

# ECOLOGY AND MANAGEMENT OF SUPERABUNDANT FISH POPULATIONS

by

Nathaniel T. Stewart

A THESIS

Presented to the Faculty of

The Graduate College at the University of Nebraska

In Partial Fulfillment of Requirements

For the Degree of Master of Science

Major: Natural Resource Sciences

Under the Supervision of Professor Kevin L. Pope and Professor Christopher J. Chizinski

Lincoln, Nebraska

May 2015

# ECOLOGY AND MANAGEMENT OF SUPERABUNDANT FISH POPULATIONS

Nathaniel Thomas Stewart, M.S.

University of Nebraska, 2015

Advisors: Kevin L. Pope and Christopher J. Chizinski

Fish population biomasses can reach extreme levels; we term these populations superabundant fish populations. Superabundant fish populations may negatively affect aquatic communities and anglers, necessitating the effective management of the superabundant fish populations. However, there are gaps in our understanding of these populations. The gaps in our understanding hamper our ability to predict effects on valuable sportfisheries and to effectively manage superabundant fish populations. The overall goal of my thesis research is to provide further insight into the ecology of superabundant fish populations and to provide information that will aid in their effective management. First, we described a new method for estimating abundances and biomasses of superabundant fish populations in lentic systems using generalized N-mixture models with data from consumer-grade sonar, vertical gillnets, and a boat electrofisher. These open population models use point-count data with covariates to estimate site-specific abundances and detection probabilities. I used this method to estimate that there were 1.1-1.4 million white perch (*Morone americana*) and 0.5-1.1 million gizzard shad (*Dorosoma cepedianum*) in Branched Oak Lake, Nebraska. Second, we determined how the spatial distributions of superabundant white perch populations related to the spatial distributions of gizzard shad populations present in the same waterbodies by using the site-specific abundances estimated with the generalized N-mixture models. White perch and gizzard shad spatial distributions were positively

related in Branched Oak Lake and Pawnee Reservoir, Nebraska. We suspect that large population sizes and similar diets contributed to the observed relationship. Third, we evaluated the effect of a low-dose-rotenone application on white perch and gizzard shad populations in Pawnee Reservoir, Nebraska. The low-dose rotenone application in Pawnee Reservoir led to a large reduction (83%) in the white perch population biomass and extirpated, or nearly extirpated, gizzard shad from the reservoir. By filling in the gaps in our knowledge of superabundant populations we can more effectively manage them for the good of our fisheries resources and their users by improving growth and abundance of sportfish.

## Acknowledgements

There are numerous people who have contributed to getting me here and I thank them all. I thank my family for their love, moral support, and patience. Specifically I thank my parents Jeffery and Karen Stewart for providing an environment that allowed me to develop a strong mental and spiritual base, for all of the advice over the years, and for being excellent role models. I thank my brothers Ian and Will Stewart for moral support and comic relief. I also thank both of my grandmothers for all of the cookies they baked over the years and both of my grandfathers for teaching me to fish and for providing examples of solid work ethics, honesty, and putting family first.

I thank my advisers Dr. Kevin Pope and Dr. Christopher Chizinski. I thank you both for challenging me, for all of the time and ink spent editing, and for maintaining an environment to foster learning, exploration, and constructive criticism. Specifically I thank Kevin for helping me to think at more of a systems level rather than just about the components that make up systems and for helping me improve my critical thinking skills. I also thank you for all of the enthusiasm that you brought to our meetings and the project as a whole. I thank Chris for all of the help with R, with population modeling, and for challenging me to think beyond the standard fisheries approaches to data analysis. Thank you also for all of your patience as I learned R and worked through the population models for this project.

I thank the rest of my other committee members Dr. Larkin Powell, Dr. Mark Pegg, Dr. Richard Holland, and Jeffery Jackson for all of their insight and interest in my

graduate education. I thank Dr. Larkin Powell for all of his assistance trouble shooting our population models. I thank Dr. Mark Pegg for helping me think about the big picture and for bringing a riverine perspective to our meetings. I thank Dr. Richard Holland for always asking questions and for pushing me to look further into what my results meant. I thank Jeffery Jackson for always bringing a management perspective to the table and for his cooperation with my field sampling.

I thank my fellow graduate students in the Nebraska Cooperative Fish and Wildlife Research Unit and Mark Pegg's lab for feedback on presentations, writing, and for discussions of my project. Specifically I thank Christopher Wiley, Dustin Martin, Robert Kill, Kelly Turek, William Smith, Lucas Kowalewski, Brian Harmon, Danielle Haak, Alexis Fedele, Nick Cole, Conner Chance-Ossowski, Nathan Bieber, and Stephen Siddons for assistance with fieldwork. I especially thank Lucas Kowalewski for all of his assistance with fieldwork, assistance designing sampling gear, and for all of the discussions we had about my project while out on the boat. You helped get my graduate school career off to a good start. I thank Kelly Turek for all of the assistance with fieldwork during the fall of 2014. I also thank Valerie Egger and Caryl Cashmere for all of their help with the logistics of graduate school. Without their help I would have had a lot more trouble getting field equipment, traveling as part of my master's program, and getting to and from my field sites.

I thank the Nebraska Game and Parks Commission for funding my research. I thank all of the Nebraska Game and Parks fisheries staff for their interest in and

contributions to my research. I especially thank the southeast district fisheries staff for always being willing to discuss my project when I stopped by.

Finally I thank the fisheries professionals who got me into fisheries and who convinced me to pursue a graduate education. I thank Jana Prey for showing me that you could actually make a career out of working in fisheries. I thank Jason Spaeth for introducing me to fieldwork in fisheries. I thank Dr. Daniel Isermann and Dr. Justin Sipiorski for providing me opportunities to conduct research as an undergraduate student. I thank Ryan Doorenbos for encouraging me to pursue a graduate education.

This project was funded by Federal Aid in Sport Fish Restoration, project F-193-R, administered by the Nebraska Game and Parks Commission. Reference to trade names does not imply endorsement by the author or any U.S. government. The Nebraska Cooperative Fish and Wildlife Research Unit is jointly supported by the U.S. Geological Survey, the Nebraska Game and Parks Commission, the University of Nebraska, the U.S. Fish and Wildlife Service, and the Wildlife Management Institute. Portions of this work were completed utilizing the Holland Computing Center of the University of Nebraska.

## Table of Contents

Chapter 1. Introduction .....	1
Thesis goal and outline .....	4
References .....	5
Chapter 2 Defining superabundant populations and challenges in estimating their size....	8
Study Reservoirs .....	14
Branched Oak Lake .....	14
Pawnee Reservoir .....	14
Methods.....	15
Sampling Design .....	15
Approach: Water Depths > 2 m.....	16
Approach: Water Depths $\leq$ 2 m.....	18
Analysis .....	19
Application: Branched Oak Lake .....	24
Application: Pawnee Reservoir .....	26
Results.....	28
Sonar validation.....	28
Branched Oak Lake .....	28
Pawnee Reservoir .....	35
Discussion .....	38
References.....	46
Chapter 3 Seasonal distribution patterns of white perch and gizzard shad in reservoirs	107
Study Reservoirs .....	110
Branched Oak Lake .....	110
Pawnee Reservoir .....	111
Methods.....	111
Results.....	113

Branched Oak Lake .....	113
Pawnee Reservoir .....	115
Discussion .....	116
References .....	120
Chapter 4. Controlling superabundant fish populations .....	139
Methods .....	142
Study Site .....	142
Application .....	142
Abundance estimation and analysis .....	143
Non-target effects .....	144
Results .....	145
Non-target effects .....	146
Discussion .....	147
References .....	152
Chapter 5 Conclusions, management recommendations, and research needs .....	176
Management needs .....	178
Research questions .....	179
Conclusions .....	183
References .....	185
Appendix A. Diel distribution of white perch and gizzard shad in a flood-control reservoir .....	186
Methods .....	188
Study Site .....	188
Sampling Design .....	188
Approach Water Depths $> 2$ m .....	189
Approach Water Depths $\leq 2$ m .....	190
Analysis .....	190
Results .....	192



Discussion .....	194
References .....	197
Appendix B. Striped bass diet and condition.....	207
Reference .....	212

## List of Tables

Table 2-1. Methods that fisheries scientists can use to estimate fish abundance and each method's advantages. .... 50

Table 2-2. Candidate generalized N-mixture models used to estimate white perch and gizzard shad abundances on Branched Oak Lake and Pawnee Reservoir, Nebraska. Data were collected with a consumer grade sonar unit used in conjunction with vertical gillnets (SN) and with a boat electrofisher (EF). In each model,  $\lambda$  is site and specific abundance,  $\gamma$  is site and time specific recruitment,  $\Omega$  is site and time specific apparent survival, and  $p$  is site and time specific detection probability. The covariates in the models are the mean depth of cells (D), whether the mean slope was  $< 1\%$  or  $\geq 1\%$  (S), the period in which a sample was taken (P), whether the cell was adjacent to shore and whether the adjacent shoreline had rip rap (H), and presence or absence of timber (T). .... 51

Table 2-3. Generalized N-mixture models ranked with AIC used to model white perch abundance on Branched Oak Lake, Nebraska during 2013 (K: number of model parameters, AIC: Akaike Information Criterion score,  $\Delta$ AIC: difference between AIC score for the specified model and for the top model, AICwt: AIC weight, cumwt: cumulative AIC weight). Count data were collected with a consumer grade sonar unit used in conjunction with vertical gillnets (SN) in waters with total depths  $\geq 2$  m and a boat electrofisher (EF) used to electrify points in water with total depths  $< 2$  m. In each model,  $\lambda$  is site and time specific abundance,  $\gamma$  is site and time specific recruitment,  $\Omega$  is site and time specific apparent survival, and  $p$  is site and time specific detection probability. The covariates in the models are the mean depth of cells (D), whether the mean slope was  $< 1\%$  or  $\geq 1\%$  (S), the period in which a sample was taken (P), whether the cell was adjacent to shore and whether the adjacent shoreline had rip rap (H), and presence or absence of timber (T). .... 53

Table 2-4. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass on the north arm of Branched Oak Lake, Nebraska during 2013. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $< 1\%$  slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: June 25, category B: July 31, and category B: October 16). This model also included dispersion parameter that is a measure of how much overdispersion the model was relative to a Poisson model. .... 55

Table 2-5. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass on the north arm of Branched Oak Lake, Nebraska during 2013. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), Timber (whether or not a sampling cell contained flooded timber; category 0: timber absent and category 1: timber present) and Period (the period in, which sampling took place; category A: June 25, category B: July 31, and category B: October 16). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were..... 57

Table 2-6. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass on the south arm of Branched Oak Lake, Nebraska during 2013. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: June 25, category B: July 31, and category B: October 16). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model. .... 59

Table 2-7. Generalized N-mixture models ranked with AIC used to model white perch abundance on Branched Oak Lake, Nebraska during 2014 (K: number of model parameters, AIC: Akaike Information Criterion score,  $\Delta$ AIC: difference between AIC score for the specified model and for the top model, AICwt: AIC weight, cumwt: cumulative AIC weight). Count data were collected with a consumer grade sonar unit used in conjunction with vertical gillnets (SN) in waters with total depths  $\geq 2$  m and a boat electrofisher (EF) used to electrify points in water with total depths  $< 2$  m during. In each model,  $\lambda$  is abundance,  $\gamma$  is recruitment,  $\Omega$  is apparent survival, and  $p$  is detection probability. The covariates in the models are depth (D), slope (S), sampling period (P), and shoreline habitat (H)..... 61

Table 2-8. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass on the north arm of Branched Oak Lake, Nebraska during 2014. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and

time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: April 1, category B: July 7, and category B: October 13). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model. .... 63

Table 2-9. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass on the north arm of Branched Oak Lake, Nebraska during 2014. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), Timber (whether or not a sampling cell contained flooded timber; category 0: timber absent and category 1: timber present) and Period (the period in, which sampling took place; category A: April 1, category B: July 7, and category B: October 13). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were. .... 65

Table 2-10. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass on the south arm of Branched Oak Lake, Nebraska during 2014. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: April 1, category B: July 7, and category B: October 13). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model. .... 67

Table 2-11. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass on the south arm of Branched Oak Lake, Nebraska during 2014. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), Timber

(whether or not a sampling cell contained flooded timber; category 0: timber absent and category 1: timber present) and Period (the period in, which sampling took place; category A: April 1, category B: July 7, and category B: October 13). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were..... 69

Table 2-12. Generalized N-mixture models ranked with AIC used to model gizzard shad abundance on Branched Oak Lake, Nebraska during 2013 (K: number of model parameters, AIC: Akaike Information Criterion score,  $\Delta$ AIC: difference between AIC score for the specified model and for the top model, AICwt: AIC weight, cumwt: cumulative AIC weight). Count data were collected with a consumer grade sonar unit used in conjunction with vertical gillnets (SN) in waters with total depths  $\geq 2$  m and a boat electrofisher (EF) used to electrify points in water with total depths  $< 2$  m. In each model,  $\lambda$  is abundance,  $\gamma$  is recruitment,  $\Omega$  is apparent survival, and p is detection probability. The covariates in the models are depth (D), slope (S), sampling period (P), and shoreline habitat (H)..... 71

Table 2-13. Parameter estimates for generalized N-mixture model used to estimate gizzard shad abundance and biomass on the north arm of Branched Oak Lake, Nebraska during 2013. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and p is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: June 25, category B: July 31, and category B: October 16). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model. .... 72

Table 2-14. Parameter estimates for generalized N-mixture model used to estimate gizzard shad abundance and biomass on the north arm of Branched Oak Lake, Nebraska during 2013. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and p is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), Timber (whether or not a sampling cell contained flooded timber; category 0: timber absent and category 1: timber present) and Period (the period in, which sampling took place; category A: June 25, category B: July 31, and category B: October 16). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were. .... 74

Table 2-15. Parameter estimates for generalized N-mixture model used to estimate gizzard shad abundance and biomass on the south arm of Branched Oak Lake, Nebraska during 2013. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1: <1% slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: June 25, category B: July 31, and category B: October 16). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model. .... 76

Table 2-16. Generalized N-mixture models ranked with AIC used to model gizzard shad abundance on Branched Oak Lake, Nebraska during 2014 (K: number of model parameters, AIC: Akaike Information Criterion score,  $\Delta AIC$ : difference between AIC score for the specified model and for the top model, AICwt: AIC weight, cumwt: cumulative AIC weight). Count data were collected with a consumer grade sonar unit used in conjunction with vertical gillnets (SN) in waters with total depths  $\geq 2$  m and a boat electrofisher (EF) used to electrify points in water with total depths < 2 m. In each model,  $\lambda$  is abundance,  $\gamma$  is recruitment,  $\Omega$  is apparent survival, and  $p$  is detection probability. The covariates in the models are depth (D), slope (S), sampling period (P), and shoreline habitat (H)..... 78

Table 2-17. Parameter estimates for generalized N-mixture model used to estimate gizzard shad abundance and biomass on the north arm of Branched Oak Lake, Nebraska during 2014. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1: <1% slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: April 1, category B: July 7, and category B: October 13). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model. .... 80

Table 2-18. Parameter estimates for generalized N-mixture model used to estimate gizzard shad abundance and biomass on the north arm of Branched Oak Lake, Nebraska during 2014. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1: <1% slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip

rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), Timber (whether or not a sampling cell contained flooded timber; category 0: timber absent and category 1: timber present) and Period (the period in, which sampling took place; category A: April 1, category B: July 7, and category B: October 13). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were. .... 82

Table 2-19. Parameter estimates for generalized N-mixture model used to estimate gizzard shad abundance and biomass on the south arm of Branched Oak Lake, Nebraska during 2014. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: April 1, category B: July 7, and category B: October 13). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model. .... 84

Table 2-20. Parameter estimates for generalized N-mixture model used to estimate gizzard shad abundance and biomass on the south arm of Branched Oak Lake, Nebraska during 2014. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), Timber (whether or not a sampling cell contained flooded timber; category 0: timber absent and category 1: timber present) and Period (the period in, which sampling took place; category A: April 1, category B: July 7, and category B: October 13). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were. .... 86

Table 2-21. Abundance and biomass with 95% confidence intervals estimated for white perch (WHP) and gizzard shad (SHAD) in Branched Oak Lake (BOL) and Pawnee Reservoir (PWR), Nebraska. Estimates were made using generalized N-mixture models with data collected with a consumer-grade sonar unit, vertical gillnets, and a boat electrofisher..... 88

Table 2-22. Generalized N-mixture models ranked with AIC used to estimate white perch abundance and biomass on Pawnee Reservoir, Nebraska (K: number of model parameters, AIC: Akaike Information Criterion score,  $\Delta$ AIC: difference between AIC score for the specified model and for the top model, AICwt: AIC weight, cumwt:

cumulative AIC weight). Count data were collected with a consumer grade sonar unit used in conjunction with vertical gillnets (SN) in waters with total depths  $\geq 2$  m and a boat electrofisher (EF) used to electrify points in water with total depths  $< 2$  m. In each model,  $\lambda$  is abundance,  $\gamma$  is recruitment,  $\Omega$  is apparent survival, and  $p$  is detection probability. The covariates in the models are depth (D), slope (S), sampling period (P), and shoreline habitat (H)..... 89

Table 2-23. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass in Pawnee Reservoir, Nebraska during 2013. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: June 17, category B: July 25, category C: September 9, category D: October 8). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model..... 90

Table 2-24. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass in Pawnee Reservoir, Nebraska during 2013. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), Timber (whether or not a sampling cell contained flooded timber; category 0: timber absent and category 1: timber present) and Period (the period in, which sampling took place; category A: June 17, category B: July 25, category C: September 9, category D: October 8). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were..... 92

Table 2-25. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass in Pawnee Reservoir, Nebraska during 2014. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth the mean depth of cells (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: May 2, category B: May 14, category C: May 21, category D: June 20, category E: September



18, category F: October 7). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model.... 94

Table 2-26. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass in Pawnee Reservoir, Nebraska during 2014. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), Timber (whether or not a sampling cell contained flooded timber; category 0: timber absent and category 1: timber present) and Period (the period in, which sampling took place; category A: May 2, category B: May 14, category C: May 21, category D: June 20, category E: September 18, category F: October 7). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were..... 96

Table 2-27. Generalized N-mixture models ranked with AIC used to model gizzard shad abundance on Pawnee Reservoir, Nebraska during 2013 (K: number of model parameters, AIC: Akaike Information Criterion score,  $\Delta$ AIC: difference between AIC score for the specified model and for the top model, AICwt: AIC weight, cumwt: cumulative AIC weight). Count data were collected with a consumer grade sonar unit used in conjunction with vertical gillnets (SN) in waters with total depths of 2 m or more and a boat electrofisher (EF) used to shock points in water with total depths  $< 2$  m. In each model,  $\lambda$  is abundance,  $\gamma$  is recruitment,  $\Omega$  is apparent survival, and  $p$  is detection probability. The covariates in the models are depth (D), slope (S), sampling period (P), and shoreline habitat (H)..... 98

Table 2-28. Parameter estimates for generalized N-mixture model used to estimate gizzard shad abundance and biomass in Pawnee Reservoir, Nebraska during 2013 We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: June 17, category B: July 25, category C: September 9, category D: October 8). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model. .... 99

Table 2-29. Parameter estimates for generalized N-mixture model used to estimate gizzard shad abundance and biomass in Pawnee Reservoir, Nebraska during 2013. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific

abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), Timber (whether or not a sampling cell contained flooded timber; category 0: timber absent and category 1: timber present) and Period (the period in, which sampling took place; category A: June 17, category B: July 25, category C: September 9, category D: October 8). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were. .... 101

Table 4-1. Species-specific rotenone toxicity estimates with standard error if available as reported in the literature; (\* rough estimates of LC 100). .... 155

Table 4-2. Generalized N-mixture models ranked with AIC used to model white perch abundance on Pawnee Reservoir, Nebraska prior to (pre) and following (post) a low-dose rotenone treatment during November 2013 (K: number of model parameters, AIC: Akaike Information Criterion score,  $\Delta AIC$ : difference between AIC score for the specified model and for the top model, AICwt: AIC weight, cumwt: cumulative AIC weight). Count data were collected with a consumer grade sonar unit used in conjunction with vertically set gillnets (SN) in waters with total depths  $\geq 2$  m and a boat electrofisher (EF) used to electrify points in water with total depths  $< 2$  m. In each model,  $\lambda$  is abundance,  $\gamma$  is recruitment,  $\Omega$  is apparent survival, and  $p$  is detection probability. The covariates in the models are depth (D), slope (S), sampling period (P), and shoreline habitat (H). .... 157

Table 4-3. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass in Pawnee Reservoir, Nebraska during 2013. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: June 17, category B: July 25, category C: September 9, category D: October 8). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model..... 158

Table 4-4. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass in Pawnee Reservoir, Nebraska during 2013. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit

scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), and Period (the period in, which sampling took place; category A: June 17, category B: July 25, category C: September 9, category D: October 8). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were..... 160

Table 4-5. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass in Pawnee Reservoir, Nebraska during 2014. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: May 2, category B: May 14, category C: May 21, category D: June 20, category E: September 18, category F: October 7). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model..... 162

Table 4-6. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass in Pawnee Reservoir, Nebraska during 2014. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), and Period (the period in, which sampling took place; category A: May 2, category B: May 14, category C: May 21, category D: June 20, category E: September 18, category F: October 7). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were..... 164

Table 4-7. Generalized N-mixture models ranked with AIC used to model gizzard shad abundance on Pawnee Reservoir Nebraska prior to a low-dose rotenone treatment during November 2013 (K: number of model parameters, AIC: Akaike Information Criterion score,  $\Delta$ AIC: difference between AIC score for the specified model and for the top model, AICwt: AIC weight, cumwt: cumulative AIC weight). Count data were collected with a consumer grade sonar unit (SN) used in conjunction with vertically set gillnets in waters with total depths of 2 m or more and a boat electrofisher (EF) used to shock points in water with total depths less than 2 m. In each model,  $\lambda$  is abundance,  $\gamma$  is recruitment,

$\Omega$  is apparent survival, and  $p$  is detection probability. The covariates in the models are depth (D), slope (S), sampling period (P), and shoreline habitat (H). ..... 166

Table 4-8. Parameter estimates for generalized N-mixture model used to estimate gizzard shad abundance and biomass in Pawnee Reservoir, Nebraska during 2013. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: June 17, category B: July 25, category C: September 9, category D: October 8). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model..... 167

Table 4-9. Parameter estimates for generalized N-mixture model used to estimate gizzard shad abundance and biomass in Pawnee Reservoir, Nebraska during 2013. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), and Period (the period in, which sampling took place; category A: June 17, category B: July 25, category C: September 9, category D: October 8). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were..... 169

Table 4-10. Daily observed mortality of non-target fish species counted along seven, 10-m sections of shoreline 2, 3, 5, and 7 days post low-dose rotenone application on Pawnee Reservoir, Nebraska. .... 171

Table A-1. The order of polynomial used to remove global trends and mean prediction error for universal kriging analysis carried out using geostatistical analyst tools in ArcGIS10 to assess changes in fish spatial distribution in Branched Oak Lake during diel cycles between August 11 and 29 of 2014. Data were collected using a consumer grade sonar unit..... 199

Table A-2. Comparisons of the number of fish captured with a boat electrofisher between periods over diel cycles in Branched Oak Lake, Nebraska from August 11 to 29, 2014. Analyses were carried out using generalized linear models for data with negative binomial distribution. .... 200

Table A-3. Results of comparisons of number of fish targets identified using consumer-grade sonar between periods within depth layers. Data were collected between August 11 and 29, 2014 in Branched Oak Lake, Nebraska. Analyses were carried out using generalized linear models for data with negative binomial distribution.....	201
Table A-4. Results of comparisons of number of fish captured with vertical gillnets in the top 4 meters of the water column between periods. Data were collected between August 11 to 29, 2014 in Branched Oak Lake, Nebraska. Analyses were carried out using generalized linear models for data with negative binomial distribution.....	202
Table B-2. Length, weight, relative weight ( $W_r$ ), and gut content information for striped bass ( <i>Morone saxatilis</i> ) captured in Branched Oak Lake, Nebraska during 2014. Effort consisted of 288, 1-2 h vertical gillnet sets (VG), 15, 1-24 h horizontal gillnet sets (GN), and 26,731 seconds of electrofishing (EF) during 2014. Fish from October were captured in Nebraska Game and Parks Commission standardized gillnets and trapnets (TN). Parameters for estimating relative weight from Brown and Murphy 1991. ....	211

## List of Figures

Figure 1-1. Conceptual model of differences in population biomass regulation between organisms that exhibit limited growth plasticity such as mammals or birds (left) and organisms that exhibit growth plasticity such as fish (right). Box number denotes the number of individuals and box width denotes the size of the individual; biomasses in all populations are the same. ....	7
Figure 2-1. Stratification system and sampling sites (with adjustments for sites moved because they were unsampleable) for estimating white perch and gizzard shad abundances, biomasses, and spatial distributions in Branched Oak Lake, Nebraska. ....	103
Figure 2-2. Stratification system and sampling sites for estimating white perch and gizzard shad abundances, biomasses, and spatial distributions in Pawnee Reservoir, Nebraska. ....	104
Figure 2-3. Electric field map for a 5.5- m boat electrofisher with a Smith-Root® 5.0 GPP control box. The effective edge of the electric field was estimated to be where power density was < 84 $\mu\text{W}/\text{cc}$ . ....	105
Figure 2-4. Relationships between vertical gillnet catch and fish density estimated using consumer grade sonar in Branched Oak Lake (top) and Pawnee Reservoir, Nebraska (bottom) during spring, summer, and fall of 2013 and 2014. ....	106
Figure 3-1. Conceptual models of hypothetical white perch ( ● ) and gizzard shad ( ● ) distributions in two habitats ( ■ and ■ ) within the same waterbody. The top panels represents no relationship between spatial distributions, the second panels represents both species sharing the same habitats, the third panels represents each species using different habitat, and the fourth panel represents white perch using all habitats and gizzard shad selecting one habitat. ....	122
Figure 3-2. Estimates of white perch relative abundances (percent of population per sampling cell) in Branched Oak Lake, Nebraska. Data were collected during July and October of 2013 and during April, July, and October of 2014 with consumer-grade sonar, vertical gillnets, and a boat electrofisher and analyzed using generalized N-mixture models. ....	124
Figure 3-3. Estimates of white perch detection probability in Branched Oak Lake, Nebraska. Data were collected during July and October of 2013 and during April, July, and October of 2014 with consumer-grade sonar, vertical gillnets, and a boat electrofisher and analyzed using generalized N-mixture models. ....	126
Figure 3-4. Estimates of gizzard shad relative abundances (percent of population per sampling cell) in Branched Oak Lake, Nebraska. Data were collected during July and	

October of 2013 and during April, July, and October of 2014 with consumer-grade sonar, vertical gillnets, and a boat electrofisher and analyzed using generalized N-mixture models. ....	128
Figure 3-5. Estimates of gizzard shad detection probability in Branched Oak Lake, Nebraska. Data were collected during July and October of 2013 and during April, July, and October of 2014 with consumer-grade sonar, vertical gillnets, and a boat electrofisher and analyzed using generalized N-mixture models. ....	130
Figure 3-6. Estimates of white perch relative abundances (percent of population per sampling cell) in Pawnee Reservoir, Nebraska. Data were collected during June and October of 2013 and during May, June, and October of 2014 with consumer-grade sonar, vertical gillnets, and a boat electrofisher and analyzed using generalized N-mixture models. ....	132
Figure 3-7. Estimates of white perch detection probability in Pawnee Reservoir, Nebraska. Data were collected during June and October of 2013 and during May, June, and October of 2014 with consumer-grade sonar, vertical gillnets, and a boat electrofisher and analyzed using generalized N-mixture models. ....	133
Figure 3-8. Estimates of gizzard shad relative abundances (percent of population per sampling cell) in Pawnee Reservoir, Nebraska. Data were collected during June and October of 2013 with consumer-grade sonar, vertical gillnets, and a boat electrofisher and analyzed using generalized N-mixture models. ....	135
Figure 3-9. Estimates of gizzard shad detection probability in Pawnee Reservoir, Nebraska. Data were collected during June and October of 2013 with consumer-grade sonar, vertical gillnets, and a boat electrofisher and analyzed using generalized N-mixture models. ....	137
Figure 4-1. Length distributions of white perch captured in Pawnee Reservoir, Nebraska with a boat electrofisher and vertical gillnets during September 2013 (top) and September 2014 (bottom). ....	172
Figure 4-2. Observed mortality of grass carp (●) and largemouth bass (○) from a Florida Lake over a 24-h period as a function of rotenone concentrations (Colle et al. 1978). ..	173
Figure 4-3. Rotenone toxicity (LC 50 $\mu\text{g/L}$ ) as a function of exposure time for green sunfish in a laboratory setting (Marking and Bills 1976). ....	174
Figure 4-4. Rotenone resistance (48 h LC 50 with standard error) of golden shiner in Connecticut ponds increasing with repeated applications of rotenone between 1957 and 1974 (Orciari 1979). ....	175

Figure A-1. Sampling used to estimating changes in fish spatial distribution in Branched Oak Lake, Nebraska over diel cycles between August 11 and 29, 2014. .... 203

Figure A-2. Fish distribution during four periods (dawn 2 h before to 2 h after sunrise, day 11:00-15:00, dusk 2 h before to 2 h after sunset, night 23:00-03:00) in three depth layers of Branched Oak Lake, Nebraska during the week of August 11, 2014. Data were collected using a consumer grade sonar unit and maps were generated using universal kriging. .... 204

Figure A-3. Fish distribution during three periods (dawn 2 h before to 2 h after sunrise, day 11:00-15:00, and dusk 2 h before to 2 h after sunset) in three depth layers of Branched Oak Lake, Nebraska during the week of August 18, 2014. Data were collected using a consumer grade sonar unit and maps were generated using universal kriging. . 205

Figure A-4. Fish distribution during three periods (dawn 2 h before to 2 h after sunrise, day 11:00-15:00, and dusk 2 h before to 2 h after sunset) in three depth layers of Branched Oak Lake, Nebraska during the week of August 25, 2014. Data were collected using a consumer grade sonar unit and maps were generated using universal kriging. . 206



## Chapter 1. Introduction

1. How can we estimate size of superabundant fish populations?
2. What are the ecological consequences of superabundant fish populations?
3. How can we reduce sizes of superabundant fish populations?

