculating a tied rank for last place. For example, we had 44 species in the simulated community (see simulation section below), so if we caught and individually ranked 40 species in a given year, the four species not captured were each assigned a tied rank of 42.5 (average of 41, 42, 43, 44) resulting in a rank shift statistic for every species every year.

MRS_{orig} and MRS_{all} as defined above provide a measure of variation in relative species rankings among consecutive years without respect to a specific baseline or starting condition. They are primarily measures of community stability over time that can be used retrospectively with knowledge of a perturbation to see if a community appears to be more or less stable coincident with a perturbation. However, managers are often interested in directly assessing changes in community structure in a before-after context. Consequently, we evaluated three additional rank shift metrics that used species rankings from the initial sampling year as a baseline and then subsequently evaluated the mean rank shift of those species (MRS_{init}) or subsets of those species consisting of the top 10 and top 20 species by rank (MRS_{10} and MRS_{20}, respectively) over future years. We used MRS_{10} and MRS_{20} to track the change in ranks of the "dominant" species over time. Yedid and Heier (2012) also used this approach to assess changes in the relative ranks of ecotypes and restricted their analyses to the top 10 ecotypes. The general equation for the three metrics evaluated is

$$MRS_{init\ or\ 10\ or\ 20} = \sum_{i \in A}^{n} \left(\left| R_{i,t_x} - R_{i,t_1} \right| \right) / n$$

where t_1 is the initial sampling/simulation year, A is the set of species at time t_1 (entire species list for MRS_{init}, or the top 10 and top 20 ranked species for MRS_{10} and MRS_{20}, respectively), and

$R_{i,tx}$ is the rank of species *i* in year *x*. In all three cases, we calculated rank shift for each species in the initial set in all subsequent years, even if the species dropped out of the initial category or was not sampled in a given year. For example, when calculating MRS_{10}, if a species was ranked eighth the first year but dropped to a rank of 20th the third year, the species received a rank shift score of 12 (20-8) though it dropped out of the top 10 in year three. As with MRS_{all}, species not captured in a given year received a tied rank for last place and that rank was used to calculate the rank shift score for MRS_{init}, MRS_{10} and MRS_{20}.

Species Rankings

All five formulations of MRS were calculated using ranks based on four metrics that summarized catch on an annual basis: The number of individuals caught per year for each species, the total weight of all individuals caught per year for each species, the Index or Relative Importance (IRI; Pinkas et al. 1971) and the Prey Specific Index of Relative Importance (PSIRI; Brown et al. 2012). IRI (and %IRI) was calculated as:

$$IRI_i = (\%N_i + \%W_i) \times \%FO_i$$

where $\%N_i$ is the percent of total annual catch by number for species *i*, $\%W_i$ is the percent of total annual catch by weight for species *i*, and *%FO* is the percent of annual samples in which species *i* occurred. The %IRI is a standardized version where the individual species IRI scores are divided by the sum of the IRI scores for all species (Cortés 1997).

%PSIRI was calculated as:

$$\%PSIRI_i = \frac{\%FO_i \times (\%PN_i + \%PW_i)}{2}$$

where $\%PN_i$ and $\%PW_i$ are prey-specific measures calculated as

$$\%PA_i = \frac{\sum_{j=1}^{n} \%A_{ij}}{n_i}$$

where $\%A_{ij}$ is the percent of species i in sample $_j$ (by number or weight), n_i is the number of samples containing species i, and n is the total number of samples.

Simulating the Fish Community

We used hurdle models from the R package pscl (Zeileis et al. 2008) to estimate species-specific catch (counts) by month from the gill-netting data. Data were pooled from all four stations each month to decrease the number of zero counts and to improve model parameter estimates. Hurdle models are two-component models with a truncated count component for positive counts and a hurdle component that models the zero counts (Zeileis et al. 2008). A binomial logit model was used to fit the "hurdle" (probability of obtaining a catch>0) and a negative binomial with a log link to model non-zero counts. Hurdle models were fit using all months in which the species was captured at least once. If a species was never captured in a given month over the 14+ year study period, the probability of catch was set to zero for that month and that month was excluded from the data used to fit the hurdle models to that species. Three parameters were estimated from the hurdle models for each of the 44 species we sampled. The hurdle parameter (P), represents the month-specific probability of capturing at least one individual of a given species. The mu (μ) and theta (θ) parameters define the negative binomial distribution with μ being the month- and species- specific mean number of fish captured, and θ being a species-specific dispersion parameter.

The three parameters from the hurdle models were subsequently used to simulate the fish community consisting of all 44 species in the original data. Catch was simulated by drawing from a zero-truncated binomial distribution with the *rposnegbin* function in the VGAM package (Yee 2015) to ensure that at least one fish was captured if the species passed the hurdle in the simulation. A few estimates of μ were extremely small for some species in some months and imprecise, especially when a single individual of a species was caught only once in a given month. In these cases, estimates of μ were set to $1.0e^{-7}$ to ensure a non-zero count of one was obtained (based on 10,000 simulated values). The annual percent increase or decrease associated with the perturbation scenarios was performed by increasing or decreasing the simulated catch by the desired percent change.

To assess how well the simulated community represented the observed community, we visually compared boxplots of the observed data to three random simulations based on 14 years of data to assess similarity in central tendency and spread of the data. The goal of the visual assessments was to ensure that the simulations reasonably characterized the observed community so any resultant conclusions based on the simulations would seem reasonable and justified. Composite metrics for the whole community included the number of individual fish captured each year and the number of individual species captured each year. We evaluated species-specific metrics for the top 10 species based on IRI ranking and included catch by month (number) and species rankings by year.

Simulated weights were calculated using the number of individuals generated from the hurdle models multiplied by a species-specific average weight. The average weight for each species was calculated from the central 99% of the raw, observed weights. Weights less than the 0.005 percentile and greater than the 0.995 percentile were excluded to resolve issues with a few anomalous weights that were suspected recording errors. When summarizing the observed data, the anomalous values were replaced with the average weight.

To ensure the average species weight provided reasonable estimates of the observed data when generating annual species rankings for MRS, total weight for each year based on the mean-derived weights was compared with the observed weights. Differences in the annual summed weights based on the average weight with those based on random deviates from a best-fitting distribution (either lognormal or Weibull) for four selected species whose weights varied in range and magnitude (threadfin shad, blueback herring, gizzard shad and striped bass) were also evaluated. For the species evaluated, weights were similar when summed over an entire year (though not presented here), so average weights were used.

Perturbation Scenarios

To derive realistic perturbation scenarios, MRS was calculated for the five MRS formulations and four ranking methods for the 14 years of gillnetting data to determine the number of species that exhibited directional changes and the magnitude of the changes in rank that resulted in the observed scores. Perturbation scenarios were designed to mimic the observed data, target differences across ranking metrics or intentionally elicit a strong directional response (Table 4-1). A total of five "perturbation" scenarios were evaluated (Table 4-1). Perturbation scenario #1 was a no change (null) scenario to provide an idea of the magnitude and range of MRS scores that resulted from the baseline stochasticity in species ranks caused by the hurdle simulations. Scenarios 2 through 5 each had a given set of species exposed to two different levels of change (%/yr) to assess the magnitude and rate of change in median MRS scores. Scenario 2 attempted to mimic the species, direction, and magnitude of the changes that resulted in the observed data. Perturbation scenario #3 included annual decreases in catch of 25% and 50% for both blueback herring *Alosa aestivalis* and threadfin shad *Dorosoma petenense*, the top two numerically dominant species. Scenario 4 was an annual decrease in catch of 25% and 50% for both hybrid bass *Morone saxatilis X Morone chrysops* and gizzard shad *Dorosoma cepedianum*, the two top-ranked species by weight. Lastly, scenario 5 included eight species that decreased the catch of the top four species overall (by 10% or 25%) and increasing catch of four lower ranked species (by 10% or 25%).

Simulations for all perturbation scenarios included four years of pre-perturbation sampling to capture baseline (stochastic) variability in MRS scores and eight years of post-perturbation sampling to assess the magnitude and pattern of changes over time. Fifty simulations were run for each perturbation scenario (and percent change) and median MRS scores were calculated and plotted for each “MRS year”. Because MRS is a difference calculation, there is one less MRS year than the years sampled. For example, MRS year one is the summed difference in ranks between years one and two. Hence, for 12 years of simulated data there are 11 “MRS years.” Notched boxplots were generated from the 50 simulated MRS scores for the first MRS year, the seventh MRS year (four years post-perturbation) and 11th year (eight years post-perturbation) to provide a qualitative assessment of the significance of differences in MRS scores based on whether the notches of the plots overlapped (Chambers et al. 1983, R Core Team 2014).

RESULTS

Comparisons between observed and simulated data

In total, 44 species were captured in 14 years of sampling over the period from 1992 to 2008. Twenty species were captured every sampling year whereas 10 species were captured in only one or two years. Catch of individual species by number varied considerably over the 14-year time span (Table 4-2). Individual species rankings based on all samples varied by the ranking metric, as expected, but overlapped considerably with respect to species designated in the top 10 or top 20 (Table 4-3). Six species were included in the top 10 across all metrics (dark shaded cells in Table 3) and 17 species were included in the top 20 designation across all metrics (dark and light shaded cells in Table 4-3). There were differences in individual species ranks between IRI and PSIRI, but both metrics had the same species list for the top 10 and shared 19 of the top 20 species.

The fish community simulated by the hurdle models was similar to the actual catch for the 14 years of record across all metrics evaluated. For the entire community, both the number of fish captured and the number of species captured per year were comparable in range and central tendency (Figure 4-1). Simulated monthly catch by number was similar to observed catch for all species as demonstrated by results for the top 10 species (Figure 4-2). Species-specific average weights also provided comparable estimates of the observed total annual weight caught for most species with only a few exceptions, such as channel catfish *Ictalurus punctatus* (Figure 4-3). Lastly, species rankings based on simulated data were similar to the observed rankings in terms central tendency, but the variation in species ranks was underestimated for species such as threadfin shad, striped bass *Morone saxatilis*, white perch *Morone americana,* and spotted sucker *Minytrema melanops* (see Figure 4-4 for ranks based on IRI score as an example).

Species rankings for the observed dataset varied considerably depending on metric used (Table 4-3) and further justified the need to evaluate the composite metrics. Small-bodied species such as blueback herring, threadfin shad, and spottail shiner *Notropis hudsonius* dominated when ranked by number (ranked 1st, 2nd and 8th, respectively), but fell to ranks of 7th, 11th and 26th, respectively when ranked by weight. Conversely, large-bodied fishes such as common carp *Cyprinus carpio* and silver redhorse *Moxostoma anisurum* were ranked 5th and 6th by weight but ranked 16th and 13th when ranked by number.

Species rankings of the top 10 species varied considerably by year over the 14 years of gillnet sampling across all ranking metrics with species ranks 6-10 typically showing more volatility than ranks 1-5 (Figure 4-5). All ranking metrics had two species drop out of the top 10 by the end of the 14 years. Threadfin shad, river carpsucker *Carpiodes carpio*, common carp, and white bass had the most precipitous declines over the 14 year period and accounted for the species that dropped out of top 10 across the four ranking metrics. River carpsucker dropped by 8 or 9 rank points across all metrics, and threadfin shad dropped 8 to 11 points across 3 of the metrics (IRI, PSIRI and weight) but only dropped four points when ranked by number. The two species with the largest increases were white perch and spotted sucker.

MRS scores based on the actual data varied in magnitude and pattern across the different MRS formulations and ranking metrics (Figure 4-6). Scores calculated on consecutive years (MRS_{orig} and MRS_{all}) were generally lower (with smaller standard errors) than those based on the initial ranking year (MRS_{init}, MRS_{10}, MRS_{20}). MRS_{all} varied considerably over time but showed no directional trend, whereas the other MRS formulations showed an increasing trend over time, but to varying degrees.

Simulated Perturbations

Results from the “no perturbation” scenario (1) showed the simulations performed as expected, with MRS scores remaining relatively constant over the 12-year simulation period for all ranking metrics and MRS formulations (Figure 4-7). Median MRS varied by MRS formulation (as expected) with MRS_{10} (subset with fewest and most stable species) having the lowest median score (around 1 for all ranking metrics) and MRS_{init} and MRS_{all} (both using all species) having the highest median MRS scores (2.5 on average).

Perturbation scenario 2 directionally perturbed the six species identified as changing the most over the 14 years in the actual data across all ranking metrics (Table 4-1). Simulated MRS scores obtained by perturbing the six species by 25% (Figure 4-8) were similar in pattern and magnitude of change over time to the observed changes (Figure 4-6), but absolute MRS scores tended to be a little lower in the simulated data for MRS_{10} and MRS_{20}. MRS_{10} increased the quickest and had the largest absolute change over time of any MRS formulation at the 25% level and was approximately equal for all ranking methods except rank by number, which was much lower. MRS_{orig} and MRS_{all} did not change over the 12-year, post-perturbation span. Perturbing six species by 50% (scenario 2b) resulted in rapid increases in MRS_{10} and MRS_{20} scores and minor increases in MRS_{init}, but still failed to produce a detectable change in MRS_{orig} or MRS_{all}. The 50% change actually resulted in MRS_{10} and MRS_{20} scores reaching an asymptote around the eighth post-perturbation year.

The pattern in MRS scores varied by the perturbation level when we reduced catch of blueback herring and threadfin shad, the two numerically dominant species (scenario 3). Decreasing blueback herring and threadfin shad by 25% per year resulted in differences (Figure 4-10) in MRS_{10} and to a lesser degree MRS_{20} across all ranking metrics with the most rapid and pronounced change observed in MRS_{10} when using PSIRI. However, substantive differences based on boxplots were not noted until 8 years after perturbation. Substantive changes were not observed for MRS_{orig}, or MRS_{all} even after 8 years at a 25% decrease. Decreasing blueback herring and threadfin shad by 50% per year resulted in substantial differences in MRS_{10} and MRS_{20} across all ranking metrics (Figure 4-11), with PSIRI attaining the largest differences in both the 4th and 8th years post-perturbation. Interestingly, rank by number was no more, and in some cases less, sensitive than the other metrics. Weight was the least sensitive ranking metric for MRS_{10} (Figure 4-11b), but was as sensitive as the other ranking metrics for the other MRS formulations. Smaller changes were observed in the MRS_{all} and MRS_{init} formulations and the changes were similar across ranking metrics. MRS_{orig} did not show discernable change in pre- versus post-perturbation scores for any ranking metric.

Results from annual reductions of hybrid bass and gizzard shad (scenario 4), the two top-ranked species by weight, generally matched expectations; weight-based MRS scores were the highest along with PSIRI-based scores across the MRS formulations (Figure 4-12). Results of the 25% reduction scenario were similar in pattern and magnitude to the two-species scenario with blueback herring and threadfin shad (scenario 3; Figure 4-10), with MRS_{10} showing the most rapid increase and largest absolute change (Figure 4-12). The 50% reduction scenario of these two large-bodies species showed pronounced increases (>2.5 absolute points) in MRS10 and MRS20 scores by the 4th post-perturbation year and were strongly asymptotic across all ranking metrics (Figure 4-13).

Perturbation scenario 5 was designed to almost totally replace the top 10 species by decreasing the top four species and increasing four lower species to take over those top four positions. Simultaneously perturbing eight species only required a 10% perturbation to illicit changes in MRS_{10} and MRS_{20} within 8 years post-perturbation when scores based on PSIRI increased approximately 1.7 points (from 1 to 2.7) and 1 point (from 1.5 to 2.5), respectively . Once again, PSIRI-based rank resulted in the fastest and largest absolute change (Figure 4-14). The 25% increase produced very rapid changes in MRS_{10} and MRS_{20} across all metrics and the highest absolute increases in MRS_{10} scores of any scenario (Figure 4-15).

DISCUSSION

The MRS formulations evaluated performed differently in their ability to discern changes in a reservoir fish community over time. MRS_{10} and MRS_{20} consistently resulted in faster and larger changes in MRS scores than the other formulations and offer the most promise for detecting changes reservoir fish assemblages (in terms of re-ordering) over a management-relevant length of time from a perturbation (e.g., 4-8 years). Our efforts to include all species in the MRS calculations each year (MRS_{all} and MRS_{init} formulations) elevated “base” scores and reduced overall sensitivity of these two metrics. Many species were only captured in a few years, and the number of species captured varied by year, with as many as 14 uncaptured species (out of 44) in a given year. As a result, assigning tied ranks to non-captured species often resulted in large calculated rank differences for species that were captured one year but not the next. For example, if 14 species were not captured in a given year, those species were each assigned a rank of 37.5 (tied rank of 31 to 44). If 14 species are not captured the following year, then catching just one individual of one of the original species the next year would result in a rank of 30 and a rank difference of 7.5 points for MRS_{all}. MRS_{init} did respond to some of the largest directional perturbations, but absolute changes were much lower and more gradual because absolute rank differences of 1-4 for the bottom 25% dampened the overall mean based on all of the species. MRS_{orig} was not useful for detecting the type of long-term, directional changes that we simulated for a reservoir fish assemblage. Given that MRS_{orig} is based on sequences of consecutive years, this result is not surprising. A perturbation resulting in a gradual downward (or upward) trend of a given species such that it goes from a rank of one to a rank of nine more or less incrementally over 8 years would result in a constant rank shift score of one in each of the consecutive, paired scoring years (years 1 and 2, 2 and 3, 3 and 4, etc.) for that species. Hence, under this type of scenario, MRS_{orig} would not detect any type of temporal change.

The asymptotic response in MRS scores observed for some scenarios was related to the number of species included, the starting rank and absolute number of individuals of those species, and the magnitude of perturbation in the scenarios. When large perturbations were exerted on just a few species, those few species quickly decreased to the bottom of the ranks or increased to the top ranks and could go no farther with respect to change in rank. How quickly they got to the top or the bottom was a function of their starting rank and abundance and the magnitude of the perturbation. Once a species reached the top or bottom of the ranks, MRS scores levelled off and returned to just reflecting the ambient noise of the remaining species. For example, the quickest asymptotic response was seen in MRS_{10} with 50% reduction of hybrid bass and gizzard shad (Figure 4-13), two species with moderate abundance whose ranks decreased rapidly under a 50% reduction. In comparison, reducing threadfin shad and blueback herring by 50% also elicited an asymptotic response in MRS_{10} (Figure 4-11), but because of their high absolute abundances, initially decreasing their ranks took a few years longer. Modifying more species decreased the asymptotic behavior in MRS scores and resulted in much larger absolute scores (Figure 4-15). Though additional validation is needed, an asymptotic response in observed MRS_{10} scores might be useful diagnostic measure for indicating that a perturbation has a very species-selective effect.

Our use and evaluation of MRS_{orig} was outside of the original intent as proposed Collins et al. (2008). MRS_{orig} was proposed as a measure of community stability over time (hence the emphasis on year to year differences) and not as a metric for comparing community composition in a before /after context. In fact, Collins et al. (2008) specifically suggested that proportional persistence be used as a compliment to MRS for looking at species persistence over time. Because Collins et al's (2008) use of MRS_{orig} was able to clearly document rapid transition and stabilization of vegetation communities after major perturbations such as burning and fertilization, we thought evaluation of MRS_{orig} in a reservoir fisheries context was warranted for both assessing stability and change. Based on the simulated responses noted above and longer expected lag times for species turn-over to occur in reservoir fish assemblages (relative to a vegetative response to burning), MRS_{orig} will not be very sensitive for detecting changes or assessing community stability if changes are directional and occur over several consecutive years.

The metric (e.g., %IRI or PSIRI) used to rank species had serious implications, under some of the scenarios, with respect to the rate and magnitude of change in MRS_{10} and MRS_{20}. PSIRI performed better than the other ranking metrics by consistently detecting changes sooner and having one of the largest (if not the largest) absolute responses, regardless of whether the change consisted mostly of numerous, small-bodied fishes or less-numerous, large-bodied fishes. The other ranking metrics were not as consistent as PSIRI and were not always predictable. For example, scenario 3a decreased the two most abundant (but small-bodied) species by 25%/year, yet rank by number, the metric expected to respond the quickest to that change, was the slowest to respond out to year 12 at that level of perturbation (Figure 4-10). In contrast, PSIRI responded much quicker in scenario 3a and by year 10 resulted in a difference in MRS score of greater than a point compared to rank by number (Figure 4-10b, Top10 panel).

Simulated catch generated with the hurdle models was very similar to observed catch over the 14-year period, especially the catch by month of individual species. Given the strength of concordance with the observed data, simulated changes in MRS under the different perturbation scenarios should be reasonably valid, but likely are conservative. Conservative estimates arose because we modelled average catch over the 14 years of the data and did not model individual species trajectories. As a result, variation in species rankings was underestimated for some species (as noted in Figure 4-4), which may have resulted in lower MRS scores (i.e., more homogeneous rankings equate to fewer changes in rank and lower MRS scores for all formulations). This outcome may also explain the discrepancy we see in the "ambient" MRS scores between the observed data (initial values around 2; Figure 4-6) and the simulated data for MRS_{10} and MRS_{20} (initial values around 1; Figure 4-7). The range of MRS_{orig} scores for the observed data was also a little lower than those observed for two estuary fish assemblages (Obaza et al. 2015).

Application of MRS_{10} and MRS_{20} with other fisheries datasets is warranted to better understand the magnitude and variability of MRS scores across different systems and fish assemblages. Of the few published assessments or applications of MRS, especially for fish communities, other authors (Robinson and Yakimishyn 2013, Obaza et al. 2015) have also used subsets of species when calculating MRS to focus on dominant or core species (Magurran and Henderson 2003). However, a key difference is that those authors used the original formulation where differences were calculated for consecutive years and the emphasis was on year to year stability. Yedid and Heier (2012) used a similar version of MRS_{10} in a digital evolution context to assess changes in dominance of ecotypes in simulated communities. Our calculation of MRS10 which used the initial community as the reference, is similar to the approach of Yedid and Heier (2012) who used a pre-extinction community as a reference point against which to compare subsequent time points.

There are challenges to using our proposed version of MRS_{10} (or MRS_{20}) as an approach for assessing changes in reservoir fish assemblages relative to a perturbation in a before-after context. One challenge, and one we struggled with in this assessment, is defining what constitutes a "statistically significant" change in MRS. For this assessment, boxplots in conjunction with the median lines and associated 50 simulated timelines provided a basis for making inferences on the relative strengths of the different formulations and ranking methods for detecting changes in MRS. However, in real-world fisheries monitoring scenarios where one has a few pre- and post-perturbation MRS scores, the criteria to be used or the magnitude of change that will constitute a "biologically meaningful" difference is unknown. As proposed, MRS is essentially a graphical technique that plots the mean scores with standard errors to make inference about the relative magnitude of changes. Other authors using the original MRS formulation used a time-lag regression approach for short time series (Collins 2000) to assess whether the communities were stable or undergoing change (Robinson and Yakimishyn 2013, Obaza et al. 2015). However, given that our version of MRS calculates differences based on the initial community as opposed to consecutive paired years, the regression approach is not needed because direct comparisons about whether the community is moving away from or returning to the original community is reflected in the MRS scores. Furthermore, the plot of scores over time is directly interpretable in terms of direction and magnitude, though there is no test of significance. Another avenue to pursue might be change point analysis (Buckland et al. 2005) to see if the trajectory of the pre-perturbation MRS scores changes coincident with a perturbation.

SUMMARY

For this study we evaluated five formulations of mean rank shift as way to assess changes in the relative contribution of species in a reservoir fish assemblage over time. We also evaluated the influence of four ranking metrics on the performance of each MRS formulation. For the scenarios we evaluated, MRS_{10} and MRS_{20}, when based on PSIRI-derived rankings, were useful for detecting changes over a 4-8 year post-perturbation time span. The other MRS formulations and ranking metrics did not detect simulated changes. Additional evaluations of MRS_{10} and MRS_{20} are warranted as the approach is simple, easy to understand and explain, and addresses community changes most relevant to fishery managers.

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Table 4-1. Perturbation scenarios evaluated for each combination of ranking method and MRS formulation listing the species that were increased or decreased and the magnitude and direction of the perturbation (%/year) for two sub-scenarios (a and b).

Scenario	Species perturbed	Perturbation magnitude in percent per year for two sub-scenarios (a,b)
Scenario 1	None (no change model)	Includes stochasticity from hurdle models
Scenario 2	Threadfin shad	-25%, -50%
	River carpsucker	-25%, -50%
	Common carp	-25%, -50%
	White bass	-25%, -50%
	White perch	+25%, +50%
	Spotted sucker	+25%, +50%
Scenario 3	Blueback herring	-25%, -50%
	Threadfin shad	-25%, -50%
Scenario 4	Hybrid bass	-25%, -50%
	Gizzard shad	-25%, -50%
Scenario 5	Blueback herring	-10%, -25%
	Hybrid Bass	-10%, -25%
	Threadfin shad	-10%, -25%
	Gizzard shad	-10%, -25%
	Spotted sucker	+10%, +25%
	Common carp	+10%, +25%
	Black crappie	+10%, +25%
	Silver redhorse	+10%, +25%

Table 4-2. List of species captured sorted by mean catch, number of years each species was sampled, mean, minimum and maximum number caught by year. Numbers are the combined catch from stations 1 through 4 in J. Strom Thurmond Reservoir over a 14-year period that included March 1992 to December 1999 and January 2003 to December 2008.