Maximum size in many fish species varies due to growth plasticity. Biotic and abiotic conditions in the environment influence fish growth (Sebens 1987; Ylikarjula et al. 1999). For example, fish growth rates increase when resources become more available, decrease when fish reach maturity and divert energy to reproduction, and decrease in less than optimal temperatures (Sebens 1987; Mommensen 2001). Both organismal abundance and the body size of individuals that comprise a population interact to determine the biomass of the population (Pagel et al. 1991). Organisms with little growth plasticity, such as mammals and birds, have population biomasses determined primarily by abundance of organisms because little variation in individual body size (Weatherby 1990) (Figure 1-1). In contrast, organisms that exhibit growth plasticity, such as fish, have biomasses regulated by abundance and body size because of the larger variation among individuals in body size. Thus, fish populations can theoretically have the same biomass in multiple ways (Figure 1-1). Fish populations can exist along a continuum from a few, large individual to numerous, small individuals. In populations that are termed stunted, resource limitations due to intraspecific competition reduce individual growth and along with earlier maturity, lead to a large number of

individuals of small size (Swingle and Smith 1942; Scheffer et al. 1995; Ylikarjula et al. 1999). In some cases, as a result of growth plasticity, fish biomasses can obtain extreme levels (herein termed superabundant fish populations, Chapter 2).

Superabundant fish populations have consequences for aquatic communities and the anglers who utilize those communities. Superabundant fish populations may lead to trophic cascades altering aquatic communities through predation on lower trophic levels and competition with early life stages of organisms at higher trophic levels (Carpenter et al. 1985; Stein et al. 1995; Strock et al. 2013). For example, reduction in abundance due to reduced recruitment was observed in the Lake Erie population of white bass (*Morone chrysops*) in the presence of large numbers of white perch (*Morone americana*) during the 1980s (Madenjian et al. 2000). The hours spent angling for white bass in several Lake Erie tributaries also fell sharply following the 1980s (Ohio Division of Wildlife 2014). Superabundant fish populations may be stunted in any waterbody they inhabit making the individuals in the populations of little value to anglers who generally prefer to catch a few larger fish over many smaller fish (Petering et al. 1995).

To achieve management goals for superabundant populations, such as increased individual growth, large reductions in biomasses are often necessary. For example, for a severely stunted white perch population in Nebraska, fisheries scientists need to remove 90% of the biomass to increase maximum individual length by 50% (Chizinski et al. 2010). Superabundant populations will disperse throughout a waterbody because prime habitats will be occupied forcing portions of the populations into sub-prime habitats

(Morris 1987; Shepherd and Litvak 2004). This forced dispersion limits the control techniques that can be used to manage these populations. Some common control techniques, such as commercial seining used to remove common carp (*Cyprinus carpio*) (Bajer et al. 2011), are most effective when effort can be concentrated in a relatively small area (i.e., aggregated distribution). Furthermore, broader, less targeted control techniques need to account for the potential effects on fish communities. Attempts to control superabundant fish populations may lead to trophic cascades (Carpenter et al. 1985) that negatively affect fisheries, as observed in some gizzard shad (*Dorosoma cepedianum*) and threadfin shad (*Dorosoma petenense*) removal efforts (DeVries and Stein 1990). In addition, freeing up energetic resources could open the door to other invasive or nuisance species (Zavaleta et al. 2001). Fisheries scientists will need to repeat control efforts to maintain systems in desired states, unless managers eliminate superabundant species from systems or discover and alter the conditions that led the populations to become superabundant (Meronek 1996).

There are gaps in our understanding of superabundant fish populations. The gaps in our understanding of these populations hinder our ability to predict effects on valuable fisheries and our ability to effectively manage superabundant fish populations. We need to better understand superabundant fish populations, what they are, how they interact with other populations in aquatic systems, and how we can effectively monitor and manage them.

## **Thesis goal and outline**

The overall goal of my thesis research is to provide further insight into the ecology of superabundant fish populations and to provide information that will aid in their effective management. I define superabundant fish populations and describe methodology for estimating population size (Chapter 2). I investigate the spatial ecology of superabundant populations (Chapter 3). I evaluate the effectiveness of a control effort designed to reduce the size of superabundant populations of white perch and gizzard shad (Chapter 4). I provide a direction for future research on superabundant populations (Chapter 5).

## References

- Bajer, P. G., C. J. Chizinski, and P. W. Sorensen. 2011. Using the Judas technique to locate and remove wintertime aggregations of invasive common carp. *Fisheries Management and Ecology* 18:497-505.
- Carpenter, S. R., J. F. Kitchell, and J. R. Hodgson. 1985. Cascading trophic interactions and lake productivity. *BioScience* 35:634-639.
- Chizinski, C. J., K. L. Pope, and G. R. Wilde. 2010. A modeling approach to evaluate potential management actions designed to increase growth of white perch in a high-density population. *Fisheries Management and Ecology* 17:262-271.
- DeVries, D. R., and R. A. Stein. 1990. Manipulating shad to enhance sport fisheries in North America: an assessment. *North American Journal of Fisheries Management* 10:209-223.
- Madenjian, C. P., R. L. Knight, M. T. Bur, and J. L. Froney. 2000. Reduction in recruitment of white bass in Lake Erie after invasion of white perch. *Transactions of the American Fisheries Society* 129:1340-1353.
- Meronek, T. G., P. M. Bouchard, E. R. Buckner, T. M. Burri, K. K. Demmerly, D. C. Hateli, R. A. Klumb, S. H. Schmidt, and D. W. Coble. 1996. A review of fish control projects. *North American Journal of Fisheries Management* 16:63-74.
- Mommsen, T. P. 2001. Paradigms of growth in fish. *Comparative Biochemistry and Physiology Part B* 129:207-219.
- Morris, D. W. 1987. Density dependent habitat selection in a patchy environment. *Ecological Monographs* 57:269-281.
- Ohio Division of Wildlife. 2014. Ohio's Lake Erie fisheries 2013, Project F-69-P, Annual Status Report. Ohio Department of Natural Resources, Division of Wildlife, Lake Erie Fisheries Units, Fairport and Sandusky, Ohio.
- Pagel, M. D., P. H. Harvey, and H. C. J. Godfray. 1991. Species-abundance, biomass, and resource-use distributions. *American Naturalist* 138:836-850.
- Petering R. W., G. L. Isbell, and R. L. Miller. 1995. A survey method for determining angler preference for catches of various fish length and number combinations 15:732-735.

- Scheffer, M., J. M. Baveco, D. L. DeAngelis, E. H. R. R. Lammens, and B. Shuter. 1995. Stunted growth and stepwise die-off in animal cohorts. *The American Naturalist* 145:376-388.
- Sebens, K. P. 1987. The ecology of indeterminate growth in animals. *Annual Review of Ecology and Systematics* 18:371-407.
- Shepherd, T. D., and M. K. Litvak. 2004. Density-dependent habitat selection and the ideal free distribution in marine fish spatial dynamics: considerations and cautions. *Fish and Fisheries* 5:141-152.
- Stein, R. A., D. R. DeVries, and J. M. Dettmers. 1995. Food-web regulation by a planktivore: exploring the generality of the trophic cascade hypothesis. *Canadian Journal of Fisheries and Aquatic Science* 52:2518-2526.
- Strock, K. E., J. E. Saros, K. S. Simon, S. McGowan, and M. T. Kinnison. 2013. Cascading effects of generalist fish introduction in oligotrophic lakes. *Hydrobiologia* 71:99-113.
- Swingle, H. S., and E. V. Smith. 1942. The management of ponds with stunted fish populations. *Transactions of the American Fisheries Society* 71:102-105.
- Weatherly, A. H. 1990. Approaches to understanding fish growth. *Transactions of the American Fisheries Society* 119:662-672.
- Ylikarjula, J., M. Heino, and U. Dieckmann. 1999. Ecology and adaptation of stunted growth in fish. *Evolutionary Ecology* 13:433-453.
- Zavaleta, E. S., R. J. Hobbs, and H. A. Mooney. 2001. Viewing invasive species removal in a whole-ecosystem context. *Trends in Ecology and Evolution* 16:454-459.

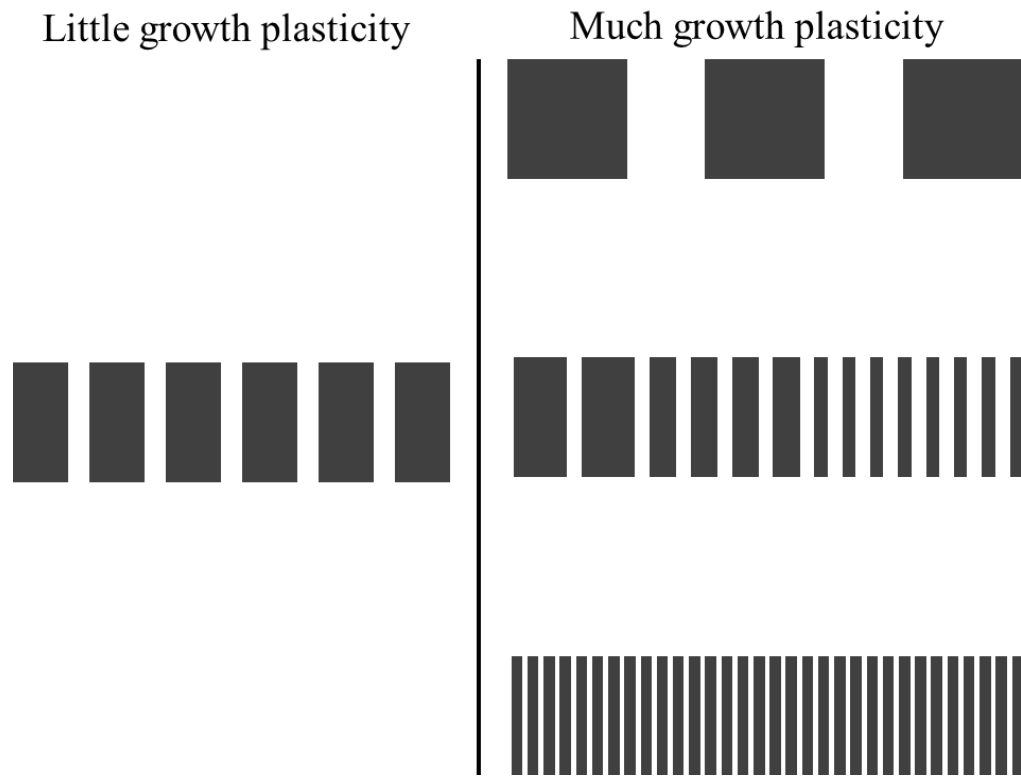


Figure 1-1. Conceptual model of differences in population biomass regulation between organisms that exhibit limited growth plasticity such as mammals or birds (left) and organisms that exhibit growth plasticity such as fish (right). Box number denotes the number of individuals and box width denotes the size of the individual; biomasses in all populations are the same.

## **Chapter 2 Defining superabundant populations and challenges to estimating their size**

A sound understanding of organism abundance is crucial to the understanding of ecology. Without an understanding of this metric, it is impossible to understand how the environment affects populations, how populations interact with each other, and how populations change through time. Effective natural resource management, in particular fishery management, necessitates an understanding of organism abundance (Hubert and Fabrizio 2007). Fisheries scientists need effective methods to estimate organism true abundance.

Within ecology and natural resource management, a variety of methods to estimate organism abundance have been developed that are applicable to fisheries (Table 2-1). Habitat and population characteristics affect the applicability of a specific method. For example, in some cases we can assume population closure whereas in others, we cannot. Whether we can make the assumption of population closure determines what statistical methods we can use to estimate true abundance (Hayes et al. 2007). The size of the population whose abundance we are trying to estimate also influences the applicable methods (Table 2-1).

With increased awareness of endangered species and the importance of diversity, researchers have focused much effort on developing methods to estimate presence or abundance of rare and elusive species. Occupancy modeling is one of the most



commonly used methods to monitor rare species. Occupancy modeling involves repeated sampling of the same area to determine the presence of species by incorporating detection probability (MacKenzie et al. 2002). From these data, fisheries scientists can then get an estimate of how species are spatially distributed across sampled habitats (MacKenzie 2006). In their most basic form, occupancy models do not estimate abundance, but trends in spatial distribution can be used to track trends in abundance (Holt et al. 2002; Joseph et al. 2006). Occupancy models have been extended to estimate abundance using repeated-count data with covariates to estimate detection probability (Royle and Nichols 2003; Royle 2004).

For populations of relatively abundant individuals, there are two primary methods used to estimate abundance, mark recapture and depletion sampling. For mark-recapture techniques, fisheries scientists must capture a large portion of the fish population, mark the individuals in a distinguishable manner, release them back into the waterbody, and resample the population noting the number of recaptures (Otis et al. 1978). In the simplest form of mark recapture, the ratio of marked fish to unmarked fish during the recapture event is used to estimate abundance. Depletion sampling involves removing fish from a waterbody during each sampling period until the catch decreases. Fisheries scientists can then plot catch against cumulative catch and fit a line to these data; the value where the line intersects the axis for cumulative catch is the estimated true abundance (Leslie and Davis 1937).

Fisheries scientists can also use hydroacoustic data to estimate population sizes of abundant fish. These data are collected with sonar equipment that sends out a pulse of sound, then retrieves and records the sound that is reflected back by any objects in the water column such as fish. These recordings can then be used to count the number of fish in the water column. Sampling generally involves mounting the sonar equipment to a boat, navigating the boat along some arrangement of transects, and recording sonar data. These data are then processed to estimate the total number of fish in the volume of water sampled (Brandt 1996). To estimate total fish abundance in a waterbody or over a predetermined area, the estimates of the number of fish sampled can be extrapolated either using area expansion or geostatistics (Brandt 1996; Rivoirard et al. 2000).

We term fish populations that are abundant and for which traditional means of sampling are ineffective superabundant fish populations. These populations can form in situations where population sizes are not naturally controlled such as species invasions or releases from predation. The methods used to estimate abundance of rare and common fish are ineffective for these populations. For occupancy modeling to effectively track trends in organism abundance, there must be sites where the organism is present and sites where the organisms is absent so that trends in the number of sites containing the species can be observed (Holt et al. 2002). If the fish species of interest is present in all or nearly all sites, changes in abundance may not result in changes in the number of occupied sites, but rather in changes in the number of individuals at sites. Changes in detection probability may track these changes, but with superabundant populations, fisheries

scientists will detect organisms in nearly all sites and thus may not provide an index of abundance with this method (Holt et al. 2002). To get precise estimates of abundance using mark-recapture methods, fisheries scientists need to mark a large proportion of the population, a difficult task if the population numbers in the millions. For example, Robson and Regier (1964) suggested that for an expected population size of 1 million individuals with a confidence interval of  $\pm 25\%$ , 8,500 organisms need to be marked and 8,500 need to be captured in subsequent sampling. To increase precision, many more fish would need to be sampled. Another method commonly used by fisheries scientists to estimate fish abundance is depletion sampling. Using depletion methods on superabundant fish populations, it may be difficult to exert enough effort to witness a decline in catch because of sheer population size unless depletion can be carried out at a small spatial scale. Additionally, this method is susceptible to the problem of hyperstability because this method assumes that catchability remains constant between capture events (DeLury 1947; Zippin 1958). Hyperstability occurs when catchability increases as true abundance decreases leading to artificially stable catches (Hilborn and Walters 1992). Fish redistributing to occupy prime habitats and gear saturation can both cause hyperstability (Rose and Kulka 1999; Hubert and Fabrizio 2007; Ward et al. 2013). If hyperstability occurred then fisheries scientists would overestimate abundance with this method. Hydoracoustic data can be used on large fish populations and does not require the capture of large portions of the fish population being studied. However, the methods used to estimate abundance with these data generally do not account for

imperfect detection (Brandt 1996). We know that detection with hydroacoustic equipment is not always perfect due to differences in acoustic returns depending how the fish are oriented in the acoustic beam (Tušer et al. 2014) and due to fish avoidance of the boats carrying the acoustic equipment (Draštík and Kubečka 2005). Abundance estimates from hydroacoustic data are at best conservative because of this imperfect detection that is unaccounted.

Wildlife scientists have developed point-count methods such as N-mixture models to estimate organism abundance that overcome some of the challenges presented by superabundant populations. N-mixture models build on occupancy models by using repeated point counts to estimate site-specific detection probabilities and abundances (Royle and Nichols 2003; Royle 2004). These models treat total abundance as a random variable that is assumed to have some prior statistical distribution (i.e. Poisson, negative binomial, zero-inflated Poisson) (Royle 2004). Maximum likelihood methods can be used to estimate site-specific detection probabilities (the estimated proportion of the individuals at a site that are sampled) based on trends in count data and the prior distribution of abundance if total abundance is integrated out of the likelihood. The estimated detection probabilities along with the counts can be used to estimate site-specific abundances. Covariate data can also be included to account for non-random patterns in detection or site abundances (Royle 2004). N-mixture models assume site closure throughout sampling; however, generalized N-mixture models have been developed for open populations (Dail and Madsen 2011). Generalized N-mixture models

relax the closure assumption by incorporating a parameter for recruitment (i.e. new organisms added to a site through births or immigration) and a parameter for apparent survival (i.e. organisms leaving a site through mortality or emigration) into the calculation. These models are ideal for superabundant populations because they do not rely on capturing a large portion of the population as both mark recapture and depletion methods do and they account for imperfect detection. However, the application of these methods to aquatic systems by fisheries scientists has been limited to small lotic (Yoichiro et al. 2014) and lentic (Kowalewski 2014) systems.

The goal of this study was to provide fisheries scientists with a tool for estimating abundances and biomasses of superabundant fish populations in lentic systems to improve management and understanding of these populations. To do this, I describe a new technique to estimate population sizes of superabundant fish in lentic waterbodies using generalized N-mixture models (Royle 2004; Dail and Madsen 2011). I then apply this technique to estimate the abundances and biomasses of four superabundant fish populations in two southeastern Nebraska reservoirs, Branched Oak Lake and Pawnee Reservoir. These two reservoirs were selected because they both contained populations of superabundant white perch (*Morone americana*) and gizzard shad (*Dorosoma cepedianum*). As of 2007 Branched Oak Lake contained a severely stunted population of white perch and a large population of gizzard shad (Chizinski 2007; Gosch 2008). In 2007, Pawnee Reservoir contained a superabundant population of white perch that was transitioning to a stunted state but did not contain gizzard shad; between 2007 and 2013,

gizzard shad established a superabundant population in Pawnee Reservoir (Chizinski 2007; Gosch 2008).

## **Study Reservoirs**

### **Branched Oak Lake**

Branched Oak Lake is a 728 ha flood-control reservoir located approximately 24 km northwest of Lincoln, Nebraska in the Salt Creek Watershed. Oak Creek and Middle Oak Creek flow into the reservoir forming two reservoir arms. Fish species present in the reservoir include white perch, gizzard shad, walleye, freshwater drum (*Aplodinotus grunniens*), hybrid striped bass (*Morone chrysops* x *Morone saxatilis*), bluegill (*Lepomis macrochirus*), green sunfish (*Lepomis cyanellus*), largemouth bass (*Micropterus salmoides*), black crappie (*Pomoxis nigromaculatus*), white crappie (*Pomoxis annularis*), flathead catfish (*Pylodictis olivaris*), channel catfish (*Ictalurus punctatus*), blue catfish (*Ictalurus furcatus*), brook silverside (*Labidesthes sicculus*), common carp (*Cyprinus carpio*), and striped bass (*Morone saxatilis*).

### **Pawnee Reservoir**

Pawnee Reservoir is a 299 ha flood-control reservoir located in the Salt Creek Watershed. The reservoir is located 14 km south of Branched Oak Lake, and is 17 km west of Lincoln, Nebraska. Like Branched Oak Lake, Pawnee Reservoir is part of a state recreation area providing water recreation opportunities for area residents. Pawnee reservoir was formed by damming Middle Creek, which enters the reservoir on the

northwest end. Fish present in Pawnee Reservoir include white perch, gizzard shad, walleye, freshwater drum, bluegill, green sunfish, largemouth bass, black crappie, white crappie, channel catfish, flathead catfish, common carp, and bigmouth buffalo (*Ictiobus cyprinellus*).

## **Methods**

### **Sampling Design**

We divided our sampling into three seasons (spring, summer, and fall). We defined spring from April 1 to June 13, summer from June 14 to October 3, and fall from October 4 to November 30. Within each season, we organized our sampling into rotations (a period when we sampled all sites once in each reservoir); each rotation took approximately one month to complete. During each year, we completed at least one sampling rotation in each reservoir during each season except for spring of 2013. We used spring of 2013 to test field equipment and finalize the sampling design.

Prior to sampling we stratified reservoirs based on longitudinal differences in water depth (areas with depths of 0.00-2.00, 2.01-4.00, 4.01-6.00, and >6.00 m) and areas perceived to be important for management (Figures 2-1 and 2-2). Within each strata, we selected two sampling transects with the exception of the deepest strata on Branched Oak Lake where we selected six transects (Figures 2-1 and 2-2). We oriented transects to run across the reservoir and up bays connected to the main reservoir (Figures 2-1 and 2-2).

**Approach: Water Depths > 2 m**

The primary sampling gear used to sample water depths >2 m was a consumer-grade sonar unit (Lowrance<sup>®</sup> HDS-9 Gen2 Touch) operating at 455 kHz. With this unit, we recorded sonar logs that consisted of sonar images, depth soundings, and associated geospatial data. Data were collected along transects on which we navigated a boat at speeds between 4.8 and 8.0 km/h; sonar logs were saved for later analysis. Surface disturbance prevented enumeration of fish in the top 1.5 m of the water column, this prevented us from effectively sampling with this gear in water  $\leq 2$  m deep.

To estimate the volume of water sampled we estimated the field of view of the sonar. We fixed ping-pong balls (Dahl and Mathisen 1983) to a weighted line at 1-m intervals; we then jigged this line at 0.5 m intervals moving away from the transducer. At each interval, we tallied the ping-pong balls that were visible and recorded their depths. From these data, we estimated the field of view based on what depth intervals were visible at varying distances from the transducer. For the 455 kHz beam, we estimated the field of view to be approximately 90°. We used this information along with image lengths to estimate the sampled volume; we used the volume estimates to account for differences in sampling effort due to differences in water depth.

To evaluate the species composition of fish signatures observed with the sonar, we set vertical gillnets in conjunction with sonar transects. We constructed vertical gillnets based on designs described by Lackey (1968) and Kohler et al. (1979). Nets were 2-m wide and 10-m high. We used 19, 25, 32, or 38-mm bar-mesh monofilament



netting with 7.9-mm polypropylene rope around the edge to construct the nets. During construction, we marked the side ropes at 1-m intervals so that we could record depths (nearest m) that fish were captured. We fixed the polypropylene rope at the bottom of the net to a length of metal pipe to hold the bottom of the net in place when set. To provide floatation, a method for storage, and for easy deployment, we attached an axle. One anchor was set off each side of the net to hold the net in place. A buoy was set in conjunction with each net to warn boaters of the net's presence. Halfway down each net we attached a spreader bar to ensure that the net remained open. When setting, the net was extended to the bottom and 0.5 m of extra net was extended to allow the axle and floatation to move up and down freely in waves.

Three sites were selected along each transect: 1) at a transect end (generally 2-m depth-contour, the end where this site was located was randomly selected on each transect), 2) center of the transect, 3) halfway between the center and end of the transect (on the end opposite the transect end where the net was set). Two nets were set at each site, a 19-mm net and a randomly selected without replacement 25, 32, or 38-mm bar-mesh net. The second net was selected such that in addition to three 19-mm nets, each transect had one net of each other mesh size. Nets were set at the sites along the transect immediately following the sonar recording. Once set, we allowed each net to soak for between 1 and 2 h before retrieval. Following retrieval, we recorded the vertical position of each fish caught per 1-m depth. We removed and enumerated all fish from the net. Within each 1-m-depth bin, we recorded total length (TL; nearest mm) and wet weight

(nearest g) from 10 white perch and 10 gizzard shad; we counted all white perch and gizzard shad.