				Number caught/yr		
Common Name	Scientific name	Acronym	Years Caught	mean	min	max
Blueback herring	*Alosa aestivalis*	BBHE	14	4,216	1,073	10,286
Threadfin shad	*Dorosoma petenense*	TFSH	14	3,331	255	7,995
Gizzard shad	*Dorosoma cepedianum*	GISH	14	1,186	857	1,870
White perch	*Morone. americana*	WTPE	14	532	46	882
Hybrid bass	*Morone saxatilis x M. chrysops*	HYBA	14	314	133	683
Striped bass	*Morone saxatilis*	STBA	14	167	96	298
Black crappie	*Pomoxis nigromaculatus*	BKCR	14	145	42	328
Spottail shiner	*Notropis hudsonius*	STSH	14	120	33	332
Longnose gar	*Lepisosteus osseus*	LNGA	14	110	71	214
Yellow perch	*Perca flavescens*	YEPE	14	100	38	236
Channel catfish	*Ictalurus punctatus*	CHCF	14	88	35	134
Spotted sucker	*Minytrema melanops*	SPSU	14	82	8	131
Silver redhorse	*Moxostoma anisurum*	SIRH	14	71	31	126
Bluegill sunfish	*Lepomis macrochirus*	BGSF	14	33	17	61
Redear sunfish	*Lepomis microlophus*	RESF	14	28	12	51
Common Carp	*Cyprinus carpio*	CARP	14	25	7	63
Largemouth bass	*Micropterus salmoides*	LMBA	14	21	11	40
River carpsucker	*Carpiodes carpio*	RICS	14	14	2	64
Golden shiner	*Notemigonus crysoleucas*	GOSH	14	12	1	36
Warmouth sunfish	*Lepomis gulosus*	WMSF	14	6	2	11
White bass	*Morone chrysops*	WTBA	13	9	0	21
Chain pickerel	*Esox niger*	CHPI	13	3	0	7
Flathead catfish	*Pylodictis olivaris*	FHCF	13	3	0	7
White catfish	*Ameiurus catus*	WTCF	13	3	0	8
Whitefin shiner	*Cyprinella nivea*	WFSH	12	7	0	26
White crappie	*Pomoxis annularis*	WTCR	12	6	0	11
Quillback carpsucker	*Carpiodes cyprinus*	QBCS	12	4	0	17
Redeye bass	*Micropterus coosae*	REBA	11	3	0	13
Spotted bass	*Micropterus punctatus*	SPBA	10	5	0	25
Redbreast sunfish	*Lepomis auritis*	RBSF	9	2	0	7
Blue catfish	*Ictalurus furcatus*	BLCF	9	2	0	7
Robust redhorse	*Moxostoma robustus*	RORH	7	8	0	28
Northern hogsucker	*Hypentelium nigricans*	NOHS	6	<1	0	3
Green sunfish	*Lepomis cyanellus*	GRSF	4	<1	0	2
Yellow bullhead	*Ameiurus natalis*	YEBH	2	<1	0	2

Brown bullhead	*Ameiurus nebulosus*	BRBH	2	<1	0	3
Bluehead chub	*Nocomis leptocephalus*	BHCH	2	<1	0	1
Spotfin shiner	*Cyprinella spiloptera*	SFSH	2	<1	0	1
Banded killifish	*Fundulus diaphanus*	BAKI	2	<1	0	3
Rainbow trout	*Oncorhyncus mykiss*	RBTR	2	<1	0	3
White sucker	*Catostomus commersoni*	WTSU	1	<1	0	1
Brassy jumprock	*Moxostoma rupiscartes*	BRJR	1	<1	0	1
Sauger	*Stizostedion canadense*	SAUG	1	<1	0	1
Walleye	*Stizostedion vitreum*	WALL	1	<1	0	1

Table 4-3. Overall species rankings for each ranking metric based on the combined catch from stations 1 through 4 in J. Strom Thurmond Reservoir over a 14-year period that included March 1992 to December 1999 and January 2003 to December 2008. Within each ranking method (column), the top 10 ranked species are denoted by dark shading and species ranked 11-20 are denoted with lighter shading, to highlight similarities and differences.

Common Name	Rank by Number	Rank by Weight	Rank by IRI	Rank by PSIRI
Blueback herring	1	7	1	2
Threadfin shad	2	11	3	4
Gizzard shad	3	2	2	1
White perch	4	10	7	7
Hybrid bass	5	1	4	3
Striped bass	6	4	6	6
Black crappie	7	13	12	12
Spottail shiner	8	26	14	13
Longnose gar	9	3	5	5
Yellow perch	10	20	13	14
Channel catfish	11	9	10	10
Spotted sucker	12	8	9	9
Silver redhorse	13	6	8	8
Bluegill sunfish	14	29	18	19
Redear sunfish	15	19	17	17
Common Carp	16	5	11	11
Largemouth bass	17	15	15	15
River carpsucker	18	12	16	16
Golden shiner	19	27	23	25
White bass	20	18	20	22
Robust redhorse	21	14	19	18
Whitefin shiner	22	38	30	31
White crappie	23	28	27	27
Warmouth sunfish	24	31	28	29
Spotted bass	25	21	24	24
Quillback carpsucker	26	17	22	21
Chain pickerel	27.5	23	25	26
Redeye bass	27.5	25	29	23
Flathead catfish	29	16	21	20
White catfish	30	22	26	28
Redbreast sunfish	31	33	32	32
Blue catfish	32	24	31	30
Northern hogsucker	33	34	33	33
Green sunfish	34	40	35	39
Rainbow trout	35	32	34	41
Banded killifish	36.5	43	38	36
Brown bullhead	36.5	35	36	37
Yellow bullhead	38	41	39	38

Bluehead chub	39.5	42	42	40
Spotfin shiner	39.5	44	43	44
Brassy jumprock	42.5	37	41	35
Sauger	42.5	36	40	43
Walleye	42.5	30	37	34
White sucker	42.5	39	44	42

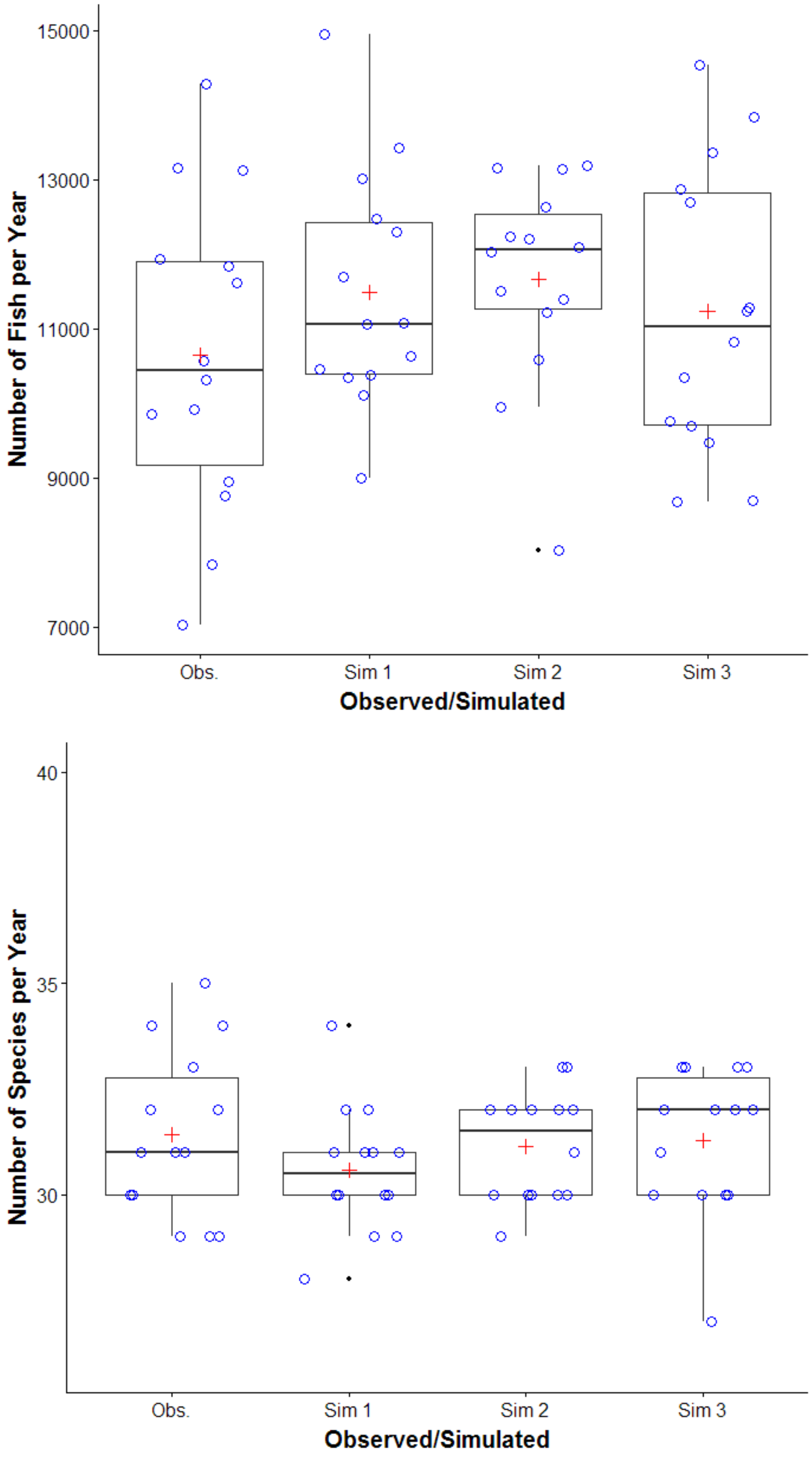

Figure 4-1. Boxplots of the number of fish per year (top panel) and number of species per year (bottom panel) from the observed data and three random draws of the simulations based on the same number of years (n=14). Red plus signs are the mean values.

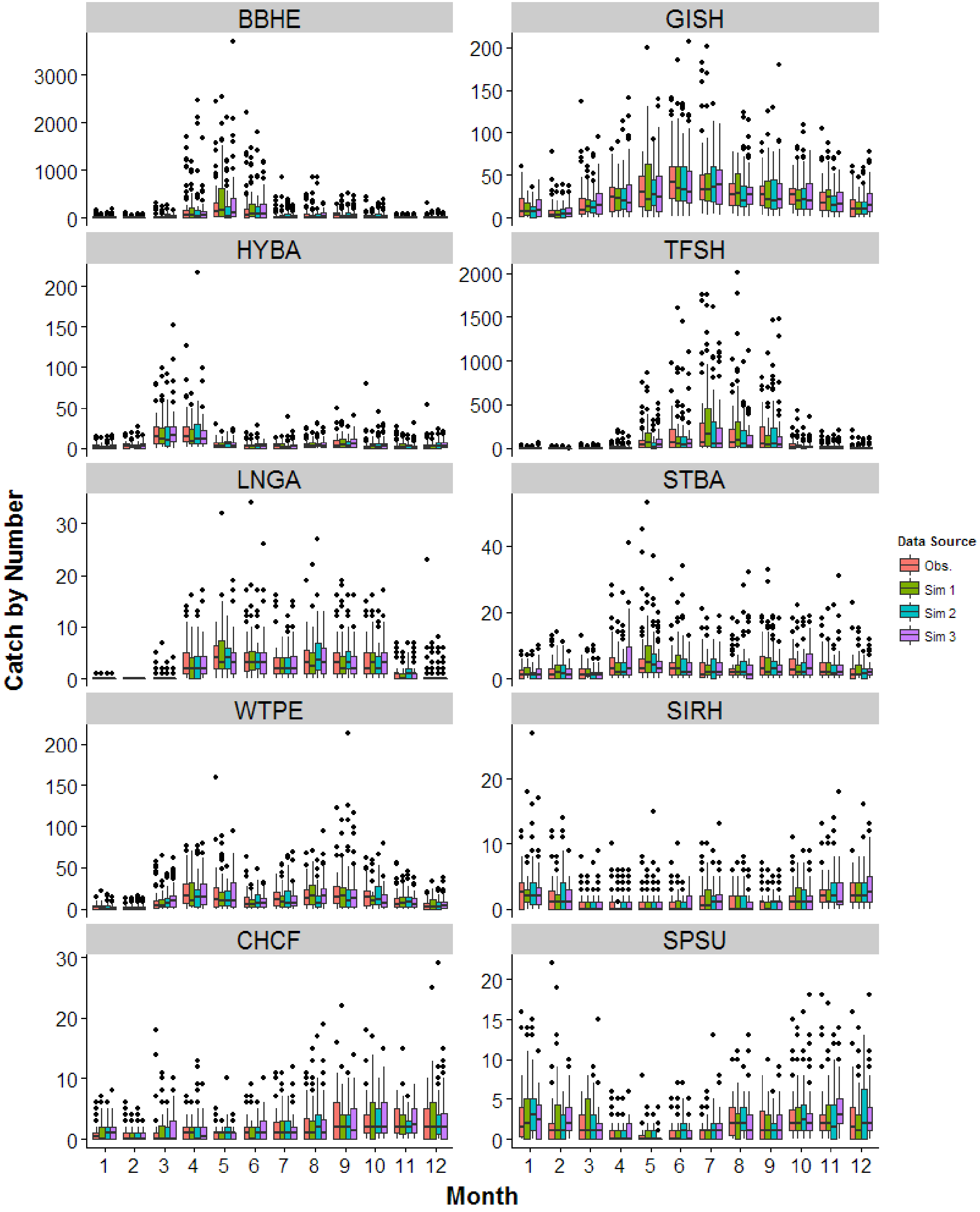

Figure 4-2. Boxplots of the number of fish per month for the top 10 species based on IRI score from the observed data and three random draws of the simulations based on the same number of years (n=14).