The gillnet data were also used to provide validation for the sonar unit. On each waterbody, we calculated the mean fish density estimated with the sonar (fish/10 m<sup>3</sup>) and the gillnet catch (fish/m of net) within each transect. We then log transformed these data and compared counts using separate Pearson correlations within each waterbody ( $\alpha = 0.05$ ).

### **Approach: Water Depths $\leq 2$ m**

To sample areas with depths  $\leq 2$ -m, we used a point-electrofishing approach. We selected sites off the ends of sonar transects and in upper reaches of the reservoirs that were at least 24 m apart to allow adequate spacing between the electric fields and for GPS error (Burkhardt and Gutreuter 1995). For each sampling event, we randomly selected the starting site and sampling direction. During each sampling event at each point, we applied power for 60 seconds using a boat electrofisher, and captured all fish with a dip net. We standardized power density during each sampling event in an attempt to maintain a constant sampling effectiveness (Temple 2009). We counted and released all non-target organisms at each site. We recorded TL (nearest mm) and wet weight (nearest g) for up to 50 white perch and 50 gizzard shad at each site. For our analysis, we did not include young of the year fish (white perch  $<100$  mm TL, gizzard shad during 2013  $<115$  mm TL, and gizzard shad during 2014  $<160$  mm TL) because catches of these fish were extremely variable and they were not vulnerable to gillnetting.

We estimated the effective field size for our boat electrofisher under standardized power density by taking measurements of voltage gradients with a Smith-Root® electric field probe at location in front of and off the sides of our electrofishing boat. To predict power density at unmeasured locations, we used inverse distance weighting in ArcMap 10's geostatistical analyst tools (ESRI 2012). Miranda (2005) estimated that a power density of 60  $\mu\text{W}/\text{cc}$  needs to be applied to a fish to stun it. With water conductivity at the time of field mapping ( $C_s = 361 \mu\text{S}/\text{cm}$ ) and assuming fish conductivity to be 115  $\mu\text{S}/\text{cm}$  (Miranda and Dolan 2003), we defined the edge of our field as where measured power density declined below 84  $\mu\text{W}/\text{cc}$  (Figure 2-3). Starting during the summer of 2014, we measured the distance that the boat drifted during the 60 seconds of sampling to the nearest m with a handheld GPS unit on the front of the boat electrofisher, these data were used to correct the field size based on median drift distance across all samples for a waterbody before the site specific counts and estimates of volume were input into the models.

## **Analysis**

We randomly selected 100-m long sonar images within each transect for analysis such that selected images were not adjacent, the number of images selected varied by transect length with more images selected on longer transects. In each image, we filtered out noise using the threshold filter for black and white images (filter range 10-114) in ImageJ (Abramoff, et al. 2004). We used the particle analysis function in ImageJ (Abramoff, et al. 2004) with target size parameters generated based on a set of test

images known to contain white perch and gizzard shad based on net sampling occurring at the same time and location (3-50 pixels). After the particle analysis function identified targets, we visually inspected the image to separate fish from noise and tallied the number of fish. For schools of fish too tightly packed for the particle analyzer to identify individuals, we measured the total area of the image occupied by each school and divided this area by the median of the range of the target size parameters (27 pixels) to estimate the number of fish in schools.

We estimated the species composition of the fish in each image using data from the vertical gillnets set immediately following the collection of the sonar sample. We scaled gillnet catch within each transect such that each mesh size was equally represented (divided the catch in 19-mm mesh nets by 3). The proportional composition of each species in the gillnet catch across the entire transect was multiplied by the number of fish signatures observed in each image from that transect to get an estimate of the number of each species present in the volume of water sampled.

To estimate abundance we input repeated counts into species-specific and gear-specific generalized N-mixture models (Dail and Madsen 2011). These models included four parameters, cell-specific abundance of white perch or gizzard shad (this is equivalent to cell specific density (fish/m<sup>3</sup>) of white perch or gizzard shad because we took into account differences in sampling volume) ( $\lambda$ ), recruitment (new white perch or gizzard shad added to a cell through births or immigration from one sampling period to another) ( $\gamma$ ), apparent survival (proportion of white perch or gizzard shad remaining in a cell from

one sampling period to another) ( $\Omega$ ), and detection probability (the estimated proportion of the white perch or gizzard shad in the area sampled that we captured or observed during a specific sampling event so detection of 0.5 means that we sampled 50% of the white perch or gizzard shad in the area we sampled) ( $p$ ). The count data used in these models were offset by sampling volume thereby accounting for differences in sampling volume and in effect converting the results to density that could then be scaled up with cell volumes. We set up these models in R version 3.0.1 (R Development Core Team 2013) with the package unmarked (Fiske and Chandler 2011). For all sonar models, we used negative binomial prior distributions, we selected this distribution because it is well suited for count data with few zeros and because our sonar counts were highly variable and this distribution allows variance to be greater than the mean (Hilborn and Mangel 1997). For electrofishing models, we used zero-inflated Poisson prior distributions to deal with the large number of zeros in the count data.

Models incorporated environmental covariates that we hypothesized to influence the model parameters (Table 2-2). To spatially link covariates and count data, we established grid cells. Grid cells were 100 x 200 m for water depths > 2 m and 50 x 50 m for water depths  $\leq$  2 m. We used rectangular cells for the water depths > 2 m with the long axis of the cell oriented approximately perpendicular to the sonar transect to allow for more positional error in that direction. Covariates included water depth (m), bottom slope (% rise), timber, shore habitat, sampling period, and the interaction between water depth and sampling period. Water depth was a continuous variable based on the mean-

water depth (m) in the grid cell at conservation pool. Bottom slope was a categorical variable based on the mean slope of the reservoir bottom in percent rise within the grid cell with categories of slopes  $< 1\%$  and slopes  $\geq 1\%$ . Timber was a categorical variable based on the presence or absence of flooded trees or brush in a grid cell that we used only for the electrofishing models. Shore habitat was a categorical variable used in electrofishing models and was based on whether or not a sampling cell intersected the shore and whether the intersected shoreline had rip rap. Period was a categorical variable based on the rotation in which we collected each sample.

From these covariates we constructed sets of candidate models (Table 2-2). We did not construct model sets of all possible combinations of covariates because many combinations did not allow the data to behave in a biologically reasonable manner such as forcing  $\gamma$  and  $\Omega$  to be constant rates through time and because the size and computational demands of these models prevented running all combinations of covariates. We hypothesized that the covariates affecting  $\gamma$  and  $\Omega$  would be the same so these two parameters had the same covariates within models (Table 2-2). We included an interaction between depth and period on  $\gamma$  and  $\Omega$  because this allowed the relationship with depth to change through time. We included depth and period as covariates on  $p$ . Depth as a covariate on  $p$  allowed  $p$  to change with depth but held it constant through time. Period as a covariate on  $p$  held  $p$  constant across space but allowed it to change through time. Models with both depth and period or the interaction between the two were too complex to converge and thus were not included in the model sets. We were able to

include an interaction term for  $p$  in the electrofishing models because the maximum counts (which determine computational difficulty) were lower than for sonar. Timber was a covariate used in electrofishing models on Branched Oak Lake but not Pawnee Reservoir because flooded timber habitat is very limited on Pawnee Reservoir. Within these conditions, we built the most complex models that were biologically reasonable and that we could get to converge with the data we collected. We then progressively simplified the models from there. Finally, all model sets also included a null model.

We selected the most parsimonious model using Akaike's Information Criterion (Akaike 1976). Akaike's Information Criterion attempts to balance the ability to explain the pattern observed in the data with model simplicity by measuring how well the model fits the data and then penalizing the model based on the number of parameters (models with more parameters are more severely penalized). The model with the greatest weight is the most parsimonious model meaning it does the best job of explaining the data without being overly complex. We had challenges getting convergence on all parameters of our models. To increase the number of models that completely converged, we scaled some of the data on gizzard shad in Branched Oak Lake, we focused on simple models that were biologically reasonable, and we used a zero-inflated Poisson distribution for the electrofishing data. Only models that had estimates of standard error for all covariates were included in the model sets with the exception of the electrofishing models for gizzard shad in Branched Oak Lake during 2014. We then used the model with the greatest AIC weight to predict abundance using area expansion (Royle 2004). We

included the volume of the top 1.5 m of the water column in the area expansion thereby estimating total abundance by assuming that densities of fish in the top 1.5 m of the water column were similar to the densities throughout the remainder of the water column. We calculated the confidence interval about the abundance estimate using the delta method (Powell 2007). To estimate biomass, we multiplied mean masses of white perch and gizzard shad captured by total abundance and estimated the variance using the method described by Goodman (1960).

#### **Application: Branched Oak Lake**

In Branched Oak Lake, strata were bays, upper arms with water depths 0.0-2.0 m, middle arms with depths 2.1-4.0 m, lower arms with water depths 4.1-6.0 m, and deep water with water depths > 6.1 m (Figures 2-1). One transect was established in each of the bays in Branched Oak Lake running along their long axis (Figure 2-1). Four transects (2 in each arm of the reservoir) were established in the middle-arms and an additional four were established in lower arms (Figure 2-1). Six transects were established (three perpendicular to each arm) in the deep-water in Branched Oak Lake (Figure 2-1). The sequences that strata and transects were sampled using the sonar were randomly selected within each reservoir arm.

Starting during the fall 2013, we collected three sets of sonar logs within each rotation of sampling in Branched Oak Lake. We recorded one set of logs for all sonar transects over a 24-h period. Another set of sonar logs was recorded over a period of several weeks and had vertical gillnets set along each transect. We recorded a final set of



sonar logs over a 24-h period following all of the other sampling conducted during that rotation. The before and after sonar logs were not processed for use in the analyses, but were used observationally to estimate the direction of any movement during the sampling period, we observed movement during the 2013 and 2014 fall samples.

We established electrofishing sites to estimate white perch and gizzard shad abundance and biomass in water < 2 m deep. Shore electrofishing sites were selected on both ends of each transect to evaluate if shoreline habitat was used by white perch or gizzard shad. We randomly selected one additional site on each transect end between the shore and the 2-m contour except where depth increased rapidly close to shore. In the deep-water stratum, we established electrofishing sites on the ends of transects that intersected the shoreline (Figure 2-1). Sites were moved in instances where transects ended on beaches to avoid swimmers. We established fourteen electrofishing sites in the upper end of each reservoir arm (Figure 2-1). We also selected four sites in the ends of each of the bays in Branched Oak Lake (Figure 2-1).

We conducted analyses separately for 2013 and 2014 to account for any large changes in abundance from one year to the next. One of the assumptions of the generalizes N-mixture model is that any movement that occurs during a sampling period is random. If the movement was not random, that would have biased the estimates of abundance either high or low depending on whether the movement leads to double counting or undercounting. By minimizing the duration of sampling periods, the chances of violating this assumption can be minimized. To minimize our chances of violating this

assumption, we analyzed data from each arm of Branched Oak Lake separately reducing computing time and the risk of violating the assumption of closure by dealing with approximately 1.5 weeks of sampling at a time rather than 3 weeks at a time. The gizzard shad models were too large to run efficiently on a standard desktop computer, so data and sampling volumes were scaled (halved) and run on the Crane supercomputer at the University of Nebraska-Lincoln's Holland Computing Center. During 2013, sampling took place between June 25 and November 6 with sampling periods beginning on June 25 (period A), July 31 (period B), and October 16 (period C). During 2014, sampling took place between April 1 and November 7 with sampling periods beginning on April 1 (period A), July 7 (period B), and October 13 (period C).

#### **Application: Pawnee Reservoir**

In Pawnee Reservoir, strata were bays, upper reservoir with water depths 0.0-2.0 m, middle reservoir with depths 2.1-4.0 m, and lower reservoir with water depths > 4.0 m (Figures 2-2). No transects were established in the bays in Pawnee Reservoir. Two transects were established in the middle-reservoir strata and an additional two were established in the lower-reservoir strata (Figure 2-2). The sequence in which the strata and transects within strata were sampled were randomly selected.

Starting during fall of 2013, we collected two sets of sonar logs within each rotation in Pawnee Reservoir. One set of sonar logs were recorded over the period of approximately a week and had associated vertical gillnets set along each transect; these data were fed into the models to estimate abundance. Another set collected over a 24-h

period following the other sampling was not used in the analyses, but was used observationally to estimate the direction of movement during the sampling period; we did observe movement during 2013 and 2014 fall samples.

We established electrofishing sites off the ends of transects, in the upper end of the reservoir and in the bays to estimate white perch and gizzard shad use of these areas. A shore electrofishing site was selected on both ends of each sonar transect to evaluate if shoreline habitat was used by white perch and gizzard shad. One additional site was randomly selected on each sonar transect end between the shore and the 2-m contour except where depth increased rapidly close to shore. We selected fourteen electrofishing sites in the upper end of the reservoir (Figure 2-2). We selected four sites in the northern bay and one in the southern bay (Figure 2-2).

We analyzed data separately for 2013 and 2014 on Pawnee Reservoir because a low-dose-rotenone treatment was carried out during November 2013 that drastically altered white perch and gizzard shad abundances in the waterbody (see Chapter 4 for details). During 2013, sampling took place between June 17 and October 17 with sampling periods beginning on June 17 (period A), July 25 (period B), September 9 (period C), and October 8 (period D). During 2014, sampling took place between May 2 and October 10 with sampling periods beginning May 2 (period A), May 14 (period B), May 21 (period C), June 20 (period D), September 18 (period E), and October 7 (period F).

## Results

### Sonar validation

Overall, sonar density estimates were positively correlated with vertical-gillnet catches. On Branched Oak Lake, the correlation coefficient was 0.32 ( $t = 3.35$ ,  $df = 94$ ,  $p = 0.001$ ) (Figure 2-4). On Pawnee Reservoir, the correlation coefficient was 0.41 ( $t = 2.80$ ,  $df = 38$ ,  $p = 0.008$ ) (Figure 2-4).

### Branched Oak Lake

#### White perch sonar model, north arm 2013

The top model for sonar sampling data used to estimate white perch abundance on the north arm of Branched Oak Lake during 2013 had 100% of the AIC weight (Table 2-3). In the top model for depths  $> 2$ -m,  $\lambda$  decreased with depth and that it was greater for sites with slopes  $\geq 1\%$  (Table 2-4). Detection probability decreased from June 25 (period A) to July 31 (period B) and then increased from July 31 (period B) to October 16 (period C) and the dispersion parameter was significant (Table 2-4). We estimated mean detection probability to be 0.53 (s.e. = 0.02) with the sonar during July 2013.

#### White perch electrofishing model, north arm 2013

The top model for electrofishing data used to estimate white perch abundance on the north arm of Branched Oak Lake during 2013 had 100% of the AIC weight (Table 2-3). In the top model for depths  $\leq 2$ -m,  $\lambda$  decreased with depth and was greater at sites

with submerged trees (Table 2-5). Detection probability increased from June 25 (period A) to July 31 (period B) and then decreased from July 31 (period B) to October 16 (period C), detection probability increased with depth, decreased where submerged timber was present, and there was a positive interaction between depth and period (Table 2-5). The zero-inflation parameter was not significant (Table 2-5). We estimated mean detection probability to be 0.36 (s.e. = 0.11) with the boat electrofisher during June 2013 (period A).

#### White perch sonar model, south arm 2013

The top model for sonar sampling used to estimate white perch abundance and biomass on the south arm of Branched Oak Lake during 2013 had 100% of the AIC weight (Table 2-3). In the top model for depths > 2-m,  $\lambda$  decreased with depth and that it was greater for sites with slopes  $\geq 1\%$  (Table 2-6). Detection probability decreased with depth and the dispersion parameter was not significant (Table 2-6). We estimated mean detection probability to be 0.65 (s.e. = 0.01) with the sonar during July 2013 (period A).

#### White perch sonar model, north arm 2014

The top model for sonar sampling data used to estimate white perch abundance and biomass on the north arm of Branched Oak Lake during 2014 had 100% of the AIC weight (Table 2-7). In the top model for depths > 2-m,  $\lambda$  decreased with depth and that it was greater for sites with slopes < 1% (Table 2-8). Detection probability increased from April 1 (period A) to July 1 (period B) then decreased from July 1 (period B) to October

13 (period C) and the dispersion parameter was significant (Table 2-8). We estimated mean detection probability to be 0.09 (s.e. =  $< 0.01$ ) with the sonar during April 2014 (period A).

#### White perch electrofishing model, north arm 2014

The top model for electrofishing data used to estimate white perch abundance and biomass on the north arm of Branched Oak Lake during 2014 had 100% of the AIC weight (Table 2-7). In the top model for depths  $\leq 2$ -m,  $\lambda$  decreased with depth and was less at sites adjacent to shore (Table 2-9). Detection probability decreased from April 1 (period A) to October 13 (period C), detection probability decreased with depth and there was a negative interaction between depth and period (Table 2-9). The zero-inflation parameter was not significant (Table 2-9). We estimated mean detection probability to be 0.47 (s.e. = 1.0) with the boat electrofisher during April 2014 (period A).

#### White perch sonar model, south arm 2014

The top model for sonar sampling data used to estimate white perch abundance and biomass on the south arm of Branched Oak Lake during 2014 had 100% of the AIC weight (Table 2-7). In the top model for depths  $> 2$ -m,  $\lambda$  decreased with depth and was greater for sites with slopes  $\geq 1\%$  (Table 2-10). Detection probability increased from June 25 (period A) to July 31 (period B) then decreased from July 31 (period B) to October 16 (period C) and the dispersion parameter was significant (Table 2-10). We estimated

mean detection probability to be 0.05 (s.e. = 0.01) with the sonar during April 2014 (period A).

#### White perch electrofishing model, south arm 2014

The top model for electrofishing used to estimate white perch abundance and biomass on the south arm of Branched Oak Lake during 2014 had 94% of the AIC weight (Table 2-7). In the top model for depths  $\leq 2$ -m,  $\lambda$  decreased with depth and was greater at sites along the shore (Table 2-11). Detection probability increased from June 25 (period A) to July 31 (period B) and then decreased from July 31 (period B) to October 16 (period B), detection probability decreased with depth, and there was a negative and a positive interaction between depth and period (Table 2-11). The zero-inflation parameter was not significant (Table 2-11). We estimated mean detection probability to be 0.99 with the boat electrofisher during April 2014 (period A).

#### Gizzard shad sonar model, north arm 2013

The top model for sonar sampling data used to estimate gizzard shad abundance and biomass on the north arm of Branched Oak Lake during 2013 had 95% of the AIC weight (Table 2-12). In the top model for depths  $> 2$ -m,  $\lambda$  decreased with depth (Table 2-13). Detection probability increased with depth and the dispersion parameter was significant (Table 2-13). We estimated mean detection probability to be 0.34 (s.e. = 0.02) with the sonar during July 2013.

#### Gizzard shad electrofishing model, north arm 2013

The top model for electrofishing used to estimate gizzard shad abundance and biomass on the north arm of Branched Oak Lake during 2013 had 88% of the AIC weight (Table 2-12). In the top model for depths  $\leq 2$ -m,  $\lambda$  decreased with depth and was greater at sites with submerged trees (Table 2-14). Detection probability decreased from June 25 (period A) to October 16 (period C), detection probability decreased with depth, decreased where submerged timber was present, and there was a negative interaction between depth and period (Table 2-14). The zero-inflation parameter was not significant (Table 2-14). We estimated mean detection probability to be 0.10 (s.e. = 0.08) with the boat electrofisher during June 2013 (period A).

#### Gizzard shad sonar model, south arm 2013

The top models for sonar sampling used to estimate gizzard shad abundance and biomass on the south arm of Branched Oak Lake during 2013 had 100% of the AIC weight (Table 2-12). In the top model for depths  $> 2$ -m,  $\lambda$  decreased with depth (Table 2-15). Detection probability decreased from June 25 (period A) to July 31 (period B) then increased from July 31 (period B) to October 16 (period C) and the dispersion parameter was significant (Table 2-15). We estimated mean detection probability to be 0.16 (s.e. = 0.02) with the sonar during June of 2013 (period A).

#### Gizzard shad sonar model, north arm 2014



The top model for sonar sampling data used to estimate gizzard shad abundance and biomass on the north arm of Branched Oak Lake during 2014 had 100% of the AIC weight (Table 2-16). In the top model for depths  $> 2$ -m,  $\lambda$  decreased with depth (Table 2-17). Detection probability increased through time, and the dispersion parameter was significant (Table 2-17). We estimated mean detection probability to be 0.08 (s.e. = 0.01) with the sonar during April 2014 (period A).

#### Gizzard shad electrofishing model, north arm 2014

The top model for sonar sampling data used to estimate gizzard shad abundance and biomass on the north arm of Branched Oak Lake during 2014 had 67% of the AIC weight (Table 2-16). In the top model for depths  $\leq 2$ -m,  $\lambda$  increased with depth and was greater at sites with submerged trees (Table 2-18). Detection probability increased from April 1 (period A) to July 1 (period B), detection probability increased with depth, decreased where submerged timber was present, and there was a positive interaction between depth and period (Table 2-18). The model was unable to estimate the effect of the third sampling period or the interaction between the third sampling period and depth on detection probability (Table 2-18). We estimated mean detection probability to be 0.43 (s.e. = 0.36) with the boat electrofisher during April 2014 (period A).

#### Gizzard shad sonar model, south arm 2014

The top model for sonar sampling data used to estimate gizzard shad abundance and biomass on the south arm of Branched Oak Lake during 2014 had 100% of the AIC weight (Table 2-16). In the top model for depths  $> 2\text{-m}$   $\lambda$  decreased with depth and that it was greater for sites with slopes  $< 1\%$  (Table 2-19). Detection probability increased with depth, and the dispersion parameter was not significant (Table 2-19). We estimated mean detection probability to be 0.38 (s.e. = 0.02) with the sonar during April 2014 (period A).

#### Gizzard shad electrofishing model, south arm 2014

The top model electrofishing used to estimate gizzard shad abundance and biomass on the south arm of Branched Oak Lake during 2014 had 59% of the AIC weight (Table 2-16). In the top model for depths  $\leq 2\text{-m}$ ,  $\lambda$  decreased with depth and was greater at sites without submerged trees (Table 2-20). Detection probability increased from April 1 (period A) to July 1 (period B) then decreased from July 1 (period B) to October 13 (period C), detection probability increased with depth, decreased where submerged timber was present, and there was a negative interaction between depth and period (Table 2-20). The zero-inflation parameter was not significant (Table 2-20). We estimated mean detection probability to be 0.58 (s.e. = 1.0) with the boat electrofisher during April 2014 (period A).

## Overall abundance

In total, we estimated that there were 1,195,571 (95% CI: 1,135,337– 1,255,804; 63 kg/ha 95% CI: 1-125 kg/ha) white perch present in Branched Oak Lake during July 2013 (period A) (Table 2-21). During April 2014 (period A), we estimated that there were 1,195,213 (95% CI: 1,123,831–1,266,595; 58 kg/ha 95% CI: 8-108 kg/ha) white perch present (Table 2-21). We estimated that there were 906,287 (95% CI: 774,438– 1,038,136; 109 kg/ha 95% CI: 1-232 kg/ha) gizzard shad present in Branched Oak Lake during July 2013 (period A) (Table 2-21). During April 2014 (period A), we estimated that there were 698,018 (95% CI: 540,961– 855,076; 143 kg/ha 95% CI: 35-250 kg/ha) gizzard shad present (Table 2-21).

## Pawnee Reservoir

### White perch sonar 2013

The top models for the sonar sampling data used to estimate white perch abundance and biomass during 2013 had 100% of the AIC weight (Table 2-22). In the top model for depths > 2-m,  $\lambda$  decreased with depth and that it was greater for sites with slopes  $\geq 1\%$  (Table 2-23). Detection probability increased with depth, and the dispersion parameter was significant (Table 2-23). We estimated detection probability to be 0.81 (s.e. = 0.01) with the sonar during June of 2013 (period A).

### White perch electrofishing 2013

The top models for the electrofishing used to estimate white perch abundance and biomass during 2013 had 100% of the AIC weight (Table 2-22). In the top model for depths  $\leq 2$ -m,  $\lambda$  decreased with depth (Table 2-24). Detection probability increased from June 17 (period A) to September 9 (period B) then decreased from September 9 (period B) to October 8 (period C), detection probability increased with depth, and there was a negative interaction between depth and period (Table 2-24). We estimated detection probability to be 0.64 (s.e. = 0.05). The zero-inflation parameter was not significant (Table 2-24).

### White perch sonar 2014

The top model for the sonar sampling data used to estimate white perch abundance and biomass during 2014 had 100% of the AIC weight (Table 2-22). In the top model for depths  $> 2$ -m,  $\lambda$  increased with depth and that it was greater for sites with slopes  $< 1\%$  (Table 2-25). Detection probability increased from May 2 (period A) to June 20 (period D), decreased from June 20 (period D) to September 18 (period E), then increased from September 18 (period E) to October 7 (period F), and the dispersion parameter was significant (Table 2-25). We estimated detection probability to be 0.15 (s.e. = 0.03) with the sonar during May of 2014 (period A).

### White perch electrofishing 2014

The top model for the electrofishing used to estimate white perch abundance and biomass during 2014 had 100% of the AIC weight (Table 2-22). In the top model for depths  $\leq 2$ -m,  $\lambda$  was greater for sites with slopes  $< 1\%$  (Table 2-26). Detection probability decreased from May 2 (period A) to June 20 (period D), increased from June 20 (period D) to September 18 (period E), then decreased from September 18 (period E) to October 7 (period F), and the zero-inflation parameter was significant (Table 2-26). We estimated detection probability to be 0.63 (s.e. = 0.22) with the boat electrofisher during May 2014 (period A).

### Gizzard shad sonar 2013

The top models for the sonar sampling data used to estimate gizzard shad abundance prior to the application had 100% of the AIC weight (Table 2-27). In the top model for depths  $> 2$ -m,  $\lambda$  decreased with total depth and that it was greater for sites with slopes  $\geq 1\%$  (Table 2-28). We estimated detection probability to be 0.64 (s.e. = 0.05) with the sonar during June 2013 (period A).

### Gizzard shad electrofishing 2013

The top models for the electrofishing used to estimate gizzard shad abundance prior to the application had 100% of the AIC weight (Table 2-27). The top model for depths  $\leq 2$ -m, indicated that  $\lambda$  decreased with depth (Table 2-29). Detection probability

increased from June 17 (period A) to September 9 (period C) and then decreased from September 9 (period C) to October 8 (period D), and there was a negative interaction between depth and period (Table 2-29). The zero-inflation parameter was significant (Table 2-29). We estimated detection probability to be 0.15 (s.e. = 0.04) with the boat electrofisher during June 2013 (period A).

#### Overall abundance

During June 2013 (period A) we estimated that there were 1,589,537 (95% CI: 1,487,757– 1,691,317; 146 kg/ha 95% CI: 74-218 kg/ha) white perch present in Pawnee Reservoir (Table 2-21). We estimated the white perch population size to be 273,105 (95% CI: 232,751– 313,459; 26 kg/ha 95% CI: 15-37 kg/ha) during May 2014 (period A) (Table 2-21). During June 2013 (period A), we estimate the gizzard shad total abundance to be 638,819 (95% CI: 593,202– 684,435; 101 kg/ha 95% CI: 35-168 kg/ha) in Pawnee Reservoir (Table 2-21).

## Discussion

We attempted to provide some validation for the sonar we were using by comparing it to vertical-gillnet catches. We found significant positive correlations between the two gears in both reservoirs. The noise in correlations could be related to many factors, in particular these two gears collect data on different scales (number per m<sup>3</sup> for sonar and number per m for gillnets) and have different selectivities (Murphy and Willis 1996). This does provide some rudimentary support for the use of our consumer-

grade sonar unit to assess fish abundance. However, further assessment to provide validation for the sonar unit would strengthen the support and should be a part of any future projects using this gear. This did not provide any validation for our approach as a whole because it did not consider any of the population modeling that was part of our abundance estimation.

The method for sampling abundance that we described provides fishery scientists with a new tool for estimating the size of superabundant fish populations in lentic waterbodies. We were able to apply this method to white perch and gizzard shad populations to generate estimates of abundance and biomass. In Branched Oak Lake, we estimated there were 1,195,571 (95% CI: 1,135,337– 1,255,804) white perch along with 906,287 (95% CI: 774,438– 1,038,136) gizzard shad in 2013 and 1,241,922 (95% CI: 1,155,653–1,328,191) white perch along with 698,018 (95% CI: 540,961– 855,076) gizzard shad during 2014. In Pawnee Reservoir, we estimated that there were 1,589,537 (95% CI: 1,487,757– 1,691,317) white perch along with 269,327 (95% CI: 228,982– 309,671) gizzard shad during 2013 and 638,819 (95% CI: 593,202– 684,435) white perch along with zero gizzard shad during 2014.

Our total biomass estimates fall within the range observed in other lakes and reservoirs. Our greatest biomass estimate for white perch was 146 kg/ha in Pawnee Reservoir during 2013 and our greatest estimate for gizzard shad was 143 kg/ ha in Branched Oak Lake during 2014. Over a four-year period on Acton Lake, Ohio researchers documented gizzard shad biomasses up to 400 kg/ha (Schaus et al. 2002).

Northern pike (*Esox lucius*) biomasses among 11 lakes and reservoirs worldwide, the greatest biomass was 51 kg/ha (Craig 1996). In an assessment of fish production in 38 lakes worldwide, largemouth (*Micropterus salmoides*) biomass was up to 129 kg/ha and bluegill (*Lepomis macrochirus*) biomass was up to 771 kg/ha (Downing and Plante 1993). In Australia, biomasses of common carp in lakes have been observed as great as 690 kg/ha (Smith 2005). Our biomasses fall within this range but even combined do not approach the maximum observed for single species in some other systems meaning that in certain circumstances, fish biomasses can be even more extreme than what we observed.

We observed some general patterns among model covariates in Branched Oak Lake and Pawnee Reservoir. Among most models,  $\lambda$  decreased with total depth. This pattern held among both species, both waterbodies, and both gears. However, the exception was for white perch in Pawnee Reservoir during 2014 in water >2 m deep, where abundance significantly increased with depth total depth. This may be due to changes in white perch distribution because of reduced abundance following a low-dose-rotenone application. The application was carried out during November 2013 and resulted in an approximately 83% reduction in white perch biomass and extirpated or nearly extirpated gizzard shad from the waterbody (Chapter 4), either of which could have influenced white perch spatial distribution. Slope also had effects on  $\lambda$ , but there was no overarching pattern to these effects, in some cases, abundance was greater in cells with high slope and in other cases, it was greater in cells with lower slopes. For both



recruitment and apparent survival, there were no overarching patterns in the covariates that were significant. We often had large amounts of uncertainty for both of these model components, which likely contributed to the lack of a pattern. Sampling period, depth, and the interaction between sampling period and depth all appeared in detection models. However, there was no overarching pattern in how the detection probabilities changed with these covariates. Detection probability was consistently greater for white perch than for gizzard shad. This is due to greater variability in gizzard shad counts possibly caused by greater short-term movement of the species. Sonar detection probabilities were greater for both species in both waterbodies for the 2013 samples used to estimate abundance than for the 2014 samples. The pattern reversed for electrofishing with detection probabilities higher during the 2014 samples than during the 2013 samples. A possible cause of this relationship is that during 2013 the first sample occurred during summer when water temperatures were warmer whereas during 2014 the samples occurred during spring. This may have affected our ability to detect fish with the sonar because fish were more dispersed throughout the water column where we could better detect them during summer, but during spring were mostly near the bottom where they are difficult to detect (Brandt 1996). For electrofishing, warmer temperatures may have allowed more fish to escape the electric field during 2013 thereby reducing our detection probabilities (Reynolds 1996). The detection portion of the model for gizzard shad abundance in the north arm of Branched Oak Lake during 2014 based on the electrofishing data (Table 2-16) returned nulls for the standard error for the sampling

period that began on October 13 and for the interaction between depth and sampling period that began on October 13. During this period, we only captured gizzard shad at four of the 38 sites sampled; the small number of sites sampled with gizzard shad is the most likely cause of the nulls in the model. There was a large amount of variability in the estimates of detection probability for sonar. A number of factors could have contributed to this variability including physical factors such as water temperature or wind speed and direction, which contributed to the amount of noise in the sonar data. Biological factors such as large numbers of phytoplankton or zooplankton could also have contributed to the variation in detection probabilities by increasing the amount of noise in the data. Random or systematic variation in counts could also have driven the drastic swings in detection probabilities. We suspect that movement during sampling periods led to increased variation in counts for white perch and reductions in detection probability during certain periods. We suspect that random variation in counts led to the swings in detection probabilities.

One advantage of the approach we used is that the spatial distribution of fish can be estimated at the same time and with the same data used to estimate abundance. This is possible because these models generate abundance estimates that are site specific. When we map these site-specific estimates across the waterbody, we get an estimate of organism spatial distribution. It is possible to get site-specific abundance estimates during each sampling period using the  $\gamma$  and  $\Omega$  parameters (Chapter 3), and thus how the spatial distribution of the species changes through time can also be assessed. Also,

through the use of covariates in the models, insight can be gained into how the site abundance of a species is related to specific habitat conditions. By estimating how organisms are spatially distributed, how these distributions change through time, and how site abundances are related to habitat covariates, we can better understand how superabundant populations interact with their environment, interact with other populations, and suggest approaches to better manage superabundant fish populations (Chapter 3).

One disadvantage is that these methods are computationally intensive. In our experience, the largest individual count determines the speed at which the models run, with larger counts leading to greater run times. We had several data sets with maximum counts between 500 and 600; on a 64-bit desktop computer with 8 GB of ram, each model in a set took approximately eight days to run. We eventually scaled the data for these models (division by 2) and ran them on the Crane supercomputer at the University of Nebraska—Lincoln's Holland Computing Center (<http://hcc.unl.edu/>). If fisheries scientists have counts greater than 500 and do not have access to a supercomputer they will need to take steps to simplify the data such as scaling or to simplify the models such as reducing the number of covariates used so that they can be assessed on a desktop computer.

We made several assumptions in the process of estimating abundance of both white perch and gizzard shad. The first assumption made was that any changes in fish spatial distribution within a sampling period were random and consistent throughout the

waterbody. If this assumption was violated, it may have led to abundances that are biased high if the fish moved from sites sampled early in the period to sites sampled later in the period due to double counting. If fish moved in the opposite pattern that would lead to undercounting and abundance estimates biased low. Based on what we observed in the before and after sonar logs, during fall 2013 on Branched Oak Lake and spring 2014 on Pawnee Reservoir, fish moved from sites sampled early in the period to sites sampled late in the period possibly leading to double counting and abundance estimates that were biased high. We assumed that the densities of fish in the top 1.5 m of the water column were similar to the densities throughout the remainder of the water column because we were not able to sample the top 1.5 m with our sonar unit. A violation of this assumption could bias abundance estimates either positively or negatively.

Observationally based on our gillnet data and additional sampling during late summer of 2014 (Appendix A), fish were not distributed uniformly through the water column.

During spring and fall, catches tended to be greater near the bottom, during summer catches tended to be greater in the midsection of the water-column and near the surface.

This assumption could be further tested with high intensity gillnet data, trawl data, or with side scanning sonar. We assumed no fright bias from the boat carrying the sonar or from the electrofishing boat. A violation of this assumption could bias abundance estimates low; however, accounting for detection probability reduces the effect of any violation of this assumption. Finally we assumed that vertical-gillnet catch was a representative proportion of the species present along each transect. A violation of this

assumption would not lead to a bias in our abundance across species but may have led to biases of abundance estimates within a species.

We have described a method for using generalized N-mixture models to estimate fish abundance in lentic systems. Despite the challenges presented by this approach, it is a new tool for fisheries scientists to estimate abundance in cases where other methods are not effective. This approach also provides spatial information that can further our understanding of species ecology. However, further research is needed to extend the applicability of this approach. Superabundant fish populations also occur in lotic systems; Asian carp (*Hypophthalmichthys spp.*) populations are an example of this. A sampling scheme needs to be designed to collect point-count data from all available lotic habitats so that generalized N-mixture models can be applied to populations occupying lotic systems. Evaluation of this approach and of consumer-grade sonar relative to other methods would also be beneficial. Further research in this area would improve our ability to sample and manage superabundant fish populations wherever they occur.

## References

- Abràmoff, M. D., P. J. Magalhães, and S. J. Ram. 2004. Image processing with ImageJ. Biophototics International. Available: <http://igitur-archive.library.uu.nl/med/2011-0512-200507/ImageJ.pdf> (August 2013)
- Akaike, H. 1976. An information criterion (AIC). *Math Science* 14:5-9.
- Brandt, S. B. 1996. Acoustic assessment of fish abundance and distributioin. Pages 385-432 in B. R. Murphy, and D. W. Willis, editors. *Fisheries techniques*, 2nd edition. American Fisheries Society, Bethesda, Maryland.
- Burkhardt, R. W., and S. Gutreuter. 1995. Improving electrofishing catch consistency by standardizing power. *North American Journal of Fisheries Management* 15:375-381.
- Chizinski, C. J. 2007. Variation in life-history traits and morphology of stunted and non-stunted fish. Doctoral dissertation. Texas Tech University, Lubbock.
- Craig, J. F. 1996. Population dynamics, predation and role in the community. Pages 201-217 in J. F. Craig, editor. *Pike Biology and Exploitation*. Chapman and Hall, London, England.
- Dahl, P. H., and O. A. Mathisen. 1983. Measurement of fish target strength and associated directivity at high frequencies. *Journal of the Acoustic Society of America* 73:1205-1210.
- Dail, D., and L. Madsen. 2011. Models for estimating abundance from repeated counts of an open metapopulation. *Biometrics* 67:1-11.
- DeLury, D. B. 1947. On the estimation of biological populations. *Biometrics* 3:145-167.
- Drašík, V., and J. Kubečka. 2005. Fish avoidance of acoustic survey boat in shallow waters. *Fisheries Research* 72:219-228.
- Downing, J. A. and C. Plante. 1993. Production of fish populations in lakes. *Canadian Journal of Fisheries and Aquatic Science* 50:110-120.
- ESRI, 2012. ArcGIS help library. ESRI, Redlands, California. Available: <http://help.arcgis.com/en/arcgisdesktop/10.0/help/> (February 2013).
- Fiske I., and R. Chandler. 2011. unmarked: an r package for fitting hierarchical models of wildlife occurrence and abundance. *Journal of Statistical Software*, 43(10), 1-23. Available: <http://www.jstatsoft.org/v43/i10/> (February 2014).

- Goodman, L. A. 1960. On the exact variance of products. *Journal of the American Statistical Association* 55:708-713.
- Gosch, N. J. C. 2008. Predation as a mechanism for the control of white perch: an investigation of food habits in two Nebraska reservoirs. Master's thesis. University of Nebraska Lincoln.
- Hayes, D. B., J. R. Bence, T. J. Kwak, and B. E. Thompson. 2007. Abundance, biomass, and production. Pages 327-374 in C. S. Guy and M. L. Brown, editors. *Analysis and interpretation of freshwater fisheries data*. American Fisheries Society, Bethesda, Maryland.
- Hilborn, R., and M. Mangel. 1997. *The ecological detective: confronting models with data*. Princeton University Press, Princeton, New Jersey.
- Hilborn, R., and C. J. Waters, editors. 1992. *Quantitative fisheries stock assessment: choice, dynamics and uncertainty*. Springer Science & Business Media, New York, New York.
- Holt, A. R., K. J. Gaston, and F. He. 2002. Occupancy-abundance relationships and spatial distribution: a review. *Basic and Applied Ecology* 3:1-13.
- Hubert, W. A., and M. C. Fabrizio. 2007. Relative abundance and catch per unit effort. Pages 279-325 in C. S. Guy and M. L. Brown, editors. *Analysis and interpretation of freshwater fisheries data*. American Fisheries Society, Bethesda, Maryland.
- Joseph, L. N., S. A. Field, C. Wilcox, and H. P. Possingham. 2006. Presence-absence versus abundance data for monitoring threatened species. *Conservation Biology* 20:1679-1687.
- Kohler, C. C., J. J. Ney, and A. A. Nigro. 1979. Compact, portable vertical gill net system. *The Progressive Fish-Culturist* 41:34-35.
- Kowalewski, L. K. 2014. Accuracy or precision: implications of sample design and methodology on abundance estimation. Master's Thesis. University of Nebraska Lincoln.
- Lackey, R. T. 1968. Vertical gill nets for studying depth distribution of small fish. *Transactions of the American Fisheries Society* 97:296-299.
- Leslie, P. H., and D. H. S. Davis. 1937. An attempt to determine the absolute number of rats on a given area. *Journal of Animal Ecology* 8:94-113.
- MacKenzie, D. I., J. D. Nichols, G. B. Lachman, S. Droege, J. A. Royale, and C. A. Langtimm. 2002. Estimating site occupancy rates when detection probabilities are less than one. *Ecology* 83:2248-2255.

- MacKenzie, D. I. editor. 2006. Occupancy estimation and modeling: inferring patterns and dynamics of species occurrence. Academic Press, Waltham, Massachusetts.
- Miranda, L. E. and C. R. Dolan. 2003. Test of a power transfer model for standardizing electrofishing. *Transactions of the American Fisheries Society* 132:1179-1185.
- Miranda, L. E. 2005. Refining boat electrofishing equipment to improve consistency and reduce harm to fish. *North American Journal of Fisheries Management* 25:609-618.
- Morris, D. W. 1987. Tests of density dependent habitat selection in a patchy environment. *Ecological Monographs* 57:269-281.
- Murphy, B. R., and D. W. Willis, editors. 1996. *Fisheries techniques*, 2nd edition. American Fisheries Society, Bethesda, Maryland.
- Otis, D. L., K. P. Burnham, G.C. White, and D.R. Anderson. 1978. Statistical inference from capture data on closed animal populations. *Wildlife Monographs* 62:3-135.
- Powell, L. A. 2007. Approximating variance of demographic parameters using the delta method: a reference for avian biologists. *The Condor* 109:949-954.
- R Development Core Team. 2013. R: a language for statistical computing, USA:R Foundation for Statistical Computing. Available: [www.R-project.org](http://www.R-project.org) (August 2013)
- Reynolds, J. B. 1996. Electrofishing. Pages 221-253 in B. R. Murphy, and D. W. Willis, editors. *Fisheries techniques*, 2nd edition. American Fisheries Society, Bethesda, Maryland.
- Rivoirard, J., J. Simmonds, K. G. Foote, P. Fernandez, and N. Bez. 2000. *Geostatistics for estimating fish abundance*. Blackwell Science, Oxford, UK.
- Robson, D. S. and H. A. Regier. 1964. Sample size in Petersen mark-recapture experiments. *Transactions of the American Fisheries Society* 93:215-226.
- Rose, G. A. and D. W. Kulka. 1999. Hyperaggregation of fish and fisheries: how catch-per-unit effort increased as the northern cod (*Gadus morhua*) declined. *Canadian Journal of Aquatic Science* 56:118-127.
- Royle, J. A. and J. D. Nichols. 2003. Estimating abundance from repeated presence-absence data or point counts. *Ecology* 84:777-790.
- Royle, J. A. 2004. N-mixture models for estimating population size from spatially replicated counts. *Biometrics* 60:108-115.



- Schaus, M. H., M. J. Vanni, and T. E. Wissing. 2002. Biomass-dependent diet shifts in omnivorous gizzard shad: implications for growth, food web, and ecosystem effects. *Transactions of the American Fisheries Society* 131:40-54.
- Smith, B. 2005. The state of the art: a synopsis of information on common carp (*Cyprinus carpio*) in Australia final technical report. SARDI Research Report Series No. 77.
- Temple, A. J. 2009. An Introduction to Electrofishing with Power v1.4. U.S. Fish and Wildlife Service National Conservation Training Center. Available: <http://electrofishing.net/2009/09/electrofishing-with-power-v141/> (June 2013).
- Tušer, M., J. Frouzová, H. Balk, M. Muška, T. Mrkvička, and J. Kubečka. 2014. Evaluation of potential bias in observing fish with a DIDSON acoustic camera. *Fisheries Research* 155:114-121.
- Ward, H. G. M., P. J. Askey, and J. R. Post. 2013. A mechanistic understanding of hyperstability in catch per unit effort and density-dependent catchability in a multistock recreational fishery. *Canadian Journal of Fisheries and Aquatic Sciences* 70:1542-1550.
- Yoichiro, K., B. H. Letcher, J. C. Vokoun, and E. F. Zipkin. 2014. Spatial variability in adult brook trout (*Salvelinus fontinalis*) survival within two intensively sampled headwater stream networks. *Canadian Journal of Fisheries and Aquatic Sciences* 71:1010-1019.
- Zippin, C. 1958. The removal method of population estimation. *The Journal of Wildlife Management* 22:82-90.

Table 2-1. Methods that fisheries scientists can use to estimate fish abundance and each method's advantages.

	Method				
	Occupancy models	Mark recapture	Depletion	Hydroacoustics with geostatistics	N-mixture models
Work for large populations				x	x
Account for catchability	x	x	x		x
Resistant to hyperstability	x	x			x
No marking	x		x	x	x
No removal	x	x		x	x
Single field effort				x	
Simple computation		x	x	x	
Spatial distribution	x			x	x

Table 2-2. Candidate generalized N-mixture models used to estimate white perch and gizzard shad abundances on Branched Oak Lake and Pawnee Reservoir, Nebraska. Data were collected with a consumer grade sonar unit used in conjunction with vertical gillnets (SN) and with a boat electrofisher (EF). In each model,  $\lambda$  is site and specific abundance,  $\gamma$  is site and time specific recruitment,  $\Omega$  is site and time specific apparent survival, and  $p$  is site and time specific detection probability. The covariates in the models are the mean depth of cells (D), whether the mean slope was  $< 1\%$  or  $\geq 1\%$  (S), the period in which a sample was taken (P), whether the cell was adjacent to shore and whether the adjacent shoreline had rip rap (H), and presence or absence of timber (T).

Waterbody	Gear	Models
Branched Oak Lake	S	$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: P
		$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: D
		$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: P
		$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: D
		$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1
	EF	$\lambda$ : D+SH+T, $\gamma$ : D*P+SH+T, $\Omega$ : D*P+SH+T, p: D+P
		$\lambda$ : D+T, $\gamma$ : D*P+T, $\Omega$ : D*P+T, p: D+P+T
		$\lambda$ : D+SH, $\gamma$ : D*P+SH, $\Omega$ : D*P+SH p: D+P
		$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: D*P
		$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: D
Pawnee Reservoir	S	$\lambda$ : S, $\gamma$ : S+P, $\Omega$ : S+P, p: P
		$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1
	EF	$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: P
		$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: D
		$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: P
		$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: D
		$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1
	EF	$\lambda$ : D+SH, $\gamma$ : D*P+SH, $\Omega$ : D*P+SH p: D+P
		$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: D*P
		$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: D
		$\lambda$ : S, $\gamma$ : S+P, $\Omega$ : S+P, p: P
		$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1

Table 2-3. Generalized N-mixture models ranked with AIC used to model white perch abundance on Branched Oak Lake, Nebraska during 2013 (K: number of model parameters, AIC: Akaike Information Criterion score,  $\Delta$ AIC: difference between AIC score for the specified model and for the top model, AICwt: AIC weight, cumwt: cumulative AIC weight). Count data were collected with a consumer grade sonar unit used in conjunction with vertical gillnets (SN) in waters with total depths  $\geq 2$  m and a boat electrofisher (EF) used to electrify points in water with total depths  $< 2$  m. In each model,  $\lambda$  is site and time specific abundance,  $\gamma$  is site and time specific recruitment,  $\Omega$  is site and time specific apparent survival, and  $p$  is site and time specific detection probability. The covariates in the models are the mean depth of cells (D), whether the mean slope was  $< 1$  % or  $\geq 1$  % (S), the period in which a sample was taken (P), whether the cell was adjacent to shore and whether the adjacent shoreline had rip rap (H), and presence or absence of timber (T).

Arm	Gear	Model	K	AIC	$\Delta$ AIC	AICwt	cumwt
North	SN	$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: P	17	1978	0	1.00	1.00
		$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: D	16	2024	46	0.00	1.00
		$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: D	13	2289	311	0.00	1.00
		$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1	5	4618	2640	0.00	1.00
	EF	$\lambda$ : D+T, $\gamma$ : D*P+T, $\Omega$ : D*P+T, p: D+P+T	21	247	0	1.00	1.00
		$\lambda$ : D+H+T, $\gamma$ : D*P+H+T, $\Omega$ : D*P+H+T, p: D+P	26	282	35	0.00	1.00
		$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: D	16	306	59	0.00	1.00
		$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: D*P	17	306	59	0.00	1.00
		$\lambda$ : S, $\gamma$ : S+P, $\Omega$ : S+P, p: P	12	331	84	0.00	1.00
		$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1	5	387	140	0.00	1.00
	South	$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: D	16	2222	0	1.00	1.00
		$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: D	13	2948	726	0.00	1.00
		$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: P	14	3276	1054	0.00	1.00
		$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1	5	4016	1794	0.00	1.00

Table 2-4. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass on the north arm of Branched Oak Lake, Nebraska during 2013. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: June 25, category B: July 31, and category B: October 16). This model also included dispersion parameter that is a measure of how much overdispersion the model was relative to a Poisson model.

Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 2.92	0.12	- 24.23	<0.001
	Depth	- 0.70	0.10	- 7.31	<0.001
	Slope 2	0.34	0.23	1.46	0.143
$\gamma$	Intercept	- 2.67	0.56	- 4.72	<0.001
	Period B	2.01	0.59	3.40	0.001
	Depth	2.72	0.38	7.18	<0.001
	Slope 2	3.12	0.16	19.31	<0.001
	Period B*Depth	0.30	0.36	0.81	0.418
$\Omega$	Intercept	42.90	31.20	1.37	0.170
	Period B	- 43.20	31.20	- 1.38	0.166
	Depth	- 44.80	33.70	- 1.33	0.183
	Slope 2	- 58.40	39.40	-1.48	0.139
	Period B*Depth	45.00	33.70	1.34	0.181
p	Intercept	0.14	0.08	1.69	0.092
	Period B	- 0.48	0.07	- 7.09	<0.001
	Period C	1.32	1.36	0.98	0.330
Dispersion		1.02	0.23	4.47	<0.001



Table 2-5. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass on the north arm of Branched Oak Lake, Nebraska during 2013. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), Timber (whether or not a sampling cell contained flooded timber; category 0: timber absent and category 1: timber present) and Period (the period in, which sampling took place; category A: June 25, category B: July 31, and category C: October 16). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were.

Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 3.04	0.34	- 8.97	<0.001
	Depth	- 0.34	0.25	- 1.32	0.185
	Timber 1	2.50	0.44	5.63	<0.001
$\gamma$	Intercept	0.58	0.25	2.32	0.020
	Period B	- 2.18	0.97	- 2.25	0.025
	Depth	- 0.80	0.27	- 3.01	0.003
	Timber 1	- 0.96	0.53	- 1.82	0.068
	Period B*Depth	- 1.28	0.80	- 1.60	0.109
$\Omega$	Intercept	6.08	2.46	2.47	0.014
	Period B	0.10	5.59	0.02	0.985
	Depth	- 6.91	3.26	-2.12	0.034
	Timber 1	- 5.07	1.83	- 2.77	0.006
	Period B*Depth	- 17.98	25.56	- 0.70	0.482
p	Intercept	1.50	1.38	1.09	0.277
	Period B	12.40	5.69	2.18	0.029
	Period C	0.37	1.68	0.22	0.823
	Depth	0.24	0.75	0.32	0.751
	Timber 1	- 5.66	1.57	- 3.60	<0.001
	Period B*Depth	9.44	4.27	2.21	0.027
	Period C*Depth	4.02	1.39	2.90	0.004
Zero-inflation		0.29	0.47	0.62	0.536

Table 2-6. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass on the south arm of Branched Oak Lake, Nebraska during 2013. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: June 25, category B: July 31, and category B: October 16). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model.

Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 3.49	0.19	- 18.03	<0.001
	Depth	- 0.47	0.19	- 2.52	0.012
	Slope 2	0.83	0.38	2.17	<0.001
$\gamma$	Intercept	3.25	0.06	53.88	<0.001
	Period B	0.26	0.07	3.93	<0.001
	Depth	0.01	0.05	0.10	0.923
	Slope 2	0.36	0.05	7.12	<0.001
	Period B*Depth	1.09	0.07	16.25	<0.001
$\Omega$	Intercept	- 239.70	249.30	- 0.96	0.336
	Period B	227.20	244.00	0.93	0.352
	Depth	- 162.00	172.70	- 0.94	0.348
	Slope 2	52.90	48.90	1.08	0.279
	Period B*Depth	218.40	245.20	0.89	0.373
p	Intercept	1.23	0.17	7.04	<0.001
	Depth	- 2.36	0.15	- 15.26	<0.001
Dispersion		0.22	0.25	0.88	0.377

Table 2-7. Generalized N-mixture models ranked with AIC used to model white perch abundance on Branched Oak Lake, Nebraska during 2014 (K: number of model parameters, AIC: Akaike Information Criterion score,  $\Delta$ AIC: difference between AIC score for the specified model and for the top model, AICwt: AIC weight, cumwt: cumulative AIC weight). Count data were collected with a consumer grade sonar unit used in conjunction with vertical gillnets (SN) in waters with total depths  $\geq 2$  m and a boat electrofisher (EF) used to electrify points in water with total depths  $< 2$  m during. In each model,  $\lambda$  is abundance,  $\gamma$  is recruitment,  $\Omega$  is apparent survival, and p is detection probability. The covariates in the models are depth (D), slope (S), sampling period (P), and shoreline habitat (H).



Table 2-8. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass on the north arm of Branched Oak Lake, Nebraska during 2014. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: April 1, category B: July 7, and category B: October 13). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model.

Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 2.86	0.12	- 24.04	<0.001
	Depth	- 0.29	0.11	- 2.65	0.008
	Slope 2	- 0.06	0.25	- 0.23	0.816
$\gamma$	Intercept	- 2.30	1.90	- 1.21	0.227
	Period B	5.56	1.90	2.93	0.003
	Depth	- 2.42	1.42	- 1.70	0.089
	Slope 2	0.35	0.14	2.45	0.014
	Period B*Depth	3.10	1.42	2.18	0.030
$\Omega$	Intercept	2.83	0.13	21.77	<0.001
	Period B	- 3.46	0.29	- 11.78	<0.001
	Depth	- 1.04	0.09	- 11.79	<0.001
	Slope 2	- 1.87	0.12	- 16.07	<0.001
	Period B*Depth	1.55	0.21	7.31	<0.001
p	Intercept	- 2.30	0.06	- 38.35	<0.001
	Period B	17.55	193.78	0.09	0.928
	Period C	1.69	0.30	5.66	<0.001
Dispersion		1.00	0.278	3.61	<0.001



Table 2-9. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass on the north arm of Branched Oak Lake, Nebraska during 2014. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), Timber (whether or not a sampling cell contained flooded timber; category 0: timber absent and category 1: timber present) and Period (the period in, which sampling took place; category A: April 1, category B: July 7, and category B: October 13). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were.

Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 1.92	5.98	-0.32	0.748
	Depth	- 1.96	2.56	-0.77	0.442
	Shore1	- 1.85	3.51	-0.53	0.597
	Shore2	- 3.76	3.66	-1.03	0.304
$\gamma$	Intercept	2.30	0.46	5.05	<0.001
	Period B	- 3.40	0.86	-3.98	<0.001
	Depth	0.25	0.36	0.69	0.492
	Shore1	- 2.89	0.85	-3.41	0.001
	Shore2	- 2.72	1.10	-2.47	0.014
	Period B*Depth	1.61	1.96	0.82	0.411
$\Omega$	Intercept	- 65.80	1414.00	-0.05	0.963
	Period B	- 28.60	759.00	-0.04	0.970
	Depth	- 53.80	1389.00	-0.04	0.969
	Shore1	44.20	749.00	0.06	0.953
	Shore2	- 77.30	4549.00	-0.02	0.986
	Period B*Depth	- 27.00	1393.00	-0.02	0.985
p	Intercept	- 0.14	6.33	-0.02	0.983
	Period B	- 0.80	5.22	-0.15	0.878
	Period C	- 2.11	6.34	-0.33	0.739
	Depth	30.89	199.93	0.15	0.877
	Period B*Depth	- 0.42	5.25	-0.08	0.936
	Period C*Depth	- 56.89	416.92	-0.14	0.891
Zero-inflation		0.51	0.52	0.98	0.330

Table 2-10. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass on the south arm of Branched Oak Lake, Nebraska during 2014. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: April 1, category B: July 7, and category B: October 13). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model.

Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 3.34	0.21	- 16.01	<0.001
	Depth	- 0.48	0.20	- 2.41	0.016
	Slope 2	0.73	0.54	1.36	0.175
$\gamma$	Intercept	2.35	0.12	19.93	<0.001
	Period B	0.35	0.14	2.55	0.011
	Depth 2	0.65	0.09	6.87	<0.001
	Slope 2	- 12.66	160.39	- 0.08	0.940
	Period B*Depth	0.04	0.11	0.35	0.726
$\Omega$	Intercept	5.93	1.29	4.61	<0.001
	Period B	- 8.55	1.68	- 5.07	<0.001
	Depth 2	- 7.80	1.72	- 4.55	<0.001
	Slope 2	2.26	0.48	4.73	<0.001
	Period B*Depth	7.87	1.73	4.56	<0.001
p	Intercept	- 2.94	0.11	- 26.33	<0.001
	Period B	13.32	46.46	0.29	0.774
	Period C	11.61	77.14	0.15	0.880
Dispersion		0.02	0.31	0.06	0.951

Table 2-11. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass on the south arm of Branched Oak Lake, Nebraska during 2014. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), Timber (whether or not a sampling cell contained flooded timber; category 0: timber absent and category 1: timber present) and Period (the period in, which sampling took place; category A: April 1, category B: July 7, and category B: October 13). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were.

Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 3.36	0.70	- 4.82	<0.001
	Depth	- 0.26	0.67	- 0.39	0.697
	Shore1	1.45	0.72	2.02	0.044
	Shore2	0.55	0.74	0.75	0.452
$\gamma$	Intercept	- 1.31	1.34	- 0.97	0.331
	Period B	0.57	0.96	0.59	0.556
	Depth	0.13	0.81	0.16	0.872
	Shore1	- 8.01	185.03	- 0.04	0.966
	Shore2	2.18	1.41	1.55	0.122
	Period B*Depth	1.58	0.74	2.13	0.033
$\Omega$	Intercept	- 0.16	1.72	-0.09	0.928
	Period B	- 23.91	7968.80	0.00	0.998
	Depth	- 1.16	2.12	-0.54	0.586
	Shore1	12.20	351.48	0.03	0.972
	Shore2	- 9.93	148.27	- 0.07	0.947
	Period B*Depth	-4.64	4867.47	0.00	0.999
p	Intercept	- 0.90	0.82	-1.10	0.270
	Period B	5.47	5.40	1.01	0.311
	Period C	- 143.17	11900.00	- 0.01	0.990
	Depth	- 0.08	0.75	- 0.11	0.914
	Period B*Depth	4.09	3.77	1.09	0.277
	Period C*Depth	-152.86	13000.00	- 0.01	0.991
Zero-inflation		- 11.50	144.00	- 0.08	0.936

Table 2-12. Generalized N-mixture models ranked with AIC used to model gizzard shad abundance on Branched Oak Lake, Nebraska during 2013 (K: number of model parameters, AIC: Akaike Information Criterion score,  $\Delta$ AIC: difference between AIC score for the specified model and for the top model, AICwt: AIC weight, cumwt: cumulative AIC weight). Count data were collected with a consumer grade sonar unit used in conjunction with vertical gillnets (SN) in waters with total depths  $\geq 2$  m and a boat electrofisher (EF) used to electrify points in water with total depths  $< 2$  m. In each model,  $\lambda$  is abundance,  $\gamma$  is recruitment,  $\Omega$  is apparent survival, and p is detection probability. The covariates in the models are depth (D), slope (S), sampling period (P), and shoreline habitat (H).

Arm	Gear	Model	K	AIC	$\Delta$ AIC	AICwt	cumwt
North	SN	$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: D	13	1443	0	0.95	1.00
		$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: D	16	1449	6	0.05	1.00
		$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1	5	1958	515	0.00	1.00
	EF	$\lambda$ : D+T, $\gamma$ : D*P+T, $\Omega$ : D*P+T, p: D+P+T	21	188	0	0.88	0.88
		$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: D	16	192	4	0.12	0.99
		$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: D*P	17	198	10	0.01	1.00
		$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1	5	414	226	0.00	1.00
	South	SN	$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: P	14	512	0	1.00
$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: P			17	1189	677	0.00	1.00
$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: D			16	1511	999	0.00	1.00
$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: D			13	1833	1321	0.00	1.00
$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1			5	2816	2304	0.00	1.00

Table 2-13. Parameter estimates for generalized N-mixture model used to estimate gizzard shad abundance and biomass on the north arm of Branched Oak Lake, Nebraska during 2013. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1: <1% slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: June 25, category B: July 31, and category B: October 16). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model.



Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 3.44	0.30	- 11.60	<0.001
	Depth	- 1.05	0.29	- 3.66	<0.001
$\gamma$	Intercept	- 3.78	2.10	- 1.80	0.070
	Period B	6.84	2.09	3.27	<0.001
	Depth	- 6.36	1.59	- 4.01	<0.001
	Period B*Depth	6.65	1.59	4.18	<0.001
$\Omega$	Intercept	1.90	0.49	3.85	<0.001
	Period B	- 61.18	202.47	- 0.30	0.763
	Depth	- 2.13	0.35	- 6.10	<0.001
	Period B*Depth	58.75	188.78	0.31	0.756
p	Intercept	- 0.86	0.11	- 7.69	<0.001
	Depth	1.29	0.11	11.92	<0.001
Dispersion		- 1.11	0.27	- 4.10	<0.001

Table 2-14. Parameter estimates for generalized N-mixture model used to estimate gizzard shad abundance and biomass on the north arm of Branched Oak Lake, Nebraska during 2013. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), Timber (whether or not a sampling cell contained flooded timber; category 0: timber absent and category 1: timber present) and Period (the period in, which sampling took place; category A: June 25, category B: July 31, and category B: October 16). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were.

Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 2.74	0.65	- 4.21	<0.001
	Depth	- 1.14	0.52	- 2.18	0.029
	Timber 1	1.75	0.62	2.83	0.005
$\gamma$	Intercept	0.92	0.52	1.79	0.073
	Period B	- 21.17	6557.00	0.00	0.997
	Depth	1.25	0.36	3.50	<0.001
	Timber 1	- 0.78	0.78	- 1.00	0.318
	Period B*Depth	7.69	4021.83	0.00	0.998
$\Omega$	Intercept	- 105.60	447.97	- 0.24	0.814
	Period B	50.00	214.20	0.23	0.816
	Depth	3.10	4.66	0.67	0.505
	Timber 1	109.30	447.95	0.24	0.807
	Period B*Depth	- 77.80	327.20	- 0.24	0.812
p	Intercept	- 1.92	0.80	- 2.40	0.016
	Period B	0.00	0.61	0.00	0.998
	Period C	- 0.51	0.80	- 0.64	0.522
	Depth	- 0.37	0.68	- 0.54	0.590
	Timber 1	- 0.63	0.72	- 0.88	0.379
	Period B*Depth	- 1.12	0.79	- 1.42	0.155
	Period C*Depth	- 3.76	1.61	- 2.34	0.019
Zero-inflation		0.43	0.47	0.93	0.352

Table 2-15. Parameter estimates for generalized N-mixture model used to estimate gizzard shad abundance and biomass on the south arm of Branched Oak Lake, Nebraska during 2013. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1: <1% slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: June 25, category B: July 31, and category B: October 16). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model.

Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 3.18	0.48	- 6.69	<0.001
	Depth	- 0.96	0.46	- 2.09	0.036
$\gamma$	Intercept	1.04	0.24	4.34	<0.001
	Period B	- 17.25	1104.29	- 0.02	0.988
	Depth	- 0.14	0.25	- 0.56	0.576
	Period B*Depth	- 4.35	823.05	- 0.01	0.996
$\Omega$	Intercept	5.68	5.85	0.97	0.331
	Period B	17.76	16.90	1.05	0.294
	Depth	- 0.09	2.12	- 0.04	0.967
	Period B*Depth	17.90	12.31	1.45	0.146
p	Intercept	- 1.64	0.16	- 10.49	<0.001
	Period B	- 0.27	0.16	- 1.61	0.107
	Period C	- 0.22	0.17	- 1.26	0.206
Dispersion		- 1.87	0.34	- 5.50	<0.001

Table 2-16. Generalized N-mixture models ranked with AIC used to model gizzard shad abundance on Branched Oak Lake, Nebraska during 2014 (K: number of model parameters, AIC: Akaike Information Criterion score,  $\Delta$ AIC: difference between AIC score for the specified model and for the top model, AICwt: AIC weight, cumwt: cumulative AIC weight). Count data were collected with a consumer grade sonar unit used in conjunction with vertical gillnets (SN) in waters with total depths  $\geq 2$  m and a boat electrofisher (EF) used to electrify points in water with total depths  $< 2$  m. In each model,  $\lambda$  is abundance,  $\gamma$  is recruitment,  $\Omega$  is apparent survival, and p is detection probability. The covariates in the models are depth (D), slope (S), sampling period (P), and shoreline habitat (H).

Arm	Gear	Model	K	AIC	$\Delta$ AIC	AICwt	cumwt
North	SN	$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: P	14	890	0	1.00	1.00
		$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: P	17	986	96	0.00	1.00
		$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: D	16	1427	537	0.00	1.00
		$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: D	13	1499	609	0.00	1.00
		$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1	5	1651	761	0.00	1.00
	EF	$\lambda$ : D+T, $\gamma$ : D*P+T, $\Omega$ : D*P+T, p: D+P+T	21	92	0	0.67	0.67
		$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: D*P	17	94	2	0.24	0.91
		$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: D	16	96	4	0.09	1.00
		$\lambda$ : S, $\gamma$ : S+P, $\Omega$ : S+P, p: P	12	148	56	0.00	1.00
		$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1	5	193	101	0.00	1.00
	South	$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: D	16	1321	0	1.00	1.00
		$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: P	14	1545	224	0.00	1.00
		$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1	5	2917	1596	0.00	1.00
		$\lambda$ : D+T, $\gamma$ : D*P+T, $\Omega$ : D*P+T, p: D+P+T	21	80	0	0.59	0.59
		$\lambda$ : D+H, $\gamma$ : D*P+H, $\Omega$ : D*P+H, p: D+P	23	80	1	0.41	1.00
		$\lambda$ : S, $\gamma$ : S+P, $\Omega$ : S+P, p: P	12	94	14	0.00	1.00
		$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1	5	95	15	0.00	1.00

Table 2-17. Parameter estimates for generalized N-mixture model used to estimate gizzard shad abundance and biomass on the north arm of Branched Oak Lake, Nebraska during 2014. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1: <1% slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: April 1, category B: July 7, and category B: October 13). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model.



Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 3.40	0.23	- 14.71	<0.001
	Depth	0.00	0.23	- 0.02	0.983
$\gamma$	Intercept	0.40	0.48	0.83	0.407
	Period B	- 8.96	9.01	- 0.99	0.320
	Depth	- 1.14	0.38	- 3.03	0.002
	Period B*Depth	- 0.44	22.82	- 0.02	0.985
$\Omega$	Intercept	40.60	24.00	1.69	0.091
	Period B	- 40.20	24.00	- 1.67	0.094
	Depth	- 21.10	12.30	- 1.72	0.086
	Period B*Depth	22.10	12.30	1.80	0.072
p	Intercept	- 2.48	0.14	- 17.94	<0.001
	Period B	0.09	0.17	0.55	0.581
	Period C	11.55	18.35	0.63	0.529
Dispersion		- 0.25	0.34	- 0.73	0.466

Table 2-18. Parameter estimates for generalized N-mixture model used to estimate gizzard shad abundance and biomass on the north arm of Branched Oak Lake, Nebraska during 2014. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), Timber (whether or not a sampling cell contained flooded timber; category 0: timber absent and category 1: timber present) and Period (the period in, which sampling took place; category A: April 1, category B: July 7, and category B: October 13). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were.

Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 13.26	11.31	- 1.17	0.241
	Depth	5.06	7.47	0.68	0.498
	Timber 1	0.95	2.88	0.33	0.741
$\gamma$	Intercept	- 4.01	0.72	- 5.60	<0.001
	Period B	- 34.35	9.46	- 3.63	<0.001
	Depth	- 2.11	0.40	- 5.27	<0.001
	Timber 1	4.19	0.71	5.92	<0.001
	Period B*Depth	28.10	5.96	4.71	<0.001
$\Omega$	Intercept	- 6.72	32.10	- 0.21	0.834
	Period B	- 13.71	11969.70	0.00	0.999
	Depth	- 16.41	58.00	- 0.28	0.777
	Timber 1	36.18	125.40	0.29	0.773
	Period B*Depth	3.78	6760.40	0.00	1.000
p	Intercept	15.61	3502.00	0.00	0.996
	Period B	18.37	3490.00	0.01	0.996
	Period C	- 1.58	NA	NA	NA
	Depth	6.36	2630.00	0.00	0.998
	Timber 1	- 35.60	232.00	- 0.15	0.878
	Period B*Depth	6.42	2630.00	0.00	0.998
	Period C*Depth	- 4.94	NA	NA	NA
Zero-inflation		- 8.36	147.00	- 0.06	0.955

Table 2-19. Parameter estimates for generalized N-mixture model used to estimate gizzard shad abundance and biomass on the south arm of Branched Oak Lake, Nebraska during 2014. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1: <1% slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: April 1, category B: July 7, and category B: October 13). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model.

Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 4.54	0.34	- 13.39	<0.001
	Depth	- 2.15	0.28	- 7.68	<0.001
	Slope 2	- 0.07	0.66	- 0.11	0.916
$\gamma$	Intercept	2.49	0.12	20.86	<0.001
	Period B	- 3.16	0.21	- 15.00	<0.001
	Depth	- 0.85	0.10	- 8.98	<0.001
	Slope 2	0.80	0.09	8.67	<0.001
	Period B*Depth	4.72	0.17	28.37	<0.001
$\Omega$	Intercept	13.08	122.00	0.11	0.915
	Period B	- 22.98	127.00	- 0.18	0.856
	Depth	- 0.14	112.00	0.00	0.999
	Slope 2	60.56	1365.00	0.04	0.965
	Period B*Depth	-31.18	138.00	- 0.23	0.821
p	Intercept	- 0.86	0.12	- 7.03	<0.001
	Depth	2.01	0.10	21.08	<0.001
Dispersion		- 0.59	0.40	- 1.50	0.134

Table 2-20. Parameter estimates for generalized N-mixture model used to estimate gizzard shad abundance and biomass on the south arm of Branched Oak Lake, Nebraska during 2014. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), Timber (whether or not a sampling cell contained flooded timber; category 0: timber absent and category 1: timber present) and Period (the period in, which sampling took place; category A: April 1, category B: July 7, and category B: October 13). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were.

Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 4.59	0.59	- 7.85	<0.001
	Depth	- 0.82	0.41	- 1.98	0.048
	Timber 1	- 9.16	209.80	- 0.04	0.965
$\gamma$	Intercept	- 4.78	2.79	- 1.71	0.087
	Period B	- 38.71	10.87	- 3.56	<0.001
	Depth	0.79	1.85	0.43	0.668
	Timber 1	6.92	2.58	2.68	0.007
	Period B*Depth	26.50	6.56	4.04	<0.001
$\Omega$	Intercept	- 13.01	46.00	- 0.28	0.777
	Period B	- 16.31	45.60	- 0.36	0.721
	Depth	- 20.74	66.90	- 0.31	0.756
	Timber 1	27.18	81.60	0.33	0.739
	Period B*Depth	2.78	17.40	0.16	0.873
p	Intercept	- 27.90	96.80	- 0.29	0.773
	Period B	35.10	109.50	0.32	0.748
	Period C	34.50	109.40	0.32	0.753
	Depth	20.70	71.10	0.29	0.770
	Timber 1	- 10.50	51.20	- 0.21	0.837
	Period B*Depth	- 21.30	71.10	- 0.30	0.765
	Period C*Depth	- 21.40	71.10	- 0.30	0.763
Zero-inflation		- 11.00	203.00	- 0.05	0.957

Table 2-21. Abundance and biomass with 95% confidence intervals estimated for white perch (WHP) and gizzard shad (SHAD) in Branched Oak Lake (BOL) and Pawnee Reservoir (PWR), Nebraska. Estimates were made using generalized N-mixture models with data collected with a consumer-grade sonar unit, vertical gillnets, and a boat electrofisher.

Waterbody	Species	Year	Abundance (millions)	Mean mass (g)	Biomass	
					kg (thousands)	kg/ha
BOL	WHP	2013	1.20(1.14-1.26)	38(1-76)	45.99(0.93-91.05)	63(1-125)
		2014	1.20(1.12-1.27)	35(5-66)	42.38(6.10-78.66)	58(8-108)
	SHAD	2013	0.91(0.77-1.04)	87(0-485)	79.46(0.00-168.54)	109(0-232)
		2014	0.70(0.54-0.86)	149(42-257)	103.83(25.76-181.90)	143(35-250)
PWR	WHP	2013	1.59(1.49-1.69)	28(14-41)	43.71(22.16-65.26)	146(74-218)
		2014	0.27(0.23-0.31)	28(17-39)	7.64(4.35-10.93)	26(15- 37)
	SHAD	2013	0.64(0.59-0.68)	47(16-79)	30.33(10.39-50.27)	101(35-168)
		2014	0	0	0.00	0



Table 2-22. Generalized N-mixture models ranked with AIC used to estimate white perch abundance and biomass on Pawnee Reservoir, Nebraska (K: number of model parameters, AIC: Akaike Information Criterion score,  $\Delta$ AIC: difference between AIC score for the specified model and for the top model, AICwt: AIC weight, cumwt: cumulative AIC weight). Count data were collected with a consumer grade sonar unit used in conjunction with vertical gillnets (SN) in waters with total depths  $\geq 2$  m and a boat electrofisher (EF) used to electrify points in water with total depths  $< 2$  m. In each model,  $\lambda$  is abundance,  $\gamma$  is recruitment,  $\Omega$  is apparent survival, and p is detection probability. The covariates in the models are depth (D), slope (S), sampling period (P), and shoreline habitat (H).

Period	Gear	Model	K	AIC	$\Delta$ AIC	AICwt	cumwt	
2013	SN	$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: D	20	1468	0	1.00	1.00	
		$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: D	17	1607	139	0.00	1.00	
		$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: P	19	1741	273	0.00	1.00	
		$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1	5	2729	1261	0.00	1.00	
	EF	$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: D*P	23	838	0	1.00	1.00	
		$\lambda$ : S, $\gamma$ : S+P, $\Omega$ : S+P, p: P	15	921	83	0.00	1.00	
		$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1	5	1098	260	0.00	1.00	
	2014	SN	$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: P	32	1070	0	1.00	1.00
			$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: D	25	1128	58	0.00	1.00
$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: P			29	1146	76	0.00	1.00	
$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: D			28	1210	140	0.00	1.00	
$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1			5	2569	1499	0.00	1.00	
EF		$\lambda$ : S, $\gamma$ : S+P, $\Omega$ : S+P, p: P	21	341	0	1.00	1.00	
		$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1	5	360	19	0.00	1.00	

Table 2-23. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass in Pawnee Reservoir, Nebraska during 2013. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: June 17, category B: July 25, category C: September 9, category D: October 8). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model.

Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 1.56	0.14	- 11.34	<0.001
	Depth	- 0.81	0.11	- 7.51	<0.001
	Slope 2	0.08	0.24	0.33	0.742
$\gamma$	Intercept	3.80	0.07	52.31	<0.001
	Period B	- 0.70	0.10	- 6.86	<0.001
	Period C	- 1.19	0.11	- 10.92	<0.001
	Depth	- 0.28	0.07	- 4.31	<0.001
	Slope 2	- 0.90	0.10	- 8.58	<0.001
	Period B*Depth	- 0.91	0.10	- 9.42	<0.001
	Period C*Depth	0.11	0.12	0.91	0.362
$\Omega$	Intercept	- 4.12	0.82	- 5.00	<0.001
	Period B	- 45.12	35.99	- 1.25	0.210
	Period C	- 9.95	1.86	- 5.36	<0.001
	Depth	0.16	0.08	1.87	0.061
	Slope 2	3.31	0.81	4.07	<0.001
	Period B*Depth	- 70.03	52.03	- 1.35	0.178
	Period C*Depth	- 8.51	1.62	- 5.26	<0.001
p	Intercept	3.83	0.33	11.60	<0.001
	Depth	3.85	0.25	15.50	<0.001
Dispersion		1.50	0.32	4.68	<0.001

Table 2-24. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass in Pawnee Reservoir, Nebraska during 2013. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), Timber (whether or not a sampling cell contained flooded timber; category 0: timber absent and category 1: timber present) and Period (the period in, which sampling took place; category A: June 17, category B: July 25, category C: September 9, category D: October 8). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were.

Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 0.29	0.26	- 1.13	0.257
	Depth	- 0.79	0.21	- 3.77	<0.001
$\gamma$	Intercept	1.51	0.23	6.72	<0.001
	Period B	- 26.30	6.57	- 4.00	<0.001
	Period C	- 4.99	1.62	- 3.09	0.002
	Depth	1.49	0.31	4.86	<0.001
	Period B*Depth	- 16.68	3.73	- 4.47	<0.001
	Period C*Depth	- 4.58	1.03	- 4.44	<0.001
$\Omega$	Intercept	1.06	0.56	1.89	0.059
	Period B	2.62	1.26	2.09	0.037
	Period C	1.71	11.71	0.15	0.884
	Depth	1.76	0.41	4.26	<0.001
	Period B*Depth	3.38	1.66	2.04	0.041
	Period C*Depth	29.66	203.01	0.15	0.884
p	Intercept	- 0.83	0.45	- 1.84	0.066
	Depth	0.58	0.38	1.54	0.124
	Period B	1.04	0.43	2.45	0.014
	Period C	1.38	0.44	3.11	0.002
	Period D	- 0.60	0.65	- 0.92	0.355
	Period B*Depth	- 2.47	0.58	- 4.28	<0.001
	Period C*Depth	- 3.55	0.64	- 5.52	<0.001
	Period D*Depth	- 4.64	1.42	- 3.26	0.001
Zero-inflation		- 0.27	0.37	- 0.73	0.465

Table 2-25. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass in Pawnee Reservoir, Nebraska during 2014. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth the mean depth of cells (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: May 2, category B: May 14, category C: May 21, category D: June 20, category E: September 18, category F: October 7). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model.

Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 3.62	0.24	- 15.02	<0.001
	Depth	0.28	0.14	1.98	0.048
	Slope 2	- 0.03	0.24	- 0.11	0.912
$\gamma$	Intercept	1.47	0.51	2.87	0.004
	Period B	1.10	0.53	2.09	0.037
	Period C	1.38	0.52	2.68	0.007
	Period D	- 9.14	5.56	- 1.65	0.100
	Period E	- 0.06	0.53	- 0.11	0.911
	Depth	0.44	0.28	1.59	0.112
	Slope 2	- 0.12	0.07	- 1.70	0.089
	Period B*Depth	0.25	0.29	0.86	0.392
	Period C*Depth	- 0.17	0.28	- 0.62	0.534
	Period D*Depth	5.26	3.22	1.63	0.103
	Period E*Depth	- 0.83	0.31	- 2.72	0.006
$\Omega$	Intercept	11.80	6.44	1.84	0.066
	Period B	- 23.40	11.04	- 2.12	0.034
	Period C	188.00	98.87	1.90	0.057
	Period D	100.70	567.61	0.18	0.859
	Period E	- 22.30	10.96	- 2.04	0.042
	Depth	- 12.40	6.06	- 2.05	0.040
	Slope 2	10.00	4.58	2.18	0.029
	Period B*Depth	10.50	6.15	1.70	0.089
	Period C*Depth	272.60	140.79	1.94	0.053
	Period D*Depth	- 81.70	452.98	- 0.18	0.857
	Period E*Depth	13.00	6.06	2.15	0.031
p	Intercept	- 1.72	0.24	- 7.29	<0.001
	Period B	2.02	0.41	4.99	<0.001
	Period C	12.47	238.00	0.05	0.958
	Period D	1.98	0.27	7.34	<0.001
	Period E	- 0.99	0.27	- 3.63	<0.001
	Period F	19.08	23800.00	0.00	0.999
Dispersion		1.90	0.61	3.13	0.002

Table 2-26. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass in Pawnee Reservoir, Nebraska during 2014. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), Timber (whether or not a sampling cell contained flooded timber; category 0: timber absent and category 1: timber present) and Period (the period in, which sampling took place; category A: May 2, category B: May 14, category C: May 21, category D: June 20, category E: September 18, category F: October 7). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were.



Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 0.52	0.49	- 1.08	0.282
	Slope 2	- 1.30	0.39	- 3.37	0.001
$\gamma$	Intercept	- 2.88	1.55	- 1.86	0.063
	Period B	3.24	68.21	0.05	0.962
	Period C	1.34	1.64	0.82	0.414
	Period D	- 5.21	27.20	- 0.19	0.848
	Period E	3.70	1.66	2.23	0.026
	Slope 2	1.25	0.74	1.68	0.092
$\Omega$	Intercept	- 9.58	59.70	- 0.16	0.873
	Period B	- 9.25	86.70	- 0.11	0.915
	Period C	- 11.52	57.20	- 0.20	0.840
	Period D	- 0.52	19.30	- 0.03	0.979
	Period E	3.60	67.30	0.05	0.957
	Slope 2	13.30	61.90	0.21	0.830
p	Intercept	0.53	0.95	0.56	0.576
	Period B	- 1.62	0.91	- 1.77	0.076
	Period C	- 3.68	71.11	- 0.05	0.959
	Period D	0.14	2.52	0.06	0.954
	Period E	3.31	32.05	0.10	0.918
	Period F	- 4.62	1.31	- 3.52	<0.001
Zero-inflation		0.93	0.42	2.20	0.028

Table 2-27. Generalized N-mixture models ranked with AIC used to model gizzard shad abundance on Pawnee Reservoir, Nebraska during 2013 (K: number of model parameters, AIC: Akaike Information Criterion score,  $\Delta$ AIC: difference between AIC score for the specified model and for the top model, AICwt: AIC weight, cumwt: cumulative AIC weight). Count data were collected with a consumer grade sonar unit used in conjunction with vertical gillnets (SN) in waters with total depths of 2 m or more and a boat electrofisher (EF) used to shock points in water with total depths < 2 m. In each model,  $\lambda$  is abundance,  $\gamma$  is recruitment,  $\Omega$  is apparent survival, and p is detection probability. The covariates in the models are depth (D), slope (S), sampling period (P), and shoreline habitat (H).

Gear	Model	K	AIC	$\Delta$ AIC	AICwt	cumwt
SN	$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: D*P	20	1058	0	1.00	1.00
	$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: D*P	17	1112	54	0.00	1.00
	$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1	5	1346	288	0.00	1.00
EF	$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: D*P	23	483	0	1.00	1.00
	$\lambda$ : D+H, $\gamma$ : D*P+H, $\Omega$ : D*P+H p: D+P	30	517	34	0.00	1.00
	$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: D	20	520	37	0.00	1.00
	$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1	5	549	66	0.00	1.00
	$\lambda$ : S, $\gamma$ : S+P, $\Omega$ : S+P, p: P	15	551	68	0.00	1.00

Table 2-28. Parameter estimates for generalized N-mixture model used to estimate gizzard shad abundance and biomass in Pawnee Reservoir, Nebraska during 2013. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: June 17, category B: July 25, category C: September 9, category D: October 8). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model.

Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 2.77	0.20	- 13.71	<0.001
	Depth	- 0.76	0.16	- 4.91	<0.001
	Slope 2	0.08	0.33	0.26	0.799
$\gamma$	Intercept	2.28	0.17	13.49	<0.001
	Period B	- 0.48	0.20	- 2.40	0.016
	Period C	- 0.89	0.27	- 3.34	<0.001
	Depth	0.15	0.10	1.48	0.1390
	Slope 2	1.15	0.15	7.50	<0.001
	Period B*Depth	- 0.09	0.15	- 0.61	0.545
	Period C*Depth	0.07	0.19	0.39	0.70
$\Omega$	Intercept	- 1.96	0.40	- 4.88	<0.001
	Period B	4.42	0.83	5.32	<0.001
	Period C	2.07	0.50	4.17	<0.001
	Depth	1.53	0.26	5.99	<0.001
	Slope 2	- 2.07	0.42	- 4.93	<0.001
	Period B*Depth	- 3.01	0.59	- 5.11	<0.001
	Period C*Depth	- 1.73	0.37	- 4.65	<0.001
p	Intercept	0.62	0.17	3.57	<0.001
	Period B	0.49	0.18	2.68	0.007
Dispersion		0.83	0.32	2.61	0.009

Table 2-29. Parameter estimates for generalized N-mixture model used to estimate gizzard shad abundance and biomass in Pawnee Reservoir, Nebraska during 2013. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), Timber (whether or not a sampling cell contained flooded timber; category 0: timber absent and category 1: timber present) and Period (the period in, which sampling took place; category A: June 17, category B: July 25, category C: September 9, category D: October 8). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were.

Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 0.59	0.23	- 2.53	0.012
	Depth	- 0.36	0.30	- 1.22	0.222
$\gamma$	Intercept	- 1.21	0.96	- 1.27	0.206
	Period B	0.70	1.06	0.66	0.509
	Period C	1.21	1.04	1.16	0.245
	Depth	1.82	0.89	2.05	0.040
	Period B*Depth	- 1.90	1.02	- 1.86	0.063
	Period C*Depth	- 0.54	1.11	- 0.49	0.627
$\Omega$	Intercept	- 1.63	0.46	- 3.57	<0.001
	Period B	- 231.51	6823.12	- 0.03	0.973
	Period C	2.84	1.55	1.84	0.066
	Depth	2.31	0.82	2.82	0.005
	Period B*Depth	329.95	9700.55	0.03	0.973
	Period C*Depth	- 1.61	1.54	- 1.05	0.294
p	Intercept	- 1.52	0.31	- 4.90	<0.001
	Depth	0.00	0.39	- 0.01	0.994
	Period B	4.09	1.20	3.41	0.001
	Period C	2.72	1.56	1.74	0.082
	Period D	13.98	8.99	1.56	0.120
	Period B*Depth	- 5.13	1.41	- 3.63	<0.001
	Period C*Depth	- 1.91	1.17	- 1.63	0.103
	Period D*Depth	- 21.85	13.13	- 1.66	0.096
Zero-inflation		- 1.22	0.49	- 2.52	0.012

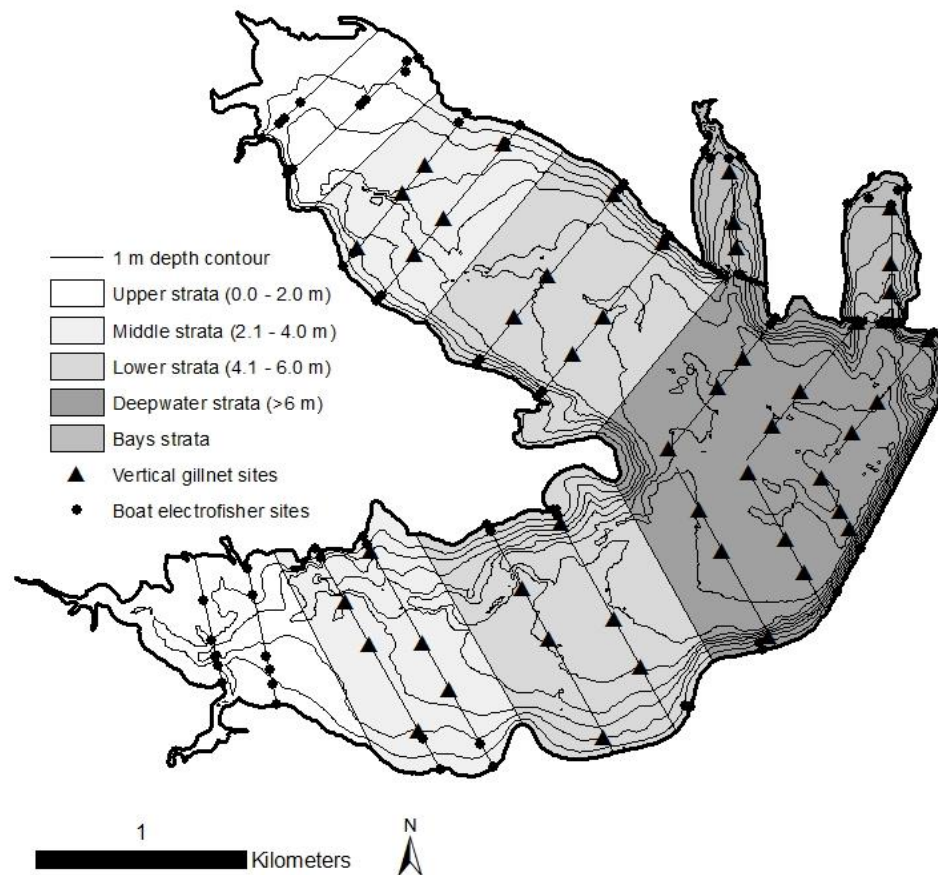


Figure 2-1. Stratification system and sampling sites (with adjustments for sites moved because they were unsamplable) for estimating white perch and gizzard shad abundances, biomasses, and spatial distributions in Branched Oak Lake, Nebraska.

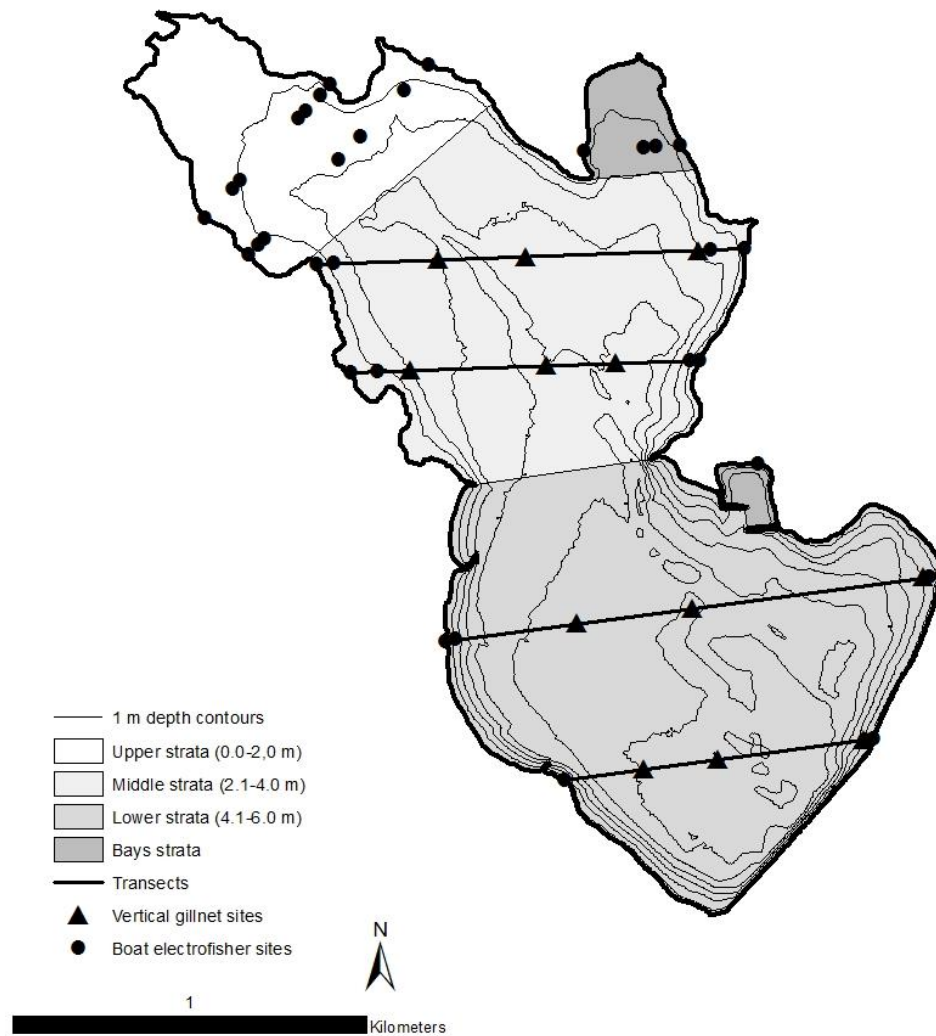


Figure 2-2. Stratification system and sampling sites for estimating white perch and gizzard shad abundances, biomasses, and spatial distributions in Pawnee Reservoir, Nebraska.



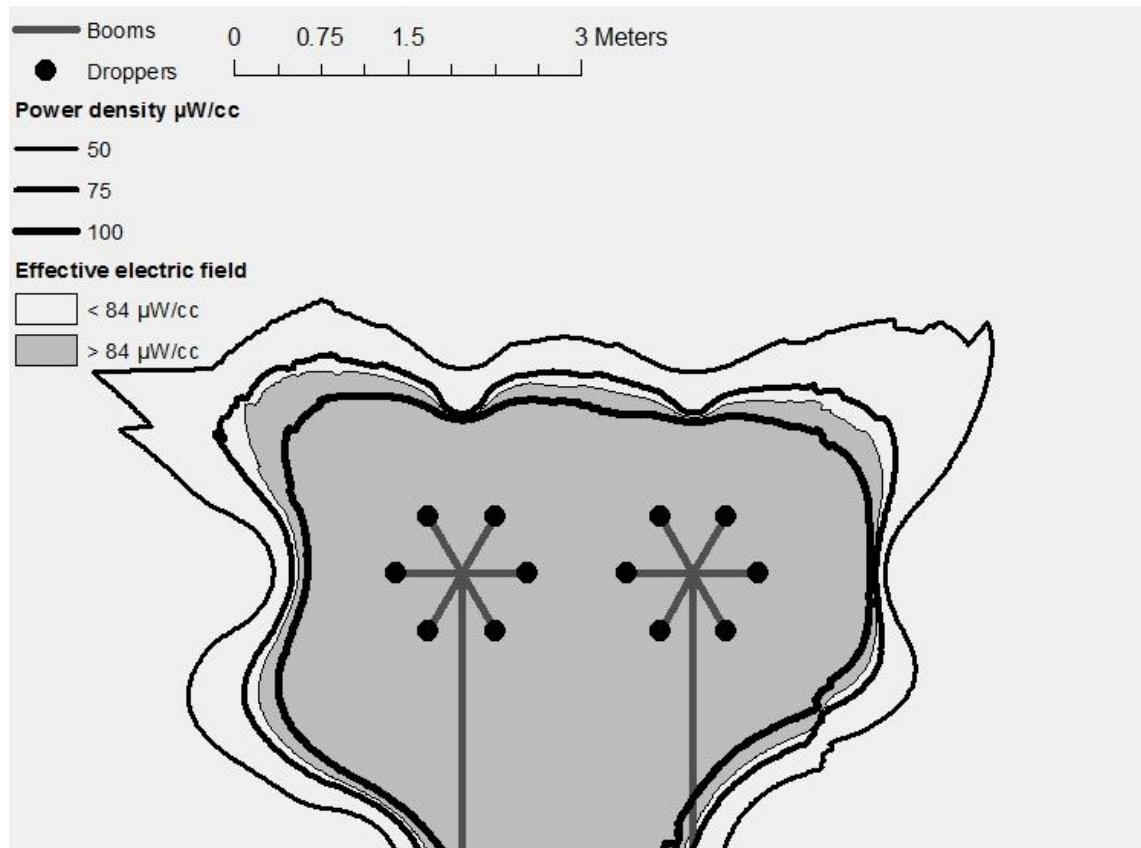


Figure 2-3. Electric field map for a 5.5- m boat electrofisher with a Smith-Root® 5.0 GPP control box. The effective edge of the electric field was estimated to be where power density was  $< 84 \mu\text{W/cc}$ .

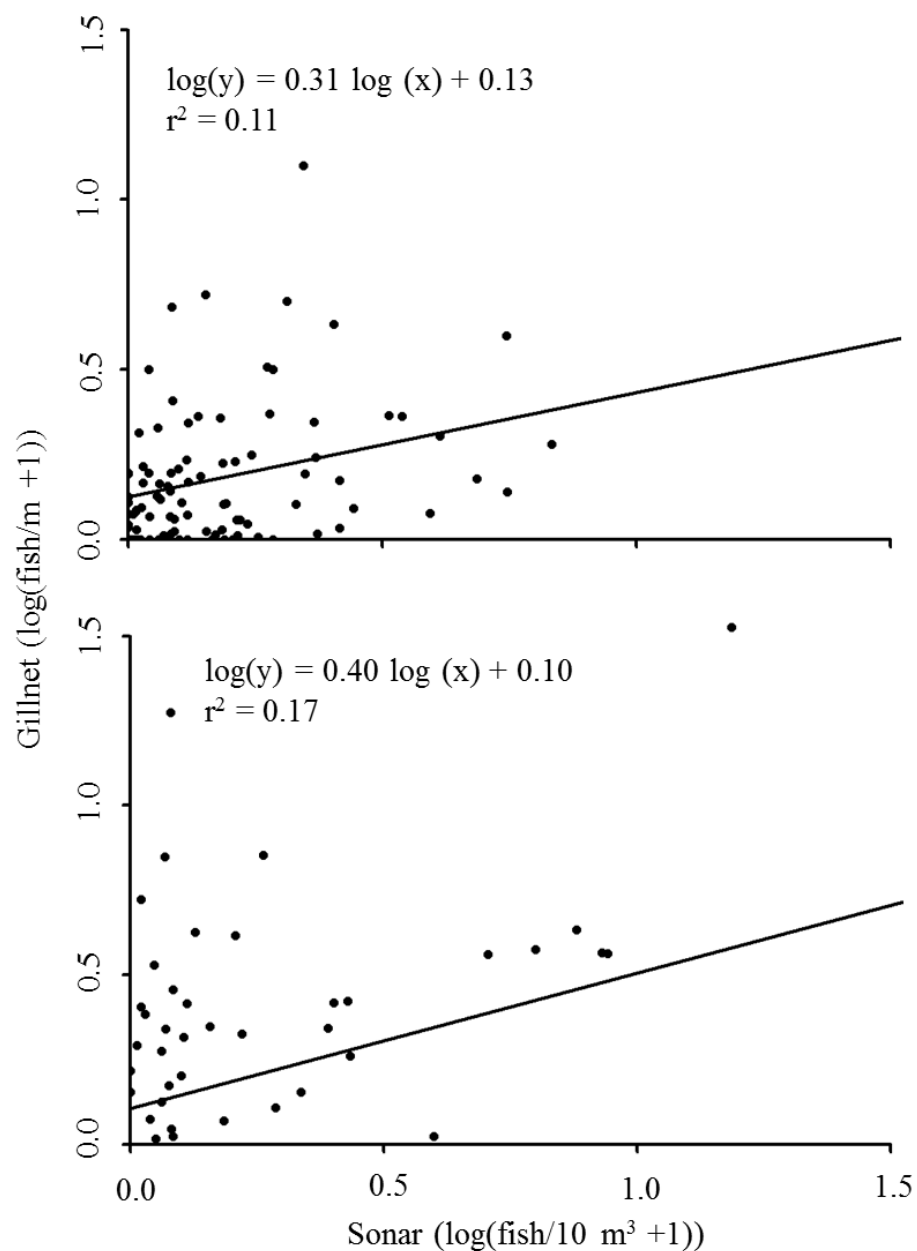


Figure 2-4. Relationships between vertical gillnet catch and fish density estimated using consumer grade sonar in Branched Oak Lake (top) and Pawnee Reservoir, Nebraska (bottom) during spring, summer, and fall of 2013 and 2014.

## **Chapter 3 Seasonal distribution patterns of white perch and gizzard shad in reservoirs**

To understand the ecology of a fish species, a sound understanding of spatial distribution is crucial. Spatial distributions are influenced by heterogeneity in habitat quality and by the distributions of other fish populations within a waterbody. Several possible relationships exist among spatial distributions of co-occurring fish populations. One possibility is that the spatial distributions are not related, which could occur if both species use different resources that occur with some spatial overlap. For example, bluegill (*Lepomis macrochirus*) and black crappie (*Pomoxis nigromaculatus*) may both use the same patches of coarse woody debris, but in addition to these areas bluegill use shallow areas with macrophytes whereas black crappie use deeper habitats (Becker 1983). From a distribution standpoint, this would appear as little similarity between the populations (Figure 3-1). In this instance, we would expect no significant relationship between the distributions.

Another possibility is that the distributions will be positively related, which could occur if the behavior of one species benefits the other species, or if both species use the same resources. For example, bluegill and redbreasted sunfish (*Lepomis auritus*) use similar littoral habitats with physical structure in southern reservoirs (Barwick 2004). From a distribution standpoint, this would appear as nearly identical distributions of the

two species (Figure 3-1). In this instance, we would expect a positive relationship between the distributions.

Spatial distributions could be exclusionary if species utilize dissimilar habitats. For example, cisco (*Coregonus artedii*) need cooler water and open areas whereas bluegill prefer warmer water and littoral habitats; when both species occur in the same waterbody there is little overlap in their habitats (Jacobson et al. 2002). This scenario could also occur if one species forces another out of certain habitats. For example, bluegill shift their distribution from vegetated areas when green sunfish (*Lepomis cyanellus*) are present in large numbers because of the competitive advantage that green sunfish have in vegetated habitats (Werner and Hall 1976; Werner and Hall 1977). From a spatial distribution standpoint, either of these scenarios would appear as opposite or completely separate distributions for the two species (Figure 3-1). In this instance, we would expect a negative relationship between the distributions.

Another possibility is that the distribution of one species may overlap completely with the other and spill over into suboptimal habitats, which could occur if one species only uses a specific habitat and the other is more of a generalist. For example, in Wisconsin streams specialist species such as brook trout (*Salvelinus fontinalis*) only exist in cold-water streams whereas white sucker (*Catostomus commersonii*) span the gradient from degraded cold-water streams to warm-water streams (Lyons et al. 1996). Spatially this would appear as some type of concentrated distribution for the specialist species and

more of a uniform distribution for the generalist species (Figure 3-1). In this instance, we would expect no significant relationship between the distributions.

A better understanding of the spatiotemporal distributions of co-occurring superabundant fish populations (Chapter 2) and how they are related could provide insight into the ecological interactions occurring between the populations. The presence of a superabundant fish population in a waterbody is ideal for study because it should lead to intense competition for food and space, exacerbating patterns in distribution. Some waterbodies in southeastern Nebraska are ideal systems to study these relationships. These waterbodies contain superabundant populations of white perch (*Morone americana*) and gizzard shad (*Dorosoma cepedianum*). We assume that both species follow an ideal-free distribution in which organisms distribute to maximize fitness (the relative amount of an organisms genetic material passed on to the next generation) based on the interaction of habitat quality and organism density over a relatively small spatial scale (area that fish can easily access with minimal movement costs) (Morris 1987; Shepherd and Litvak 2004). We hypothesized that there would be a significant positive relationship between the spatial distributions due to the large sizes of these populations (Chapter 2). Also, these species are suspected of causing declines in angler use of Nebraska reservoirs and as a result reductions in their abundances are necessary. An understanding of the spatial ecology of these species would aid in designing management actions to reduce abundance of these species.

Our goal was to determine how the spatial distribution of a superabundant white perch population related to the spatial distributions of a gizzard shad population in the same waterbody. Thus, we estimated the spatial distributions of both species seasonally across all available habitats. We then compared these distributions to determine which within-waterbody relationship (described above) likely exists between white perch and gizzard.

## **Study Reservoirs**

### **Branched Oak Lake**

Branched Oak Lake is a 728 ha, flood-control reservoir located approximately 24 km northwest of Lincoln, Nebraska in the Salt Creek Watershed. Oak Creek and Middle Oak Creek flow into the reservoir forming two reservoir arms. Fish species present in the reservoir include white perch, gizzard shad, walleye (*Sander vitreus*), freshwater drum (*Aplodinotus grunniens*), hybrid striped bass (*Morone chrysops* x *Morone saxatilis*), bluegill, green sunfish, largemouth bass (*Micropterus salmoides*), black crappie, white crappie (*Pomoxis annularis*), flathead catfish (*Pylodictis olivaris*), channel catfish (*Ictalurus punctatus*), blue catfish (*Ictalurus furcatus*) brook silverside (*Labidesthes sicculus*), common carp (*Cyprinus carpio*), and striped bass.

## **Pawnee Reservoir**

Pawnee Reservoir is a 299 ha flood-control reservoir located in the Salt Creek Watershed. The reservoir is located 14 km south of Branched Oak Lake, and is 17 km west of Lincoln, Nebraska. Like Branched Oak Lake, Pawnee Reservoir is part of a state recreation area providing water recreation opportunities for area residents. Pawnee reservoir was formed by damming Middle Creek, which enters the reservoir on the northwest end. Fish present in Pawnee Reservoir include white perch, gizzard shad, walleye, freshwater drum, bluegill, green sunfish, largemouth bass, black crappie, white crappie, channel catfish, flathead catfish, common carp, and bigmouth buffalo (*Ictiobus cyprinellus*).

## **Methods**

We estimated the spatial distributions of white perch and gizzard shad by expanding the models described in chapter 2. Briefly, we input data collected using a consumer-grade sonar unit, vertical gillnets, and a boat electrofisher into generalized N-mixture models to estimate site-specific abundance for both species. We selected the top model from a set of candidate models using AIC model selection procedures. The top model output provided us with an estimate of abundance within each cell for the first sampling event. The models also output estimates of detection probability in each cell for each sampling event, a recruitment term that incorporated immigration and recruitment in each cell (for all but the final sampling event) as well as an apparent survival term that

incorporated emigration and survival in each cell (Fiske and Chandler 2011). The model estimates of recruitment and apparent survival were used to step the estimates of abundance forward in time with the relationship,

$$N_t = \Omega * N_{t-1} + \gamma$$

where  $N_t$  is abundance at time  $t$ ,  $\Omega$  is survival and emigration,  $N_{t-1}$  is abundance during the previous time step, and  $\gamma$  is immigration and recruitment (Dail and Mathisen 2011).

Through this process, we generate estimates of abundances in each cell during the second sampling event. We then relativized these estimates by dividing each estimate by the total abundance and multiplying that by 100. We plotted these relative abundance values in ArcMap 10 (ESRI 2012) to generate an estimated spatial distribution. We repeated the process for each sampling event.

We used Spearman rank correlations ( $\alpha = 0.05$ ) to compare the spatial distributions of white perch and gizzard shad. Specifically we compared cell-specific abundances of white perch to cell-specific abundances of gizzard shad during each sampling period. We used non-parametric bootstrapping to estimate 95% confidence intervals about the correlation coefficients. This analysis was carried out in R version 3.0.1 (R Development Core Team 2013) with the package boot (Davison and Hinkley, 1997).



## Results

### Branched Oak Lake

In July 2013, white perch were distributed throughout the reservoir with the greatest abundances in the middle sections of the reservoir arms (Figure 3-2). In the north arm at this time, detection probability was relatively uniform in water with depths > 2 m, in the south arm, detection probability increased as we moved up the reservoir (Figure 3-3). Gizzard shad abundance was greatest in the mid-sections of the reservoir arms (Figure 3-4). Detection probability was greater in the north arm of the reservoir than in the south arm of the reservoir at this time (Figure 3-5). There was a positive correlation between site abundances of white perch and gizzard shad with a correlation coefficient of 0.94 (95% CI: 0.94 to 0.95).

In October 2013, most of the white perch in the north arm were near the middle of the arm and most of the white perch in the south arm were near the bottom of the arm or in the main basin of the reservoir (Figure 3-2). Detection probability in the north arm generally increased as we moved offshore and in the south arm increased as we moved up the reservoir arm (Figure 3-3). Gizzard shad abundance increased as we moved down the north arm of the reservoir, gizzard shad abundance was greatest in the upper portion of the south arm of the reservoir (Figure 3-4). Detection probability was greater in the north arm of the reservoir than in the south arm of the reservoir at this time (Figure 3-5). There was a positive correlation between site abundances of white perch and gizzard shad with a correlation coefficient of 0.53 (95% CI: 0.48 to 0.59).