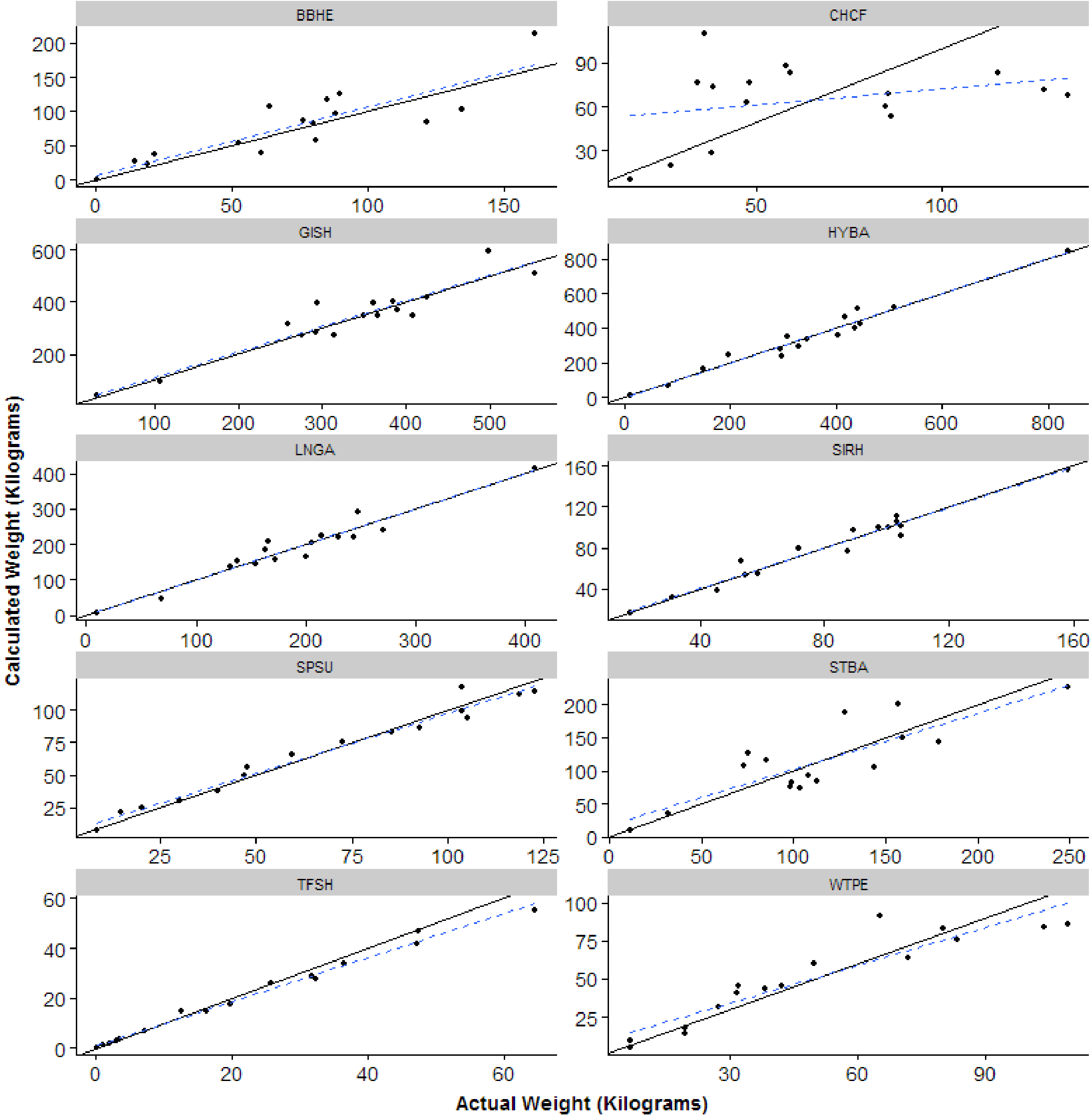

Figure 4-3. Actual weight caught per year against the calculated weight based on the species-specific mean weights for the top 10 species. The solid line is slope=1 and the blue dashed line is the regression through the points.

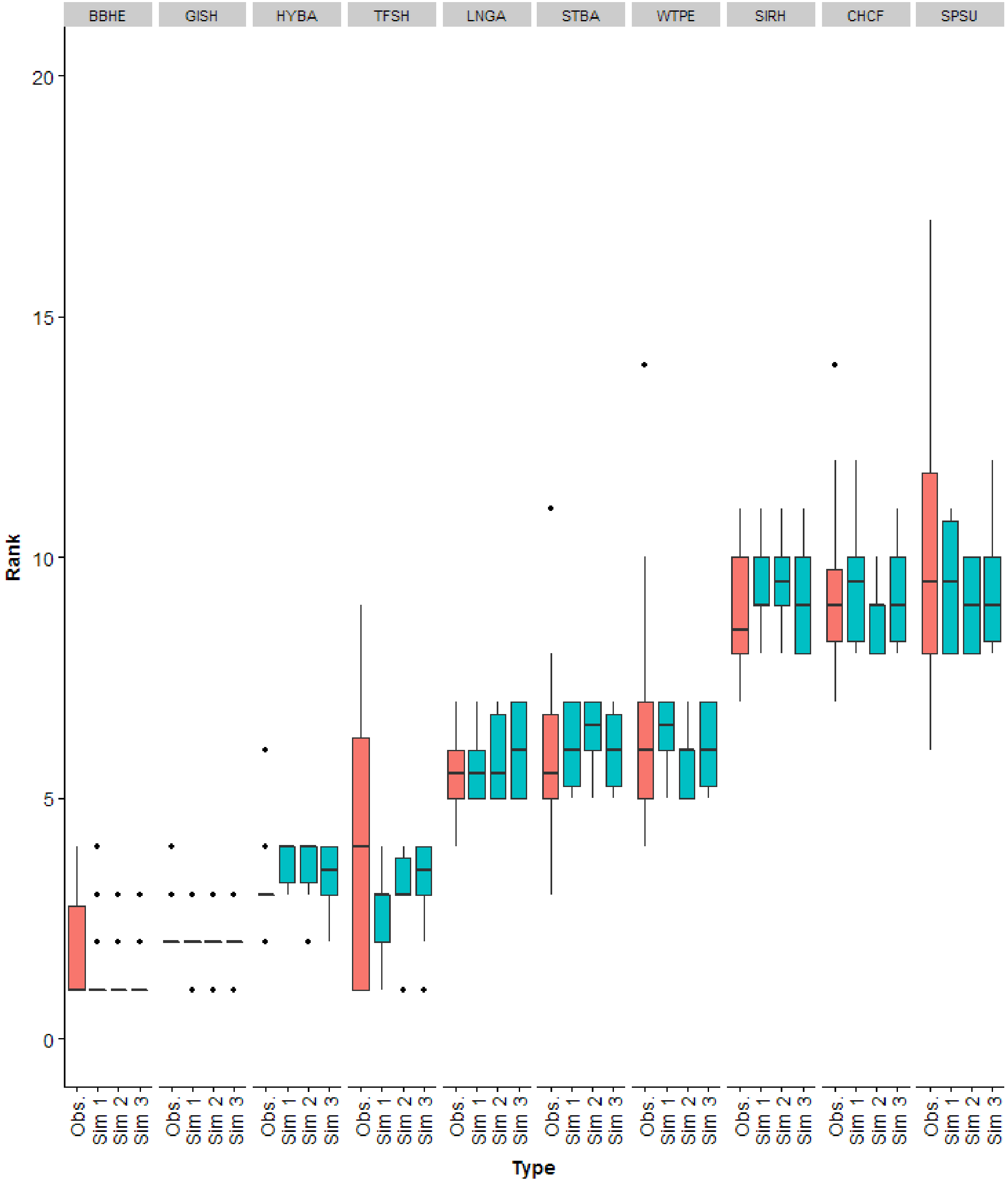

Figure 4-4. Boxplots to demonstrate degree of concurrence in species rankings (based on IRI score) for the top 10 species from the observed data (orange boxplots) and three random draws of the simulations (blue boxplots) based on the same number of years (n=14).

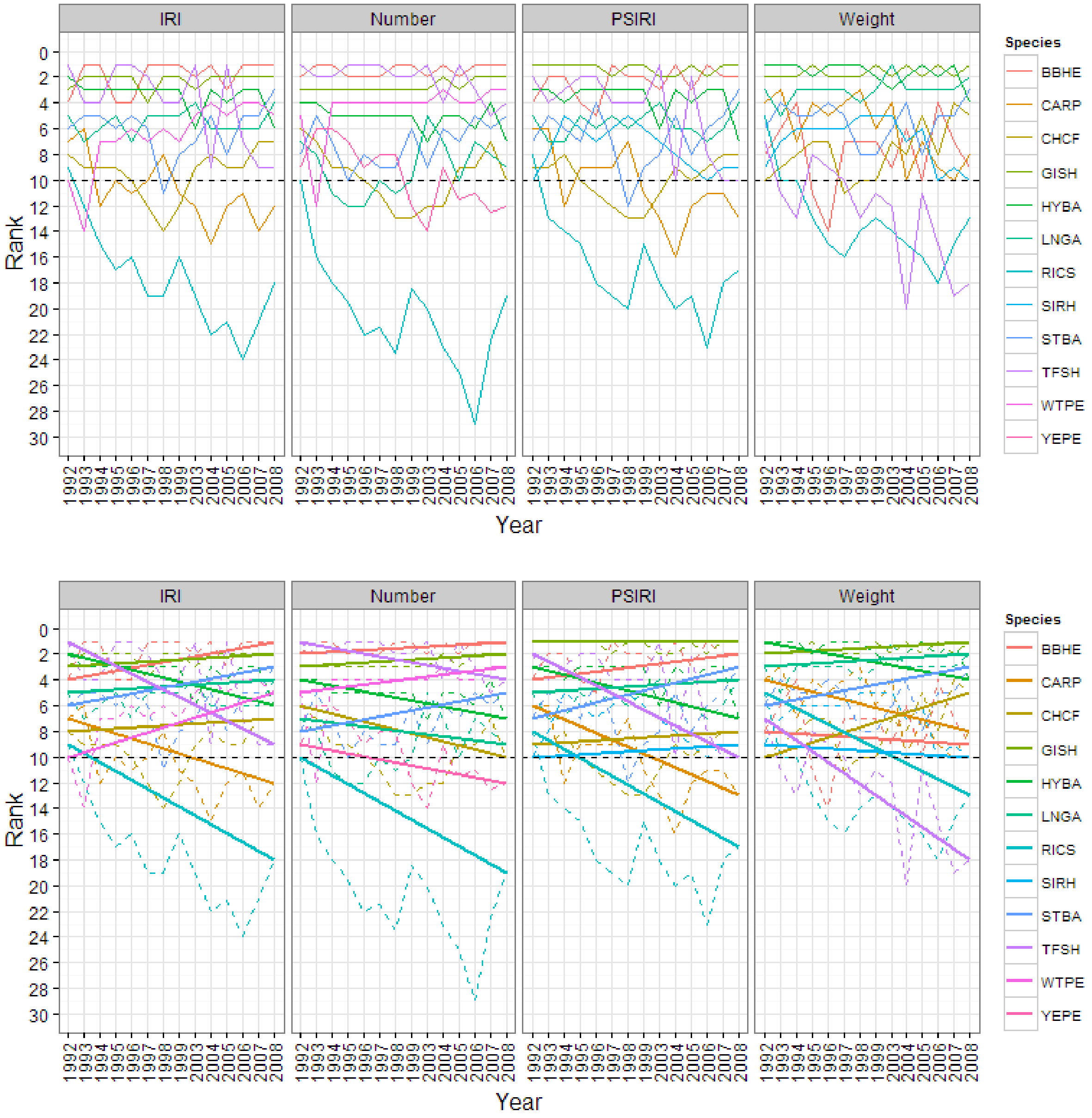

Figure 4-5. Rank of the top 10 species (starting in 1992) for each ranking method by year (top row) for the gill-netting data collected in J. Strom Thurmond Reservoir from 1992 to 1999 and 2003 to 2008. The panels in the bottom row connect each species initial ranking in 1992 with their final ranking in 2008 (solid line) to better illustrate the direction and magnitude of the differences. Note that only 10 of the 12 species listed occur in each graph panel.

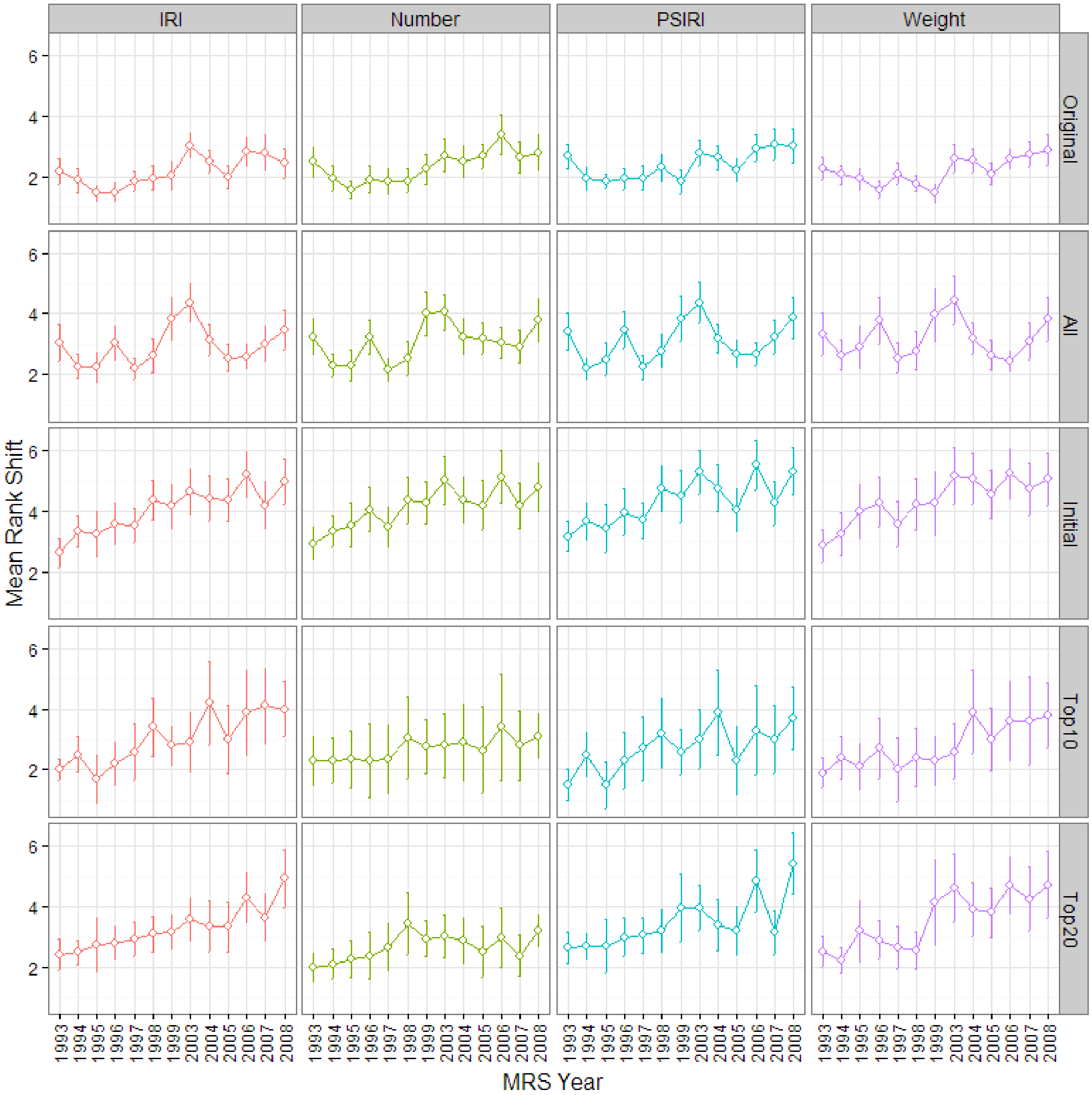

Figure 4-6. Matrix of mean rank shift (and standard error) for each ranking method (columns) and MRS formulation (rows) for the actual gill netting data collected in J. Strom Thurmond Reservoir from 1992 to 1999 and 2003 to 2008.

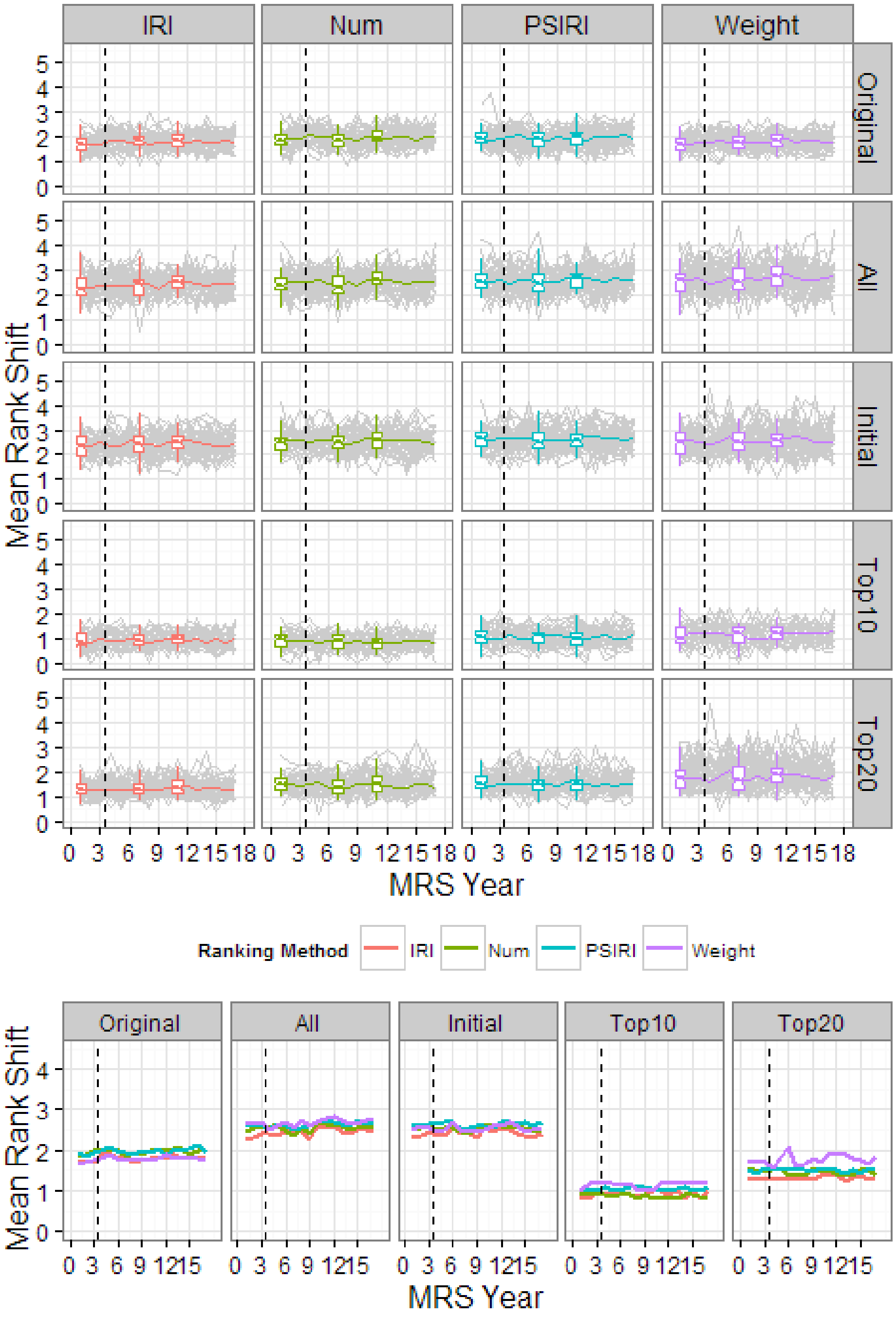

Figure 4-7. Panel A shows MRS scores over time for 50 simulations (grey lines), median MRS by ranking method and MRS formulation (colored lines), year of perturbation (dashed line), and boxplots of MRS scores for MRS year 1 (initial score), MRS year 7 (4 years post perturbation) and MRS year 11 (8 years post-perturbation). Panel B shows the median MRS line for each ranking method within each MRS formulation to facilitate comparisons of MRS scores among and within MRS formulations. All graphs are for perturbation scenario 1 as listed in Table 4-1 (No change model).

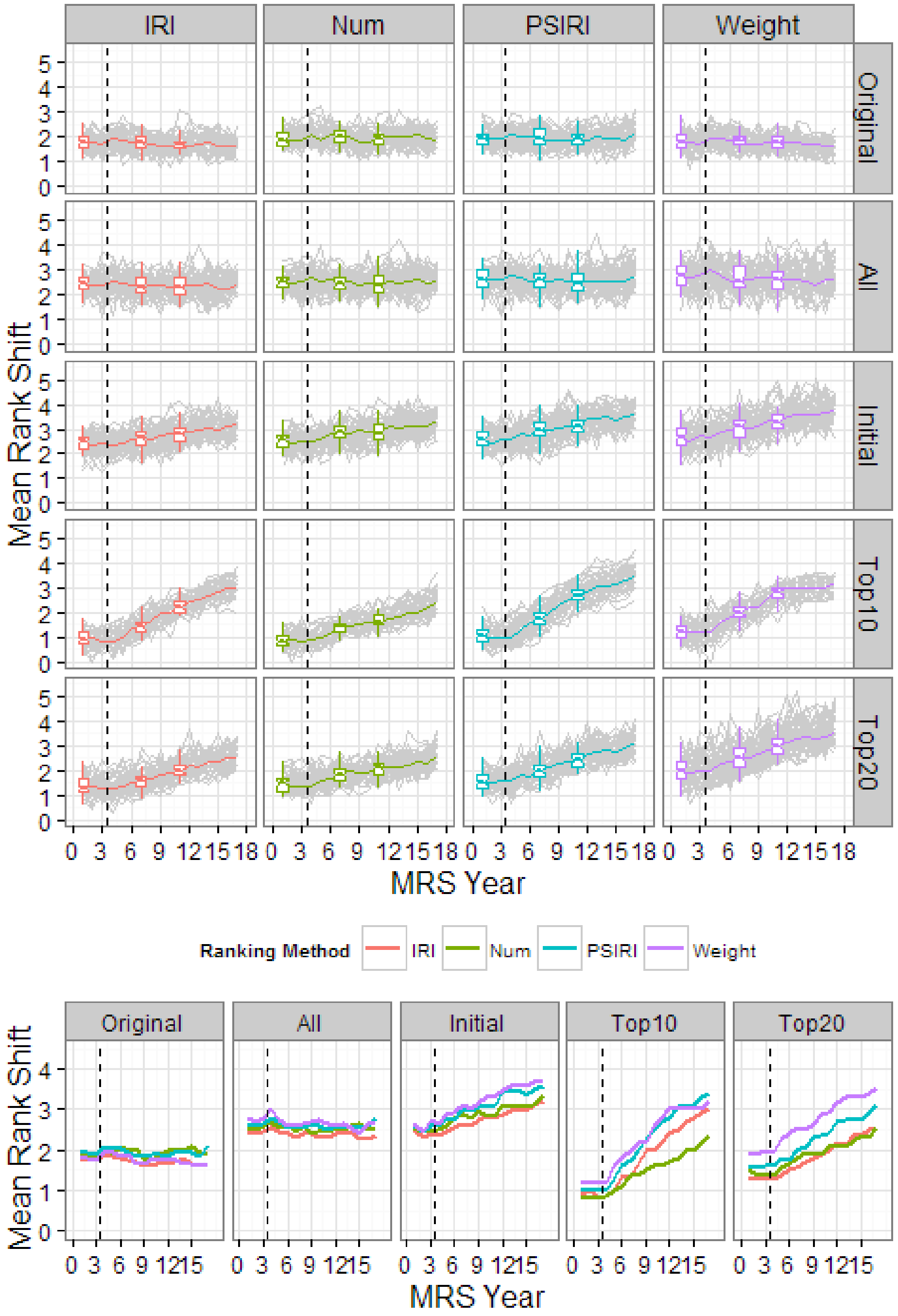

Figure 4-8. Panel A shows MRS scores over time for 50 simulations (grey lines), median MRS by ranking method and MRS formulation (colored lines), year of perturbation (dashed line), and boxplots of MRS scores for MRS year 1 (initial score), MRS year 7 (4 years post perturbation) and MRS year 11 (8 years post-perturbation). Panel B shows the median MRS line for each ranking method within each MRS formulation to facilitate comparisons of MRS scores among and within MRS formulations. All graphs are for perturbation scenario 2a listed in Table 4-1 (six species ± 25% change).