In April 2014, white perch abundance was greatest in the middle and lower portions of the north arm and the creek channel in the south arm (Figure 3-2). Across the reservoir, detection probability was greater onshore than offshore (Figure 3-3). Gizzard shad abundance increased in the north arm of the reservoir as we moved down reservoir and was also high in the midsection of the south arm (Figure 3-4). Detection probability was uniform and low in the north arm of the reservoir and peaked in the bottom of the south arm and on shore in the south arm (Figure 3-5). There was a positive correlation between site abundances of white perch and gizzard shad with a correlation coefficient of 0.09 (95% CI: 0.03 to 0.14).

In July 2014, white perch were dispersed throughout the reservoir (Figure 3-2). Across the reservoir detection probability was uniform and low (Figure 3-3). Gizzard shad abundance increased in the north arm of the reservoir as we moved down reservoir and was also high in the midsection of the south arm (Figure 3-4). Detection probability was uniform and low in the north arm of the reservoir and peaked in the bottom of the south arm and on shore in the south arm (Figure 3-5). There was a positive correlation between site abundances of white perch and gizzard shad with a correlation coefficient of 0.23 (95% CI: 0.18 to 0.28).

In November 2014, white perch aggregated in the deeper portions of the north arm with numbers increasing from up reservoir to down reservoir and in the creek channel of the south arm (Figure 3-2). Detection probability increased slightly as we moved onshore in the north arm of the reservoir and increased as we moved offshore in

the south arm (Figure 3-3). Gizzard shad abundance increased in the north arm of the reservoir as we moved down reservoir and was also high in the midsection of the south arm (Figure 3-4). Detection probability was uniform and low in the north arm of the reservoir and peaked in the bottom of the south arm and on shore in the south arm (Figure 3-5). There was a negative correlation between site abundances of white perch and gizzard shad with a correlation coefficient of -0.27 (95% CI: -0.32 to -0.22).

### **Pawnee Reservoir**

In June 2013, white perch abundance was greatest in the midsection of the reservoir, but with large numbers of white perch also present in the lower portion of the reservoir (Figure 3-6). Detection probability was high and greatest in water >2 m deep (Figure 3-7). Gizzard shad abundance was greatest in the midsection of the reservoir (Figure 3-8). Detection probability was uniform and high (Figure 3-9). There was a positive correlation between site abundances of white perch and gizzard shad with a correlation coefficient of 0.95 (95% CI: 0.94 to 0.97).

In October 2013, white perch abundance was greatest near shore and in the upper portion of the reservoir (Figure 3-6). Detection probability increased as we moved offshore (Figure 3-7). Gizzard shad were still distributed throughout the reservoir (Figure 3-8). Detection probability increased with water depth (Figure 3-9). There was a significant positive correlation between site abundances of white perch and gizzard shad with a correlation coefficient of 0.45 (95% CI: 0.36 to 0.54).

In April of 2014, white perch abundance was greatest in the lower portion of the reservoir (Figure 3-6). Detection probability decreased as we moved offshore (Figure 3-7). In July of 2014, white perch were distributed throughout the reservoir with a few larger groups in the midsection of the reservoir (Figure 3-6). Detection probability decreased as we moved offshore (Figure 3-7). In October of 2014, white perch abundance was greatest in the midsection of the reservoir and near shore (Figure 3-6). Detection probability increased as we moved offshore (Figure 3-8). During 2014 no gizzard shad were sampled in Pawnee Reservoir.

## **Discussion**

As we hypothesized, there was a significant positive relationship in the spatial (within-waterbody) distributions of these two species. Both of these species occupy a wide range of habitats in other waterbodies so we would expect some overlap in their distributions. Further, we suspect that diets of these two species may have contributed to the relationship between their spatial distributions. Adult white perch consume benthic invertebrates, crustaceans, fish, and fish eggs in freshwater habitats (Zuerlein 1981; Schaeffer and Margraf 1987). In Branched Oak Lake and Pawnee Reservoir, Gosch et al. (2010) observed that white perch populations consume cladocera and diptera larvae year round and other items seasonally. Depending on fish size, food availability and population density, gizzard shad can either consume zooplankton or filter detritus (Maynard et al. 2002). Gizzard shad  $< 30$  mm total length consume zooplankton (Yako et al. 1996). Gizzard shad  $\geq 30$  mm will continue to consume zooplankton if population

density is low. If adult gizzard shad were consuming zooplankton in these systems, they would be using similar resources to white perch. This could result in a positive relationship between the distributions.

It is possible that the relationship we observed was in part influenced by our sampling scheme. Our sampling occurred over a relatively coarse spatial scale (sampling cells were 100 x 200 m for water > 2-m deep and were 50x50 m for water  $\leq$  2-m deep). It is possible within sampling cells that the distributions of white perch and gizzard shad related in a different manner. Also, our analysis did not assess the vertical distributions of the two species, it is possible that there was some vertical separation between the species. However, during our gillnet sampling, white perch and gizzard shad were frequently captured together. To understand how distributions are related at this smaller spatial scale, further sampling would be needed including telemetry for both species and an assessment of vertical distribution.

Detection probabilities for our models were quite variable and in Branched Oak Lake, this variability sometimes resulted in detection probabilities that differed between reservoir arms. The reason for these differences computationally was that separate models were fit for each arm. Variation in the count data input into the model determines detection probability, with higher variation leading to lower detection probability. Several factors could be causing differences in the variation of counts between the arms. One factor is fish movement within a sampling period. If there was non-random fish movement during a sampling period in one arm and not the other, this could lead to

differences in count variation and differences in detection probability. We suspect this was the case for the white perch model during fall 2014 (Figure 3-2). We sampled the north arm while white perch were moving down the reservoir and the south arm after they had finished moving leading to lower detection probabilities in the north arm than the south arm. Random variation in the counts could also lead to differences in detection probability between the reservoir arms. We suspect that this is the case for gizzard shad because they do not have strong associations with any of the habitat covariates we used as white perch did and because they are extremely mobile.

In addition to providing insight into how white perch and gizzard shad distributions overlap spatially, our research provides insight into how these species individually distribute at high abundances. For white perch, we also provide information on how they distribute in Midwestern waterbodies that they have invaded. These pieces of information can aid fisheries scientists in controlling these species by providing information on when and where control efforts should be targeted for each species to maximize the numbers of fish removed per unit effort. Further research on fine-scale distribution and resource partitioning between these two species would aid in our understanding of the ecology and management of superabundant fish populations. Also, other environmental variables that may influence white perch and gizzard shad spatial distributions should be explored such as wind speed, wind direction, boat activity, and vertical position in the water column. By exploring these variables we may be better able

to map the distributions of these species thereby improving our understanding of their ecology and our ability to manage them.

## References

- Barwick, D. H. 2004. Species richness and centrarchid abundance in littoral habitats of three southern U.S. reservoirs. *North American Journal of Fisheries Management* 24:76-81.
- Becker, G. C. 1983. *Fishes of Wisconsin*. The University of Wisconsin Press, Madison, Wisconsin.
- Dail, D., and L. Madsen. 2011. Models for estimating abundance from repeated counts of an open metapopulation. *Biometrics* 67:1-11.
- Davison, A. C., and D.V. Hinkley. 1997. *Bootstrap Methods and Their Applications*. Cambridge University Press, Cambridge, UK.
- ESRI, 2012. ArcGIS help library. ESRI, Redlands, California. Available: <http://help.arcgis.com/en/arcgisdesktop/10.0/help/> (February 2013).
- Fiske I., and R. Chandler. 2011. unmarked: an r package for fitting hierarchical models of wildlife occurrence and abundance. *Journal of Statistical Software*, 43(10), 1-23. Available: <http://www.jstatsoft.org/v43/i10/> (February 2014).
- Gosch, N. J. C., J. R. Stittle, and K. L. Pope. 2010. Food habits of stunted and non-stunted white perch *Morone Americana*. *Journal of Freshwater Ecology* 25:31-36.
- Jacobson, P. C., H. G. Stefan, and D. L. Pereira. 2002. Coldwater fish oxythermal habitat in Minnesota lakes: influence of total phosphorous, July air temperature, and relative depth. *Canadian Journal of Aquatic Science* 67:2002-2013.
- Lyons, J., L. Wang, and T. D. Simson. 1996. Development and validation of an index of biotic integrity for coldwater streams in Wisconsin. *North American Journal of Fisheries Management* 16:241-256.
- Maynard, H. S., M .J. Vanni, and T. E. Wissing. 2002. Biomass dependent diet shifts in omnivorous gizzard shad: implications for growth, food web, and ecosystem effects. *Transactions of the American Fisheries Society* 131:40-50.
- Morris, D. W. 1987. Density dependent habitat selection in a patchy environment. *Ecological Monographs* 57:269-281.
- R Development Core Team. 2013. R: a language for statistical computing, USA:R Foundation for Statistical Computing. Available: [www.R-project.org](http://www.R-project.org) (August 2013).



- Schaeffer, J. S., and F. J. Margraf. 1987. Predation on fish eggs by white perch, *Morone americana* in western Lake Erie. *Environmental Biology of Fishes* 18:77-80.
- Shepherd, T. D. and M. K. Litvak. 2004. Density-dependent habitat selection and the ideal free distribution in marine fish spatial dynamics: considerations and cautions. *Fish and Fisheries* 5:141-152.
- Werner, E. E., and D. J. Hall. 1976. Niche shifts in sunfishes: experimental evidence and significance. *Science* 191:404-406.
- Werner, E. E., and D. J. Hall. 1977. Competition and habitat shift in tow sunfishes (Centrarchidae). *Ecology* 58:869-876.
- Yako, L. A., J. M. Dettmers, and R. A. Stein. 1996. Feeding preferences of omnivorous gizzard shad as influenced by fish size and zooplankton density. *Transactions of the American Fisheries Society* 125:753-759.
- Zuerlein, G. 1981. The white perch in Nebraska. Nebraska Technical Series No. 8.

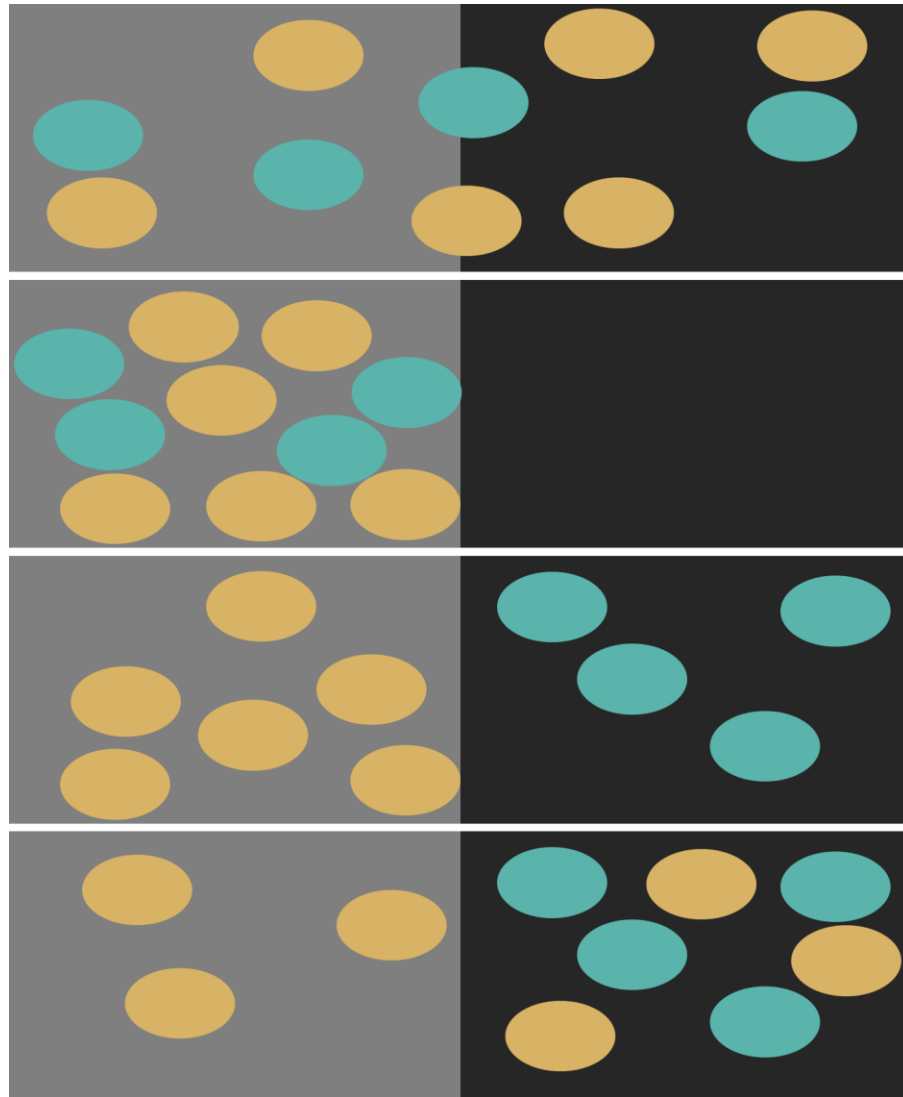


Figure 3-1. Conceptual models of hypothetical white perch ( ● ) and gizzard shad ( ● ) distributions in two habitats ( ■ and ■ ) within the same waterbody. The top panels represents no relationship between spatial distributions, the second panels represents both species sharing the same habitats, the third panels represents each species using different habitat, and the fourth panel represents white perch using all habitats and gizzard shad selecting one habitat.

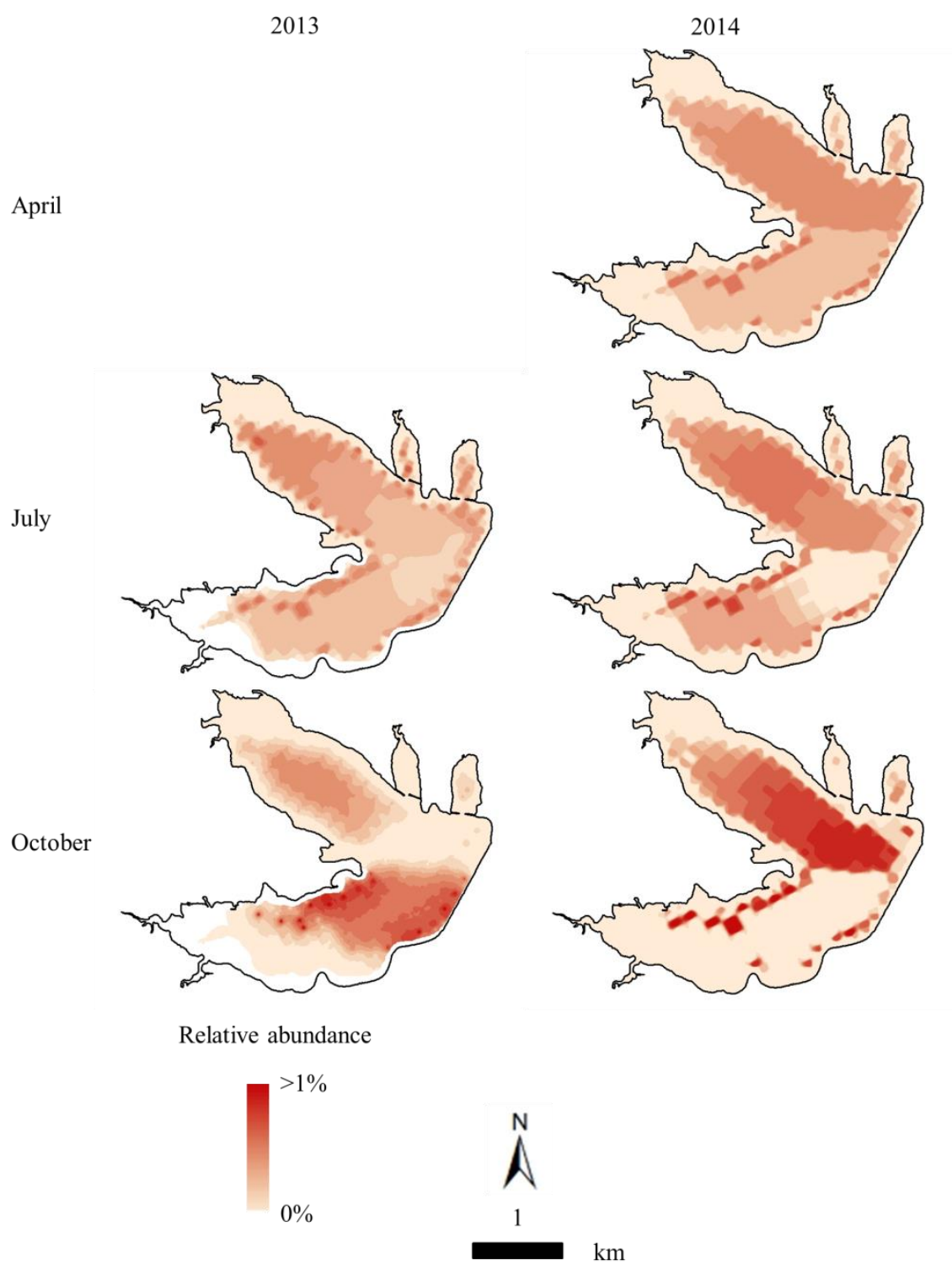


Figure 3-2. Estimates of white perch relative abundances (percent of population per sampling cell) in Branched Oak Lake, Nebraska. Data were collected during July and October of 2013 and during April, July, and October of 2014 with consumer-grade sonar, vertical gillnets, and a boat electrofisher and analyzed using generalized N-mixture models.

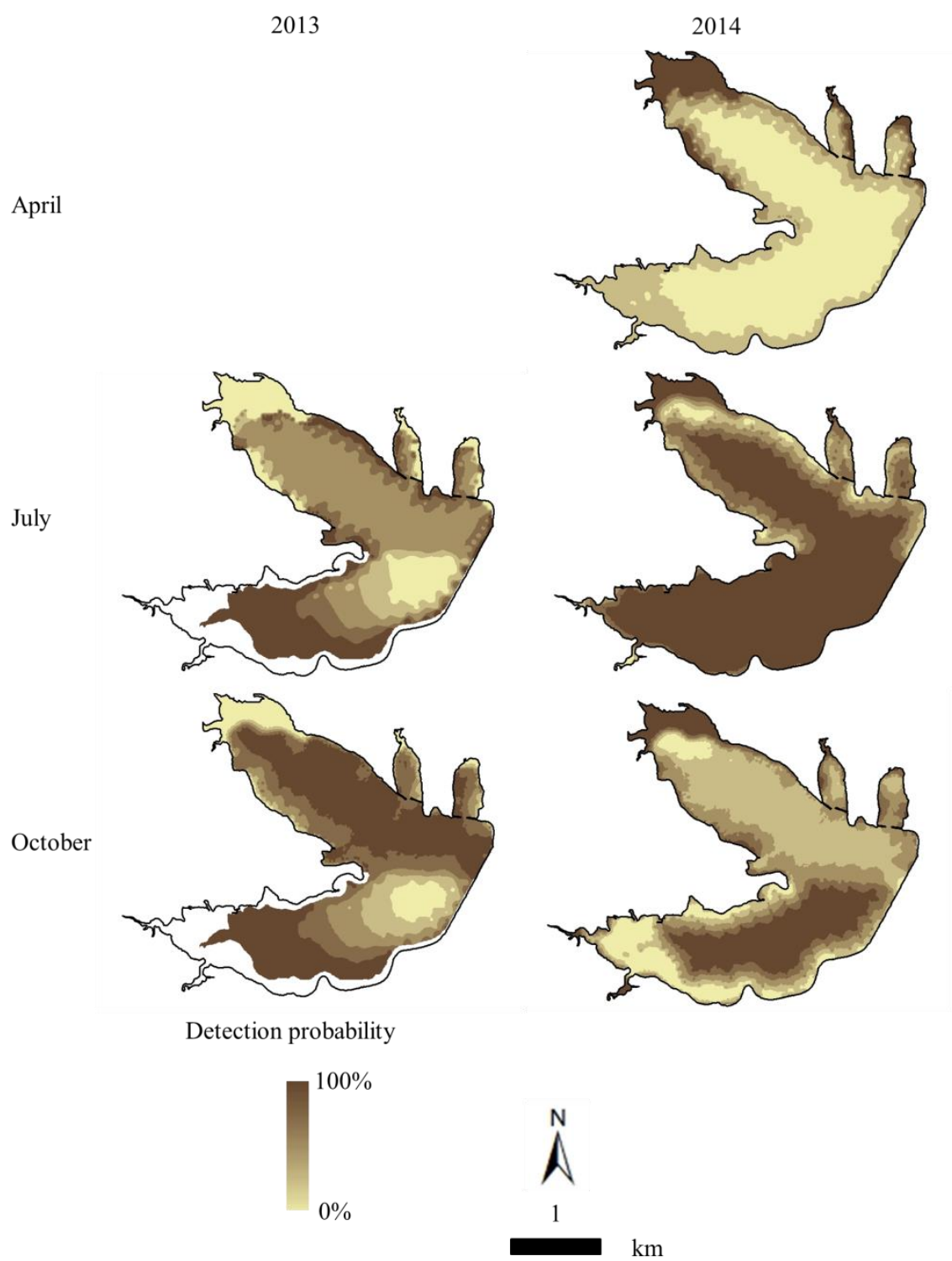


Figure 3-3. Estimates of white perch detection probability in Branched Oak Lake, Nebraska. Data were collected during July and October of 2013 and during April, July, and October of 2014 with consumer-grade sonar, vertical gillnets, and a boat electrofisher and analyzed using generalized N-mixture models.

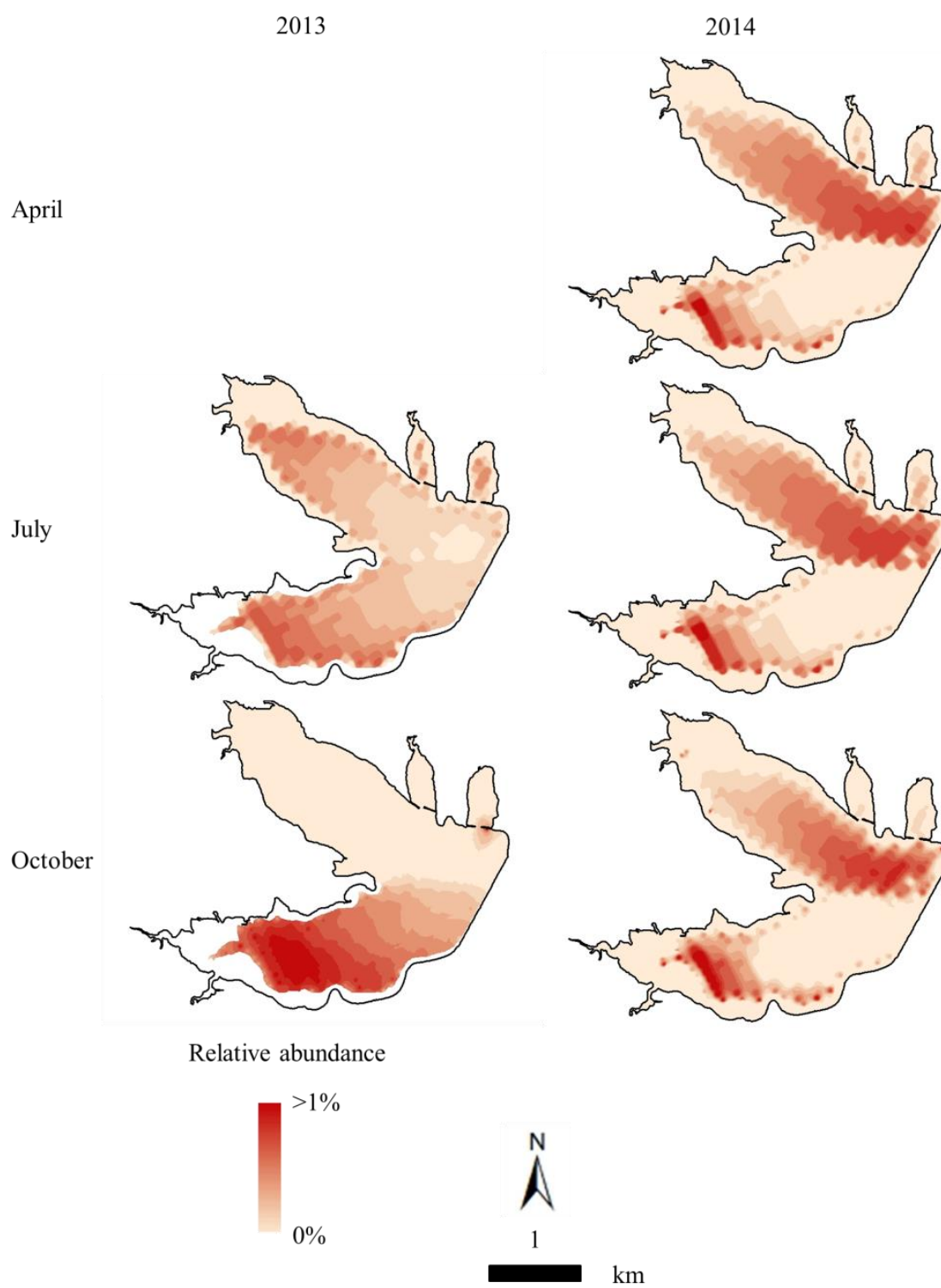


Figure 3-4. Estimates of gizzard shad relative abundances (percent of population per sampling cell) in Branched Oak Lake, Nebraska. Data were collected during July and October of 2013 and during April, July, and October of 2014 with consumer-grade sonar, vertical gillnets, and a boat electrofisher and analyzed using generalized N-mixture models.