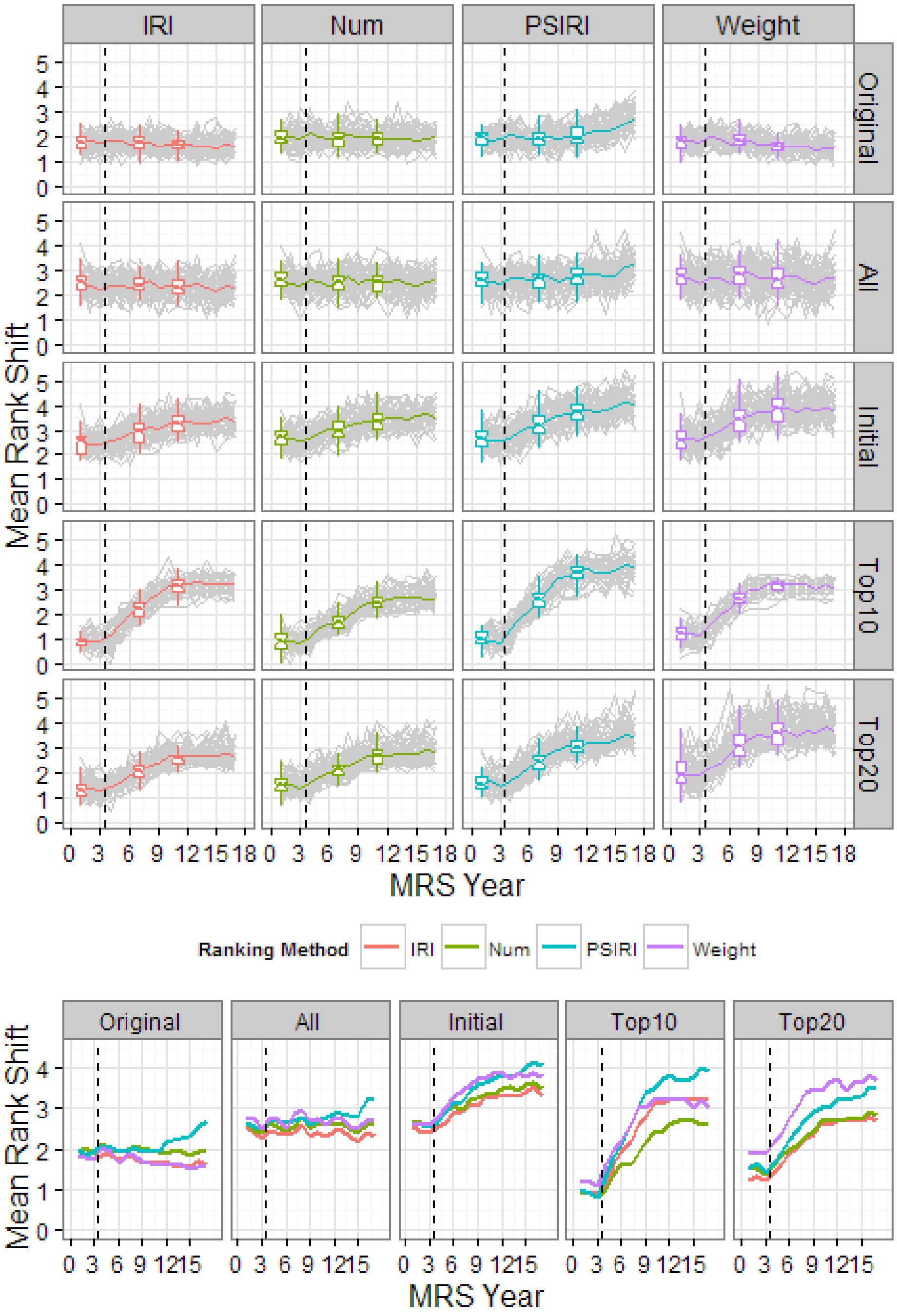

Figure 4-9. Panel A shows MRS scores over time for 50 simulations (grey lines), median MRS by ranking method and MRS formulation (colored lines), year of perturbation (dashed line), and boxplots of MRS scores for MRS year 1 (initial score), MRS year 7 (4 years post perturbation) and MRS year 11 (8 years post-perturbation). Panel B shows the median MRS line for each ranking method within each MRS formulation to facilitate comparisons of MRS scores among and within MRS formulations. All graphs are for perturbation scenario 2b listed in Table 4-1 (six species - 50% change).

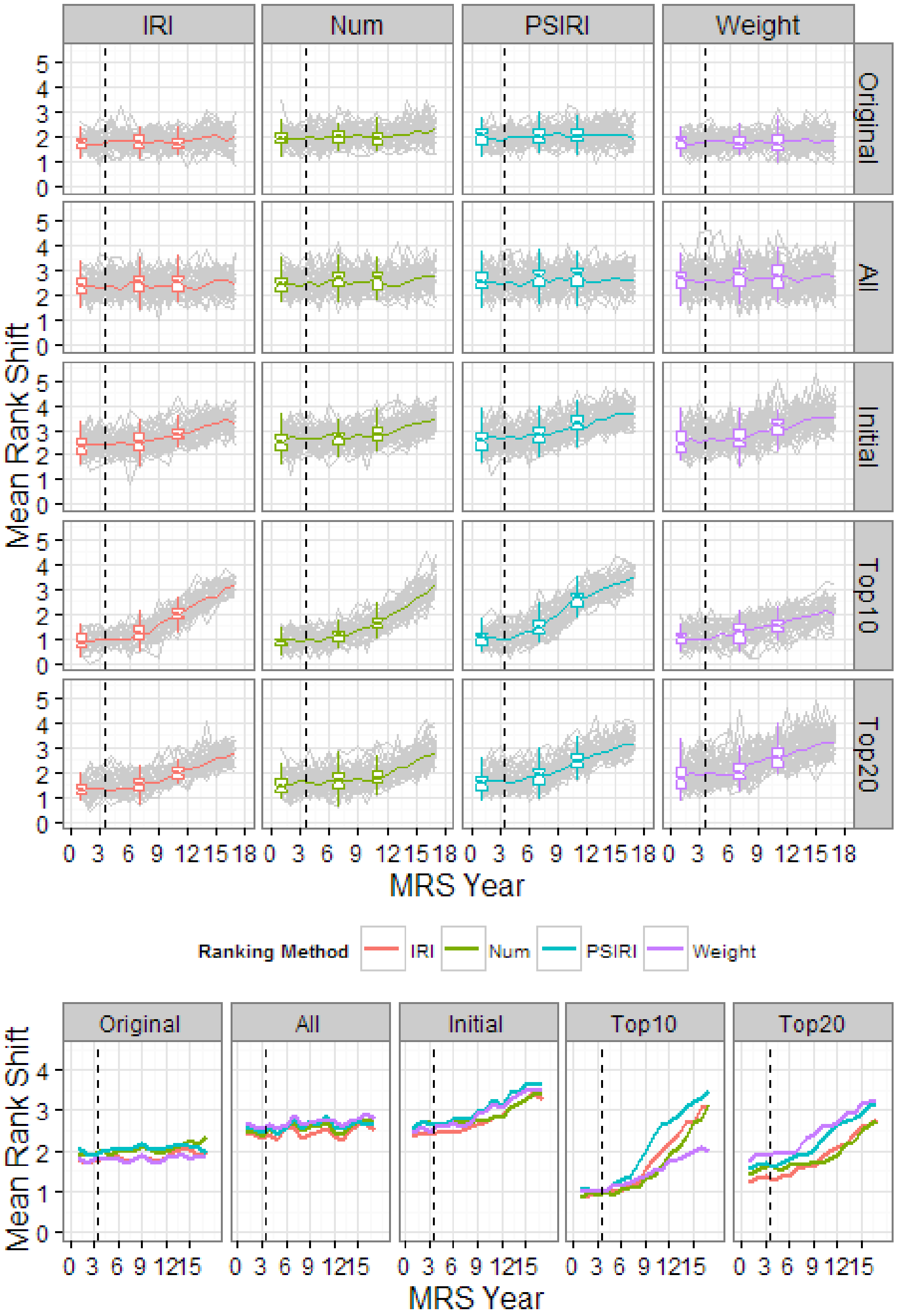

Figure 4-10. Panel A shows MRS scores over time for 50 simulations (grey lines), median MRS by ranking method and MRS formulation (colored lines), year of perturbation (dashed line), and boxplots of MRS scores for MRS year 1 (initial score), MRS year 7 (4 years post perturbation) and MRS year 11 (8 years post-perturbation). Panel B shows the median MRS line for each ranking method within each MRS formulation to facilitate comparisons of MRS scores among and within MRS formulations. All graphs are for perturbation scenario 3a listed in Table 4-1 (BBHE -25%, TFSH -25%).

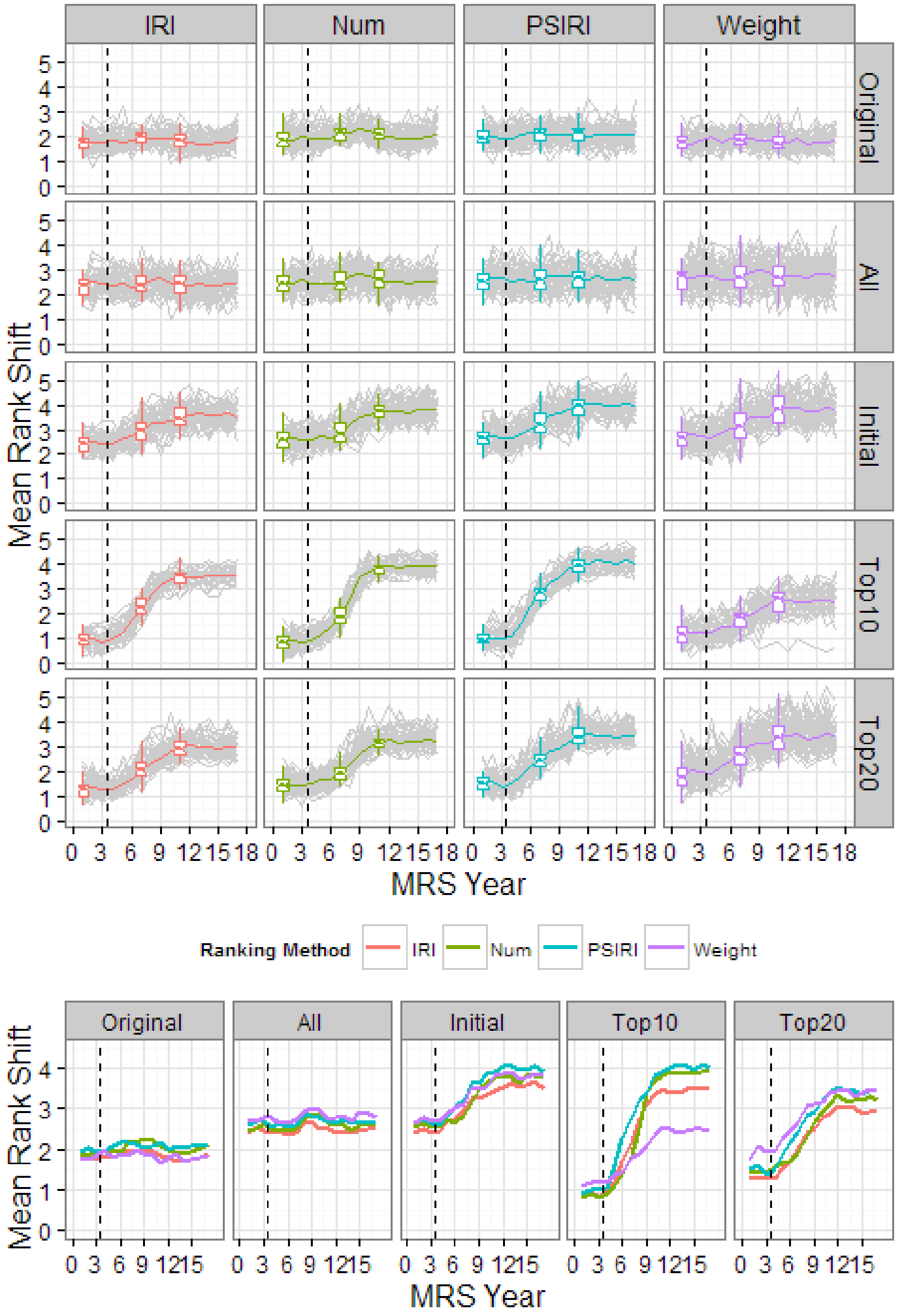

Figure 4-11. Panel A shows MRS scores over time for 50 simulations (grey lines), median MRS by ranking method and MRS formulation (colored lines), year of perturbation (dashed line), and boxplots of MRS scores for MRS year 1 (initial score), MRS year 7 (4 years post perturbation) and MRS year 11 (8 years post-perturbation). Panel B shows the median MRS line for each ranking method within each MRS formulation to facilitate comparisons of MRS scores among and within MRS formulations. All graphs are for perturbation scenario 3b listed in Table 4-1 (BBHE -50%, TFSH -50%).

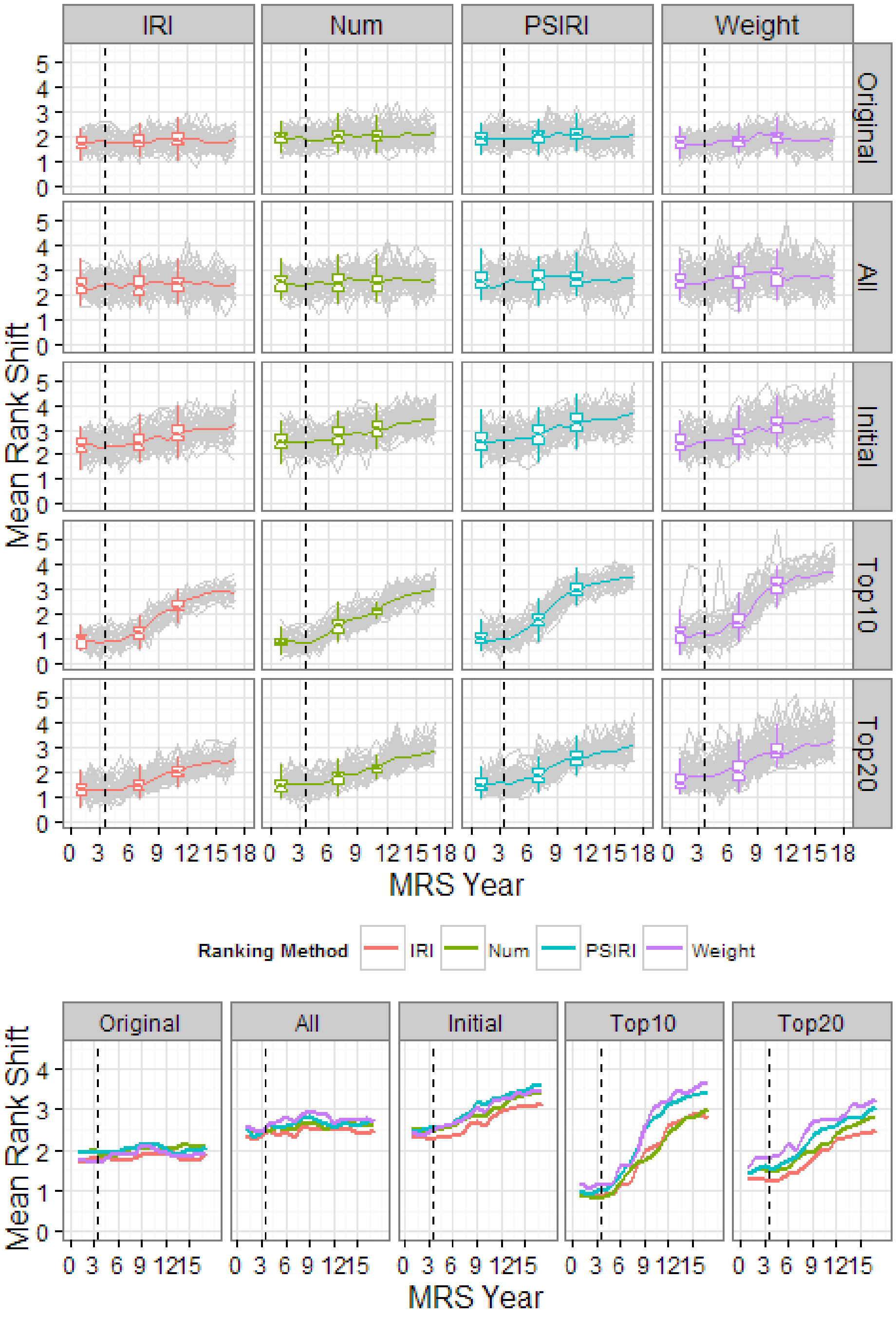

Figure 4-12. Panel A shows MRS scores over time for 50 simulations (grey lines), median MRS by ranking method and MRS formulation (colored lines), year of perturbation (dashed line), and boxplots of MRS scores for MRS year 1 (initial score), MRS year 7 (4 years post perturbation) and MRS year 11 (8 years post-perturbation). Panel B shows the median MRS line for each ranking method within each MRS formulation to facilitate comparisons of MRS scores among and within MRS formulations. All graphs are for perturbation scenario 4a listed in Table 4-1 (HYBA -25%, GISH -25%).

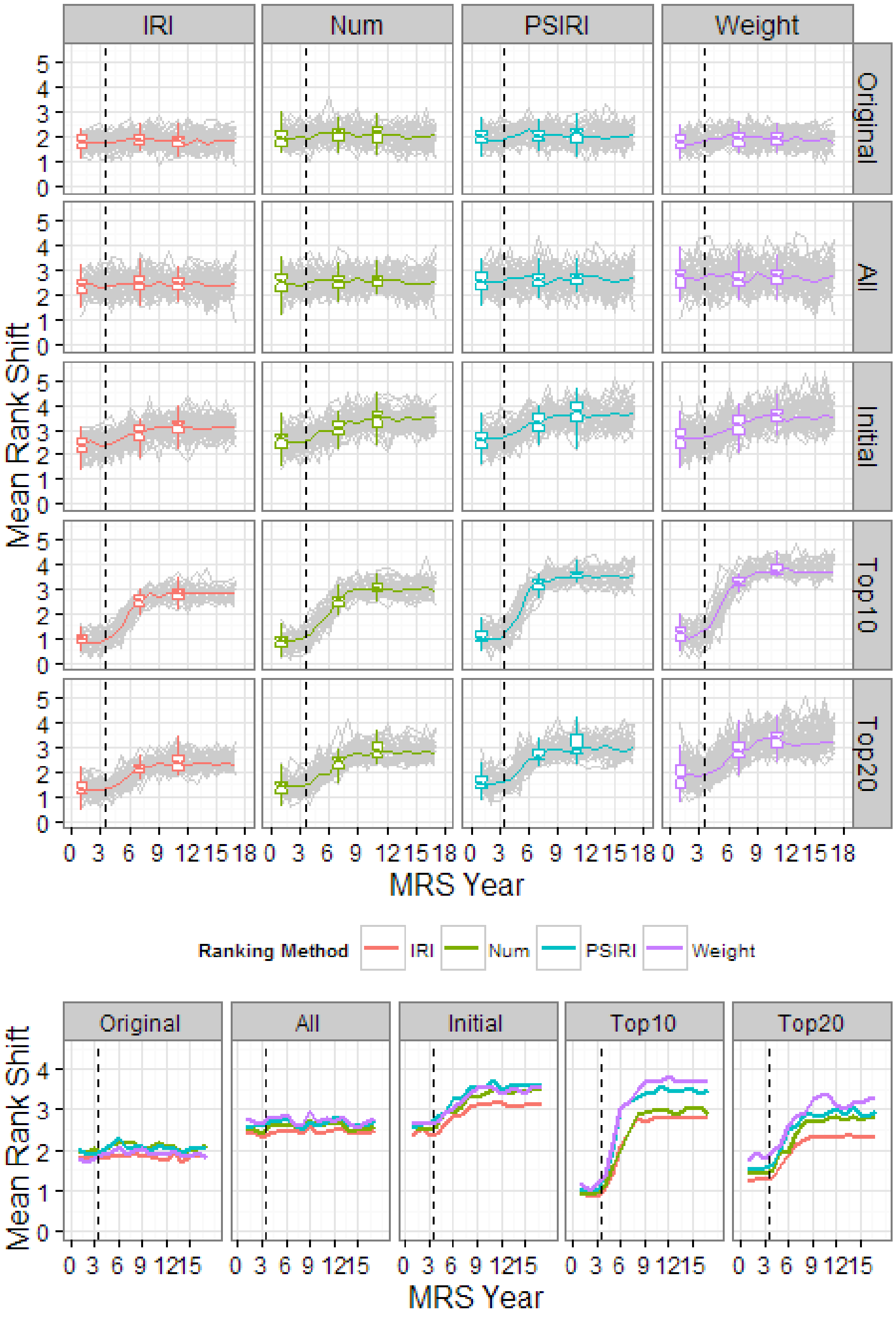

Figure 4-13. Panel A shows MRS scores over time for 50 simulations (grey lines), median MRS by ranking method and MRS formulation (colored lines), year of perturbation (dashed line), and boxplots of MRS scores for MRS year 1 (initial score), MRS year 7 (4 years post perturbation) and MRS year 11 (8 years post-perturbation). Panel B shows the median MRS line for each ranking method within each MRS formulation to facilitate comparisons of MRS scores among and within MRS formulations. All graphs are for perturbation scenario 4b listed in Table 4-1 (HYBA -50%, GISH -50%).

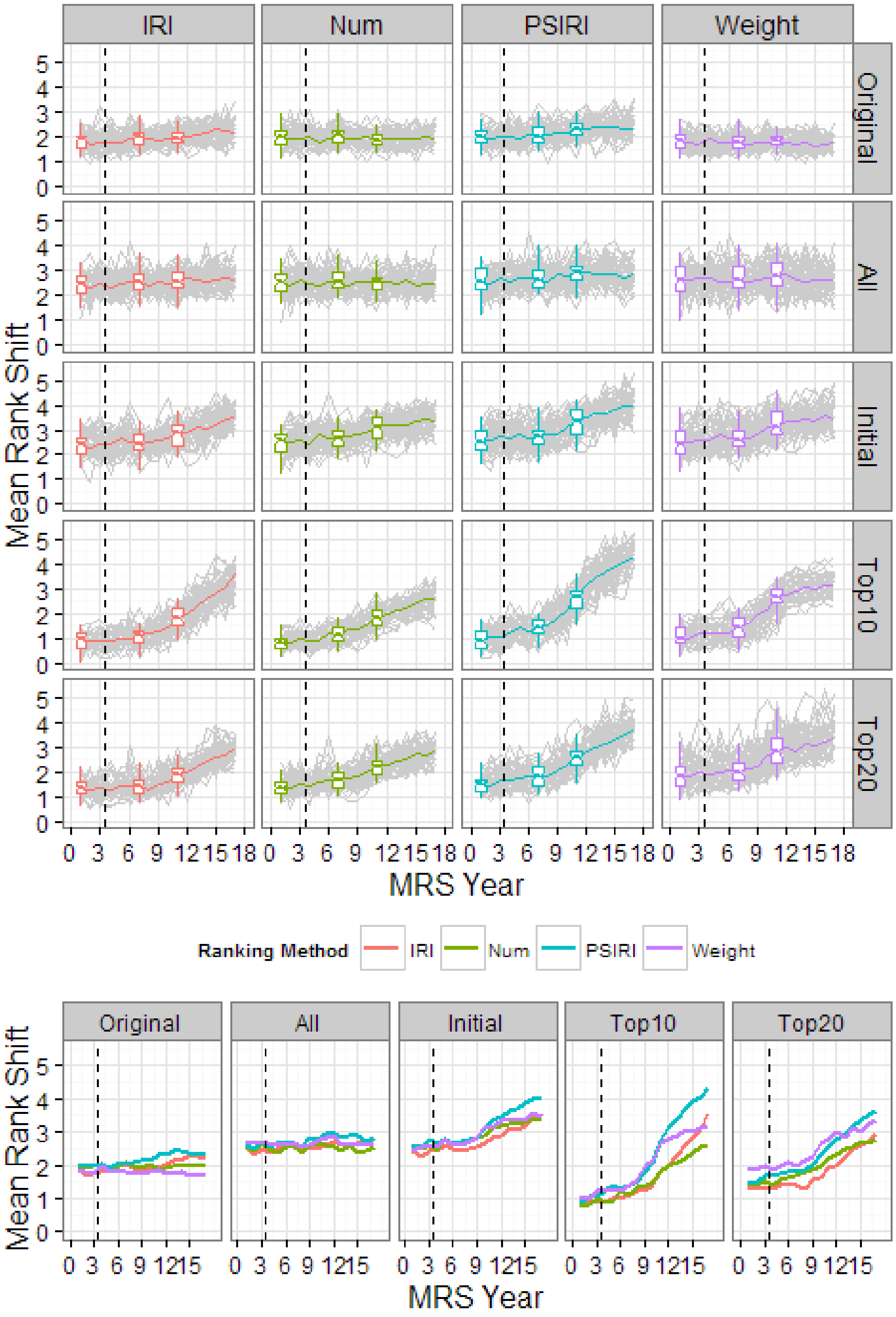

Figure 4-14. Panel A shows MRS scores over time for 50 simulations (grey lines), median MRS by ranking method and MRS formulation (colored lines), year of perturbation (dashed line), and boxplots of MRS scores for MRS year 1 (initial score), MRS year 7 (4 years post perturbation) and MRS year 11 (8 years post-perturbation). Panel B shows the median MRS line for each ranking method within each MRS formulation to facilitate comparisons of MRS scores among and within MRS formulations. All graphs are for perturbation scenario 5a listed in Table 4-1 (eight species, 10%).

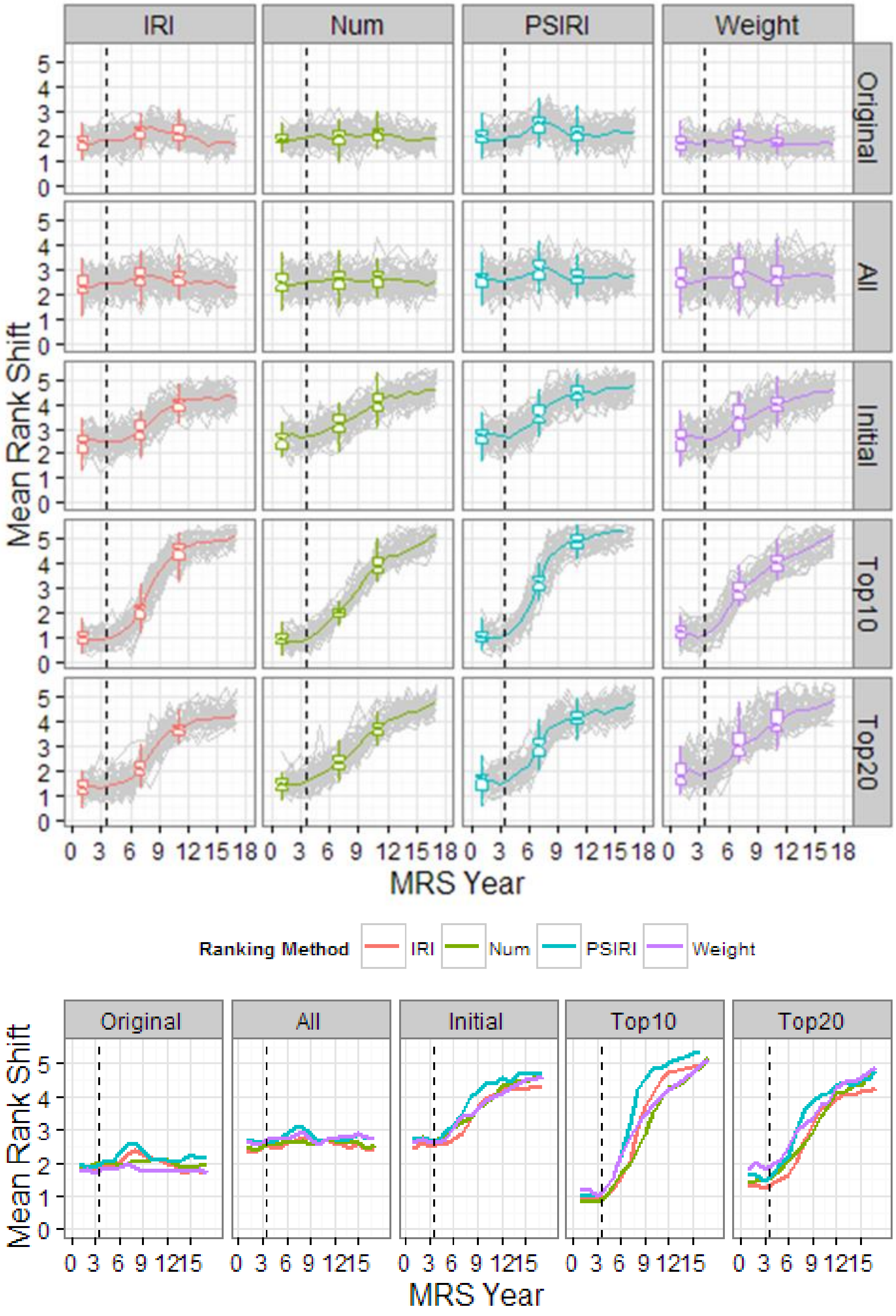

Figure 4-15. Panel A shows MRS scores over time for 50 simulations (grey lines), median MRS by ranking method and MRS formulation (colored lines), year of perturbation (dashed line), and boxplots of MRS scores for MRS year 1 (initial score), MRS year 7 (4 years post perturbation) and MRS year 11 (8 years post-perturbation). Panel B shows the median MRS line for each ranking method within each MRS formulation to facilitate comparisons of MRS scores among and within MRS formulations. All graphs are for perturbation scenario 5b listed in Table 4-1 (eight species – 25%).

CHAPTER 5

CONCLUSIONS

Reservoir managers and researchers are frequently asked to assess changes in reservoir fish assemblages as a result of management actions or other anthropogenic perturbations. Quantifying changes in any ecological assemblage is an onerous task, but reservoirs are particularly challenging. Reservoir sampling data are highly variable temporally and spatially because of variation in fish distribution and behavior (especially schooling), differential sampling efficiency across different habitats, and size selectivity of gears. For this dissertation, I analyzed data from a long-term, gill-net data set that would be typical of a standardized reservoir monitoring program (with the exception of total effort) to assess the strength of inferences about total fish abundance, determine the amount of sampling required to characterize the gill-netting fish assemblage, and evaluate novel approaches for discerning changes in reservoir fish assemblages over time. The specific results and the implications of the findings for each chapter are provided below.

In Chapter 2, I used a novel approach to model the relationship between gill-net catch and acoustic-derived densities and a variety of covariates that could reasonably be expected to affect encounter rates with gill nets. Through the modeling, I hoped to identify particular times or conditions that produced strong positive relationships between the methods so that gill-net catch could be used to make strong inferences on total fish abundance under those specific conditions. Unfortunately, I was unable to identify a set of conditions that worked well for estimating total fish abundance when including all species. The inability to develop meaningful relationships is likely caused by the complexity of interactions given the number of species involved. Similarly, Yule et al. (2013) suggested that high species richness is a major reason why gillnet catch is often weakly correlated with acoustics because with a greater numbers of species comes greater variability in fish behavior, habitat preferences, and gear selectivity. The lack of correlation is problematic and reinforced my initial concerns related to the use of passive gears for making reliable inferences on total fish abundance over space or time. Because gill-nets acquire species very quickly, they are an efficient gear for community assessments and can provide additional information on individual species (e.g., age, growth, and condition). Consequently, additional investigations on the utility of gill-nets for making inferences on abundance are warranted but likely will need to focus on the key species of the assemblage to determine the source of the bias in sample-by-sample comparisons with acoustic-derived densities. I suspect that focusing on size selectivity of a few of the most abundant species (e.g., adding additional meshes to fill selectivity gaps or tracking individual species over time to see when they hit the selectivity gaps and factoring that in to modelling) would provide some additional insight into the key factors that limit the development of meaningful relationships between acoustic abundance and gill-net catch.

For this dissertation, the lack of a meaningful relationship between acoustic derived abundances and gill-net catch was problematic and pointed towards a need to evaluate a metric that would be more robust to deviations or issues with relative abundances. As a result, I focused on rank-based approaches for assessing assemblage structure in Chapters 3 and 4. Given the disparity in individual species abundances, I believe ranks would more likely be assigned accurately even if catch varied considerably within a species. For example, in some years,the ranks of blueback herring, threadfin shad, and gizzard shad would have been unaffected by even a 50% reduction in catch.

In Chapter 3, I evaluated the similarity of inferences regarding the structure of the fish assemblage between my full gill-netting data record and temporal subsets of the data. My results suggested that sampling 3, 4 or 6 months per year across seasons reasonably characterized a reservoir fish assemblage as derived from a complete year of gill-net sampling, but the precision associated with each characterization decreased with decreasing sampling time frame. The level of effort required was mostly a function of the variance that was acceptable, as the key members and attributes of the community were similar. These findings are significant as few, if any, management agencies would have the ability to sample year-round as we did, but might be able to sample at the reduced levels identified. Even in cases where monthly sampling might be an option, our results indicate that little additional information is gained after 3 to 4 months, so those resources could be re-directed to address additional research needs and objectives.

In chapter 4, I evaluated five different formulations of mean rank shift and different ranking methods as ways to assess changes in the relative contribution of species in a reservoir fish assemblage over time. In addition to evaluating the performance of the original version of MRS that focused on changes in assemblage stability by comparing changes across consecutive years, I created and evaluated several new formulations of MRS that focused on comparing the initial community with the community subsequent to some perturbation. Based on these simulations, the two formulations that used only the top 10 and top 20 ranked species, MRS_{10} and MRS_{20}, were useful for detecting changes over a management-relevant, post-perturbation time span of 4-8 years when calculated based on PSIRI derived rankings. Both MRS and PSIRI are fairly new approaches that have not been extensively used or evaluated, so these findings add new information on the applicability of the approaches. To my knowledge, this is the first time use of PSIRI to rank species in an assemblage context. Additional evaluations of MRS_{10} and MRS_{20} based on PSIRI are warranted as the approach is simple, easy to understand and explain, and has demonstrated utility for addressing directional changes in a fish assemblage from an initial baseline assemblage. I believe the latter is the type of change that will be of most interest to fishery managers.

For all the chapters, my focus was on management-relevant issues, inferences, and sampling scales. For example, much of the recent work on diversity indices and sampling sufficiency focuses on goals and objectives related to biodiversity sampling; consequently, much interest is appropriately centered on documenting or accounting for rare species. In contrast, my focus was centered on the species that accounted for most of the information, and the management species of interest in my study were always contained within that group of species. For management purposes, I think the construct of core species, as proposed by Magurran and Henderson (2003), is a good one for establishing the set of species that should be the primary focus of any efforts when assessing changes in reservoir fish assemblages. Core species can be defined many ways based on management objectives, including those occurring in a greater than specified percent of samples or those that account for some cumulative percent of the data. Regardless of the exact definition, the idea is a subset of the species is caught often enough and in large enough numbers that they provide meaningful basis for inference. Non-core or “occasional” species are those that are captured infrequently and in such small numbers that there is likely very low inferential value, especially in a statistical sense.

The results from this dissertation point to the challenges and opportunities that face reservoir managers when assessing changes in the overall fish assemblage. Based on Chapter 2, estimating relative abundances of individual species is still a challenge that requires additional investigation, but the rank-based approaches used in Chapters 3 and 4 should be more robust to the potential biases in relative abundances. Results from Chapter 3 show that characterizing the gill-net assemblage can be performed with a 25-33% of annual effort provided sampling is carried out across seasons. Chapter 4 shows that Mean Rank Shift coupled with PSIRI shows promise for assessing changes in a community over time especially in the face of perturbations that result in directional changes. Taken together, these chapters point to new approaches for assessing reservoir fish assemblages and should provide reservoir fishery managers with better, more-cost effective, and novel approaches for assessing how reservoir fish assemblages respond to perturbations (anthropogenic or otherwise) compared to the tools being used at present.

LITERATURE CITED

Magurran, A. E., and P. A. Henderson. 2003. Explaining the excess of rare species in natural species abundance distributions. Nature 422:714-716.

Yule, D. L., L. M. Evrard, S. Cachera, M. Colon, and J. Guillard. 2013. Comparing two fish sampling standards over time: Largely congruent results but with caveats. Freshwater Biology 58:2074-2088.