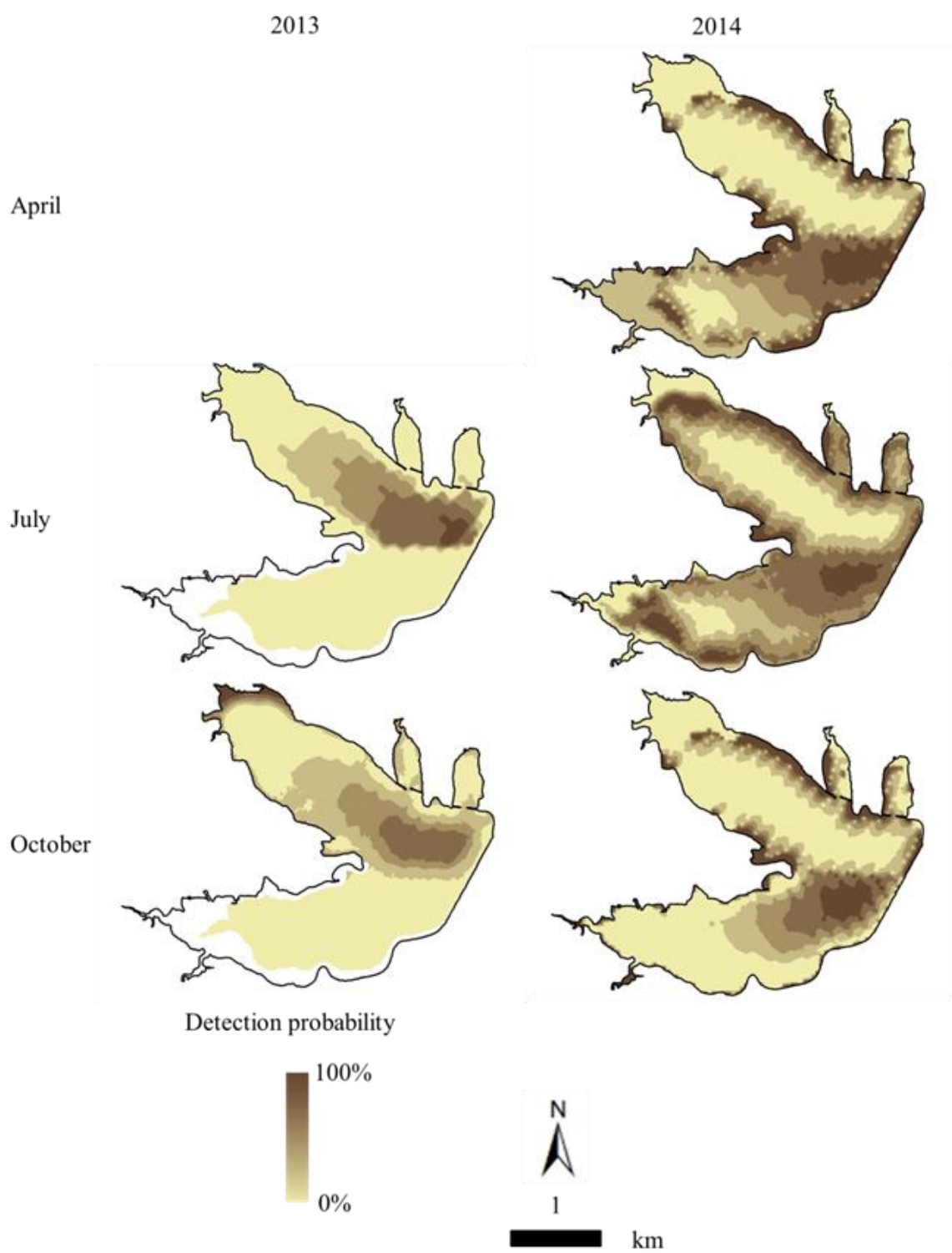


Figure 3-5. Estimates of gizzard shad detection probability in Branched Oak Lake, Nebraska. Data were collected during July and October of 2013 and during April, July, and October of 2014 with consumer-grade sonar, vertical gillnets, and a boat electrofisher and analyzed using generalized N-mixture models.

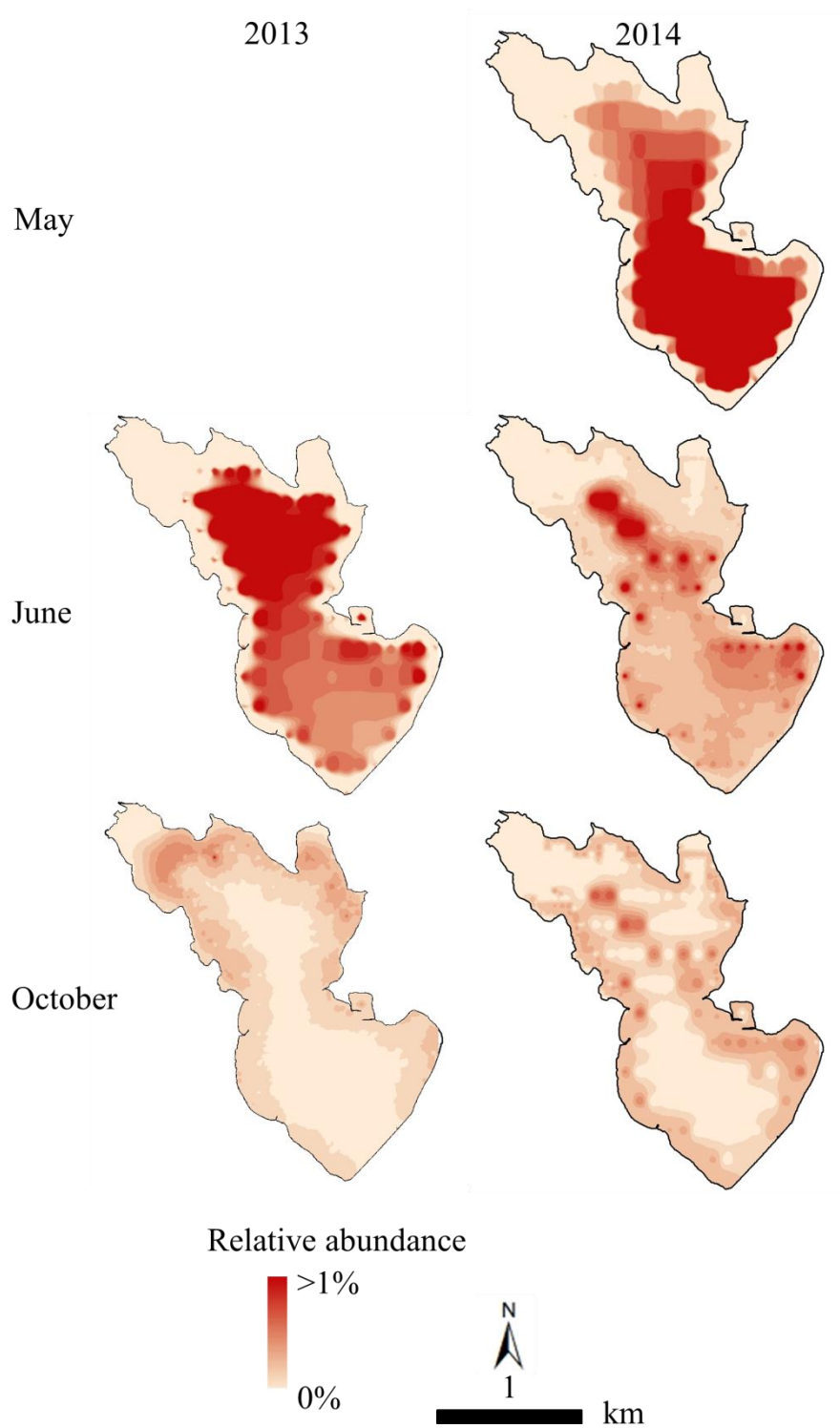


Figure 3-6. Estimates of white perch relative abundances (percent of population per sampling cell) in Pawnee Reservoir, Nebraska. Data were collected during June and October of 2013 and during May, June, and October of 2014 with consumer-grade sonar, vertical gillnets, and a boat electrofisher and analyzed using generalized N-mixture models.

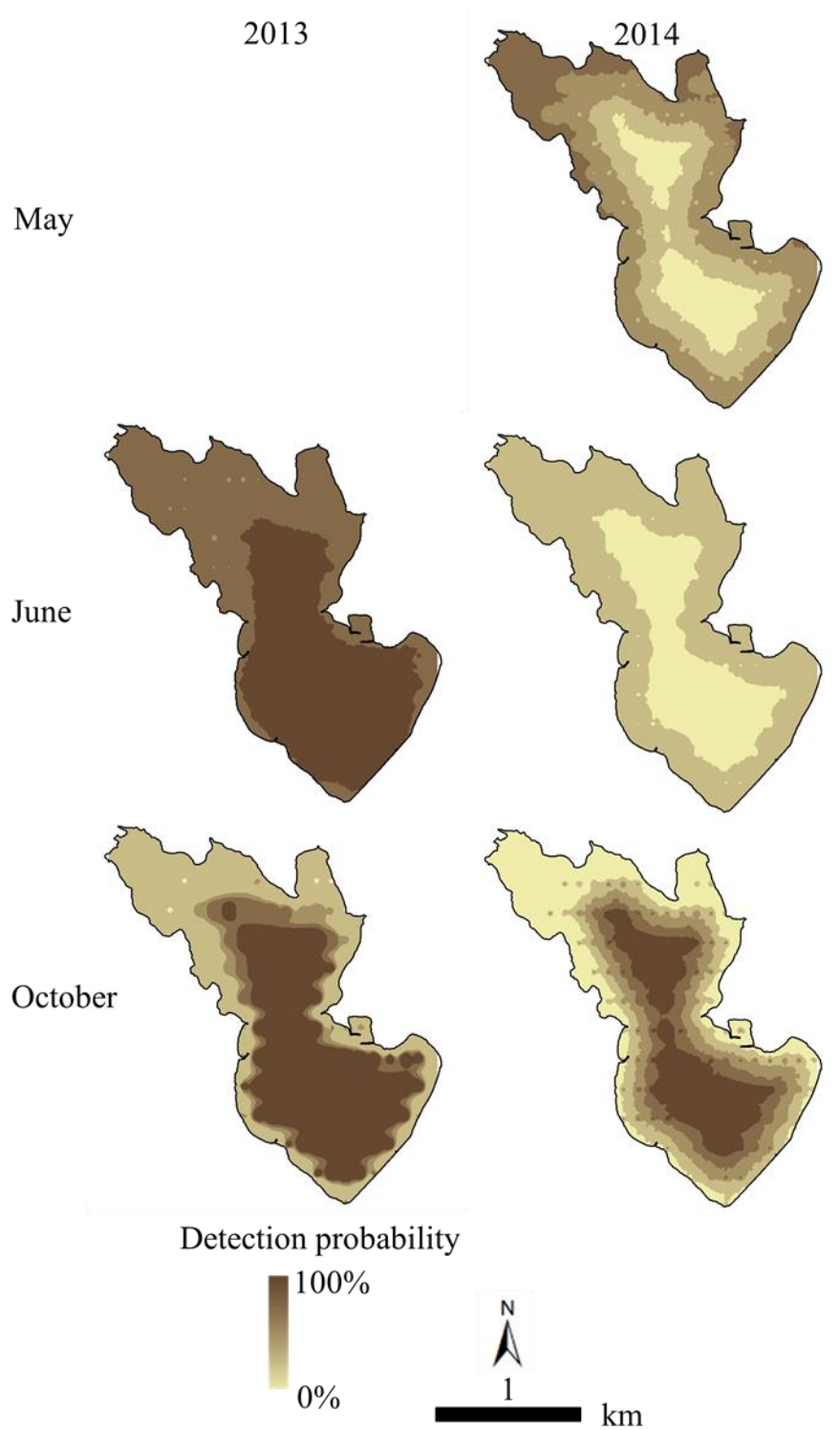


Figure 3-7. Estimates of white perch detection probability in Pawnee Reservoir, Nebraska. Data were collected during June and October of 2013 and during May, June, and October of 2014 with consumer-grade sonar, vertical gillnets, and a boat electrofisher and analyzed using generalized N-mixture models.

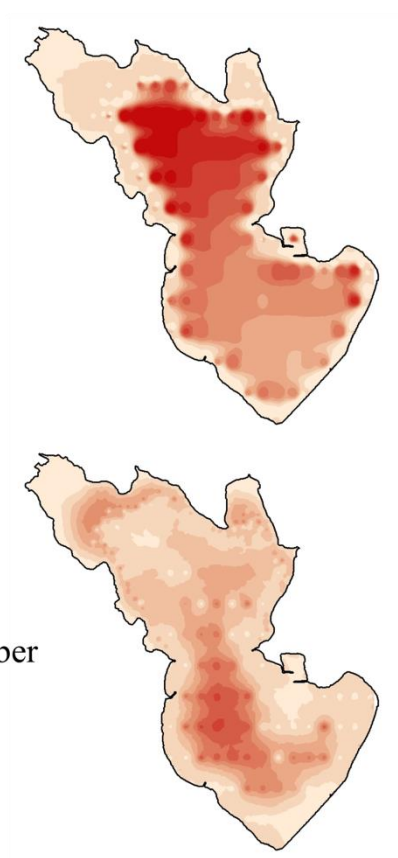
2013

2014

May

June

October



Relative abundance

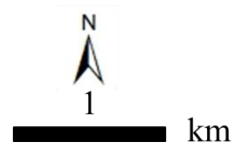
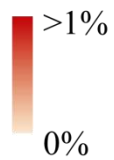


Figure 3-8. Estimates of gizzard shad relative abundances (percent of population per sampling cell) in Pawnee Reservoir, Nebraska. Data were collected during June and October of 2013 with consumer-grade sonar, vertical gillnets, and a boat electrofisher and analyzed using generalized N-mixture models.



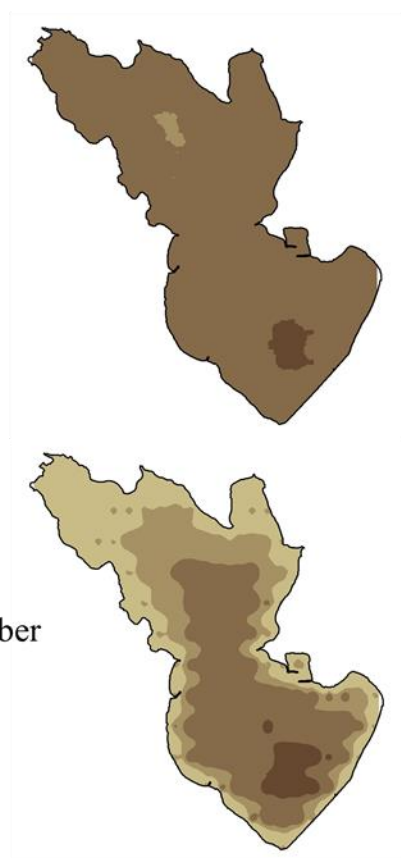
2013

2014

May

June

October



Detection probability

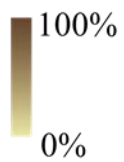


Figure 3-9. Estimates of gizzard shad detection probability in Pawnee Reservoir, Nebraska. Data were collected during June and October of 2013 with consumer-grade sonar, vertical gillnets, and a boat electrofisher and analyzed using generalized N-mixture models.

## Chapter 4. Controlling superabundant fish populations

The goal of managing superabundant fish populations, which we defined in chapter 2 is to minimize the effects they have on sportfish populations through predation and competition. To reach this goal, population size needs to be drastically reduced thereby restoring balance to the systems. A variety of methods have been used to reduce the abundances of nuisance fish populations, one of the most common is the application of the chemical rotenone to eradicate fish from the waterbody.

Rotenone, a plant derived toxin that inhibits aerobic respiration in organisms with gills, has been used to sample and control fish populations since the 1930s (Krumholz 1948). To sample with rotenone, fisheries scientists block off coves of waterbodies with nets, apply rotenone to the cove, and then collect the fish (Bettoli and Maceina 1996). When using rotenone to control fish populations, fisheries scientists generally apply sufficient concentrations ( $> 50 \mu\text{g/L}$ ) to kill all fish in a waterbody (Krumholz 1948; Bettoli and Maceina 1996). Toxicity of rotenone varies among species (Colle et al. 1978; Marking and Bills 1981; Amberg et al. 2012), and among life stages within a species (Libey and Allen 1980; Bills et al. 1988); application of a certain dosage may affect certain species more than others (Krumholz 1948; Colle et al. 1978; Wisener 2004) (Table 4-1). Fisheries scientists in Indiana have reduced gizzard shad (*Dorosoma cepedianum*) populations using rotenone doses of 5.0-6.5  $\mu\text{g/L}$  without eliminating the sportfish communities that included largemouth bass (*Micropterus salmoides*), bluegill (*Lepomis macrochirus*), yellow bass (*Morone mississippiensis*), and crappie (*Pomoxis*

*sp.*) from the waterbody (Wisener 2004). Fisheries scientists in Kentucky applied a rotenone dose of 5.0 µg/L to eliminate gizzard shad from Kentucky Lake without eliminating the fish community that included largemouth bass, bluegill, crappie, bullhead (*Ameiurue sp.*), and freshwater drum (*Aplodinotus grunniens*) (Bowers 1955). The effect of rotenone on fish is dependent on concentration and exposure time. In laboratory tests, white perch (*Morone americana*) mortality occurred in less time than white sucker (*Catostomus commersonii*), lake chub (*Couesius plumbeus*), and banded killifish (*Fundulus diaphanus*) at rotenone doses ranging from 6 to 60 µg/L (Smith 1940). In lab and field-tests rotenone doses as low as 2.5 µg/L were sufficient to kill white perch in soft-water (hardness 50 mg/L) ponds (Wujtewicz et al. 1997).

White perch is an invasive species in the Midwest of the U.S.A. where their populations can reach superabundant levels (Hergenrader and Bliss 1971; Zuerlien 1981; Hodkin 2001; Chapter 2). Researchers have linked declines in sportfish populations (Hergenrader and Bliss 1971; Wong et al. 1999; Harris 2006) to the establishment of white perch in Nebraska, North Carolina, and Virginia reservoirs. Harris (2006) documented a significant decline in white bass (*Morone chrysops*) relative abundance following the introduction of white perch in Kerr Reservoir, Virginia. Gosch (2008) documented diet overlap between white perch and juvenile sportfish such as walleye (*Sander vitreus*), largemouth bass, black and white crappie, and flathead catfish (*Pylodictis olivaris*) in two southeastern Nebraska flood-control reservoirs that may lead to competition. Schaffer and Margraf (1987) observed predation by white perch on

walleye and white bass eggs in Lake Erie tributaries and hypothesized that this predation could become problematic as white perch abundance increased. Madenjian et al. (2000) investigated declines in white bass catch-per-unit effort in Lake Erie due to a reduction in recruitment and concluded that the most probable cause of the reduction in recruitment was an increase in white perch abundance that resulted in greater predation on white bass eggs.

Fisheries managers with the Nebraska Game and Parks Commission are interested in increasing angler use by improving the sportfisheries in reservoirs with white perch and thus are seeking strategies to control white perch populations. Population models indicate that there needs to be a 90% reduction of the white perch biomass to increase white perch maximum size by 50%, this was the objective for control efforts (Chizinski et al. 2010). Previous attempts using predator management have met little success (Gosch 2008). One possible reason for this lack of success is the presence of gizzard shad in some reservoirs, which may serve as a preferred prey to introduced predators due to a lack of spines (Wahl and Stein 1988; Gosch 2008) and high caloric content (Pope et al. 2001).

The goal of this research project was to evaluate the effects of a low-dose-rotenone application intended to control white perch in a small Great Plains flood-control reservoir. The first objective was to estimate the proportion of the white perch biomass removed by the low-dose-rotenone application to determine if the application achieved the white-perch-biomass-reduction target of 90% (Chizinski et al. 2010) for eastern

Nebraska flood-control reservoirs. The second objective was to document potential mortality of non-target-fish species caused by the low-dose-rotenone application.

## **Methods**

### **Study Site**

Pawnee Reservoir is a 299-ha hypereutrophic flood-control reservoir located in the Salt Creek watershed 17 km west of Lincoln, Nebraska. The long axis of the reservoir was oriented generally north to south and winds keep the reservoir well mixed throughout most of the summer and autumn. Pawnee Reservoir had an estimated volume of 964 ha-m when at conservation pool in 2001 (NDEQ 2001). Pawnee Reservoir is the second largest waterbody in southeastern Nebraska, which along with the reservoir's proximity to the population centers of Lincoln and Omaha make this reservoir popular for water-based recreation. White perch, gizzard shad, and common carp (*Cyprinus carpio*) dominated the fish community in the reservoir. Other fish present in Pawnee Reservoir included walleye, freshwater drum, black crappie (*Pomoxis nigromaculatus*), white crappie (*Pomoxis annularis*), bluegill, green sunfish (*Lepomis cyanellus*), largemouth bass, channel catfish (*Ictalurus punctatus*), and flathead catfish (*Pylodictis olivaris*).

### **Application**

Fisheries managers applied rotenone on 13 November 2013, when the water temperature was 4.4° C. Managers selected this temperature because rotenone degrades slower at colder water temperatures (Siegler and Pillsbury 1946; Gilderhus et al. 1988;

Finlayson et al. 2000) and remained lethal to white perch for a longer period. Managers drew down the reservoir 0.6 m to a volume of 724 ha-m to reduce the quantity of rotenone needed in the application. During the two days prior to application, managers applied a full dose of rotenone ( $> 50$  mg/L) to 1.6 km of stream above the reservoir. Managers treated the stream in an attempt to eliminate any white perch that may have been present immediately above the reservoir and to eliminate this area as a possible refuge site. For the application on the reservoir itself, a concentration of  $6.0 \mu\text{g/L}$  was applied. In total managers applied 1317 L of 4.75% rotenone to the reservoir and inlet stream. The concentrated rotenone was diluted prior to application to the waterbody by combining approximately 11 L of rotenone solution with 462 L of reservoir water in tanks. Managers further diluted the chemical using a venturi system to pump the chemical from the tanks into the water. Following the application managers collected a water sample and it was analyzed to determine the actual concentration of rotenone applied.

### **Abundance estimation and analysis**

We estimated white perch and gizzard shad abundances and biomasses prior to and following the application of rotenone to evaluate the effectiveness of the treatment. We used the same data collection methods and analyses as described in chapter 2 to estimate abundance. Briefly, we input data collected using a consumer-grade sonar unit, vertical gillnets, and a boat electrofisher into generalized N-mixture models to estimate site-specific abundance for both species. We then totaled the site specific abundance

estimates to get total abundance. We estimated biomass by multiplying the mean mass of fish captured by the total abundance. We estimated pre-application abundance and biomass based on data collected during summer and fall 2013 and we estimated post-application estimates based on data collected during the spring, summer, and fall 2014. During 2013, sampling took place between June 17 and October 17 with sampling periods beginning on June 17, July 25, September 9, and October 8. During 2014, sampling took place between May 2 and October 10 with sampling periods beginning May 2, May 14, May 21, June 20, September 18, and October 7.

### **Non-target effects**

We randomly selected seven 10-m segments in areas of the shoreline that we could access on foot. On each segment, we collected all fish on the shore and within 2 m of shore. Once we collected the fish, we identified them to species and counted the number of each species present. We removed fish from the area and marked them by slicing the stomachs to prevent double counting. We collected these data 2, 3, 5, and 7 days after the application. The nature of the data collected, particularly the lack of available pre-rotenone population estimates for species other than white perch and gizzard shad, prevented us from estimating mortality rates. However, we used these data to describe the species affected by the rotenone and the time it took to observe the effects. For the purposes of this study, we treated the data as observational when we used it to assess what non-target species experienced mortality because of the low-dose-rotenone application.



## Results

The top models for the sonar sampling data and for the electrofishing data to estimate white perch abundance and biomass prior to the rotenone application both had 100% of the AIC weights (Table 4-2). The top model for sonar sampling included water depth and sampling period as covariates (Table 4-3). The top model for electrofishing included water depth, shore habitat, and period as covariates (Table 4-4). Prior to the application of the rotenone, we estimated that there were 1,589,537 (1,487,757–1,691,317) white perch present in the reservoir. White perch captured during this sampling had a mean mass of 28 g (14 – 41 g). Based on the population abundance and individual masses, we estimate that there was 43,712 kg (22,162– 65,263 kg; 74– 218 kg/ha) of white perch present in Pawnee Reservoir.

The top models for the sonar sampling data and for the electrofishing data to estimate white perch abundance and biomass following the rotenone application both had 100% of the AIC weights (Table 4-2). The top model for sonar sampling included water depth, bottom slope, and sampling period as covariates (Table 4-5). The top model for electrofishing included water depth, shore habitat, and period as covariates (Table 4-6). During spring following application, we estimated the white perch population size to be 273,105 (232,751– 313,459). Individuals captured during this sampling had mass of 28 g (17 – 39 g). We estimated that following the rotenone application the total biomass of white perch was 7,641kg (4,354– 10,929 kg; 15 – 37 kg/ha). We estimated that a total of 36,071 kg of white perch were eliminated by the low-dose-rotenone application.

The top model for the sonar sampling data to estimate gizzard shad abundance prior to the rotenone application had 100% of the AIC weight and the top model for electrofishing data had 60% of the AIC weight (Table 4-7). The top model for the sonar sampling data included water depth, bottom slope, and sampling period as covariates (Table 4-8). The top model for electrofishing data also included water depth, bottom slope, and sampling period as covariates (Table 4-9). Prior to the rotenone application, we estimated the gizzard shad total abundance to be 638,819 (593,202– 684,435) individuals with a mean mass of 47 g (16 – 79 g). The total biomass estimate was 30,331 kg (10,391– 50,271 kg; 35 – 168 kg/ha). Following the application, we did not sample any gizzard shad, so our estimates of gizzard shad abundance and biomass were 0. However, the Nebraska Game and Parks Commission did capture six gizzard shad during fall 2014 electrofishing surveys. Based on this information, either gizzard shad were not extirpated from the waterbody by the application or they were extirpated and then recolonized following the application; in either case, the low-dose-rotenone application nearly eliminated gizzard shad from Pawnee Reservoir.

### **Non-target effects**

We observed 10 species in counts on days 2, 3, 5, and 7 (Table 4-10). The most common species observed during this period were common carp, freshwater drum, and white crappie. In addition to fish mortality, we observed large numbers of dead chironomids washed up on the shoreline, while conducting shoreline counts of dead fish.

## Discussion

The goal of managing superabundant fish populations is to minimize the effects on desirable fish populations by controlling the size of the superabundant fish population. The low-dose rotenone application in Pawnee Reservoir lead to a large reduction (83%) in the white perch population biomass. This reduction was similar to the biomass-removal target of 90% as prescribed by Chizinski et al. (2010). The estimates from Chizinski et al. (2010) predicted that a reduction of this magnitude would increase white perch maximum size by 50%. We observed an increase in the mean length of white perch captured from  $132 \pm 2$  mm in September of 2013 to  $195 \pm 4$  mm (47% increase) in September 2014 (Figure 1). The removal target assumed no reduction in gizzard shad abundance; the application nearly extirpated gizzard shad from the waterbody. A biomass reduction that falls slightly short of the 90% target for white perch accompanied by substantial reductions in gizzard shad biomass may lead to 50% increases in maximum length of white perch in Branched Oak Lake given that gizzard shad may have competed with white perch or served as an alternate prey source for predators in the system (Gosch 2008).

We did observe mortality of non-target species, but the application did not eliminate the sportfish community from the reservoir. Some of the species for which we documented mortality, such as common carp, have rotenone tolerances well below the applied concentration of  $6.0 \mu\text{g/L}$  (Table 4-1), but were not eliminated from the reservoir. Other species, such as black bullhead (*Ameiurus melas*), that have tolerances well above

the applied concentrations also experienced some mortality following the application (Tables 4-1 and 4-10). This means that for the species with lower tolerances, we did not apply a concentration great enough to cause 100% mortality and for the species with higher tolerances that the dose was high enough to cause some mortality. This highlights the challenge in selecting a dose that effects the target species without causing mortality on non-target species.

The low-dose-rotenone application on Pawnee Reservoir reduced white perch abundance, but did not eliminate them from the waterbody. In the future, the white perch population in Pawnee Reservoir may become superabundant again necessitating future management actions to reduce white perch population size. Low-effort-control methods such as predator stocking may lengthen the time before managers need to take further actions. Fisheries scientists need to define measureable action thresholds such as growth and catch-per-unit effort values. When white perch populations reach these action thresholds, management actions to reduce white perch abundance need to be taken. Monitoring on Pawnee Reservoir should focus on determining where the population is in relation to these action thresholds.

When planning a low-dose-rotenone application fisheries scientists need to consider the toxicity of rotenone to both target and non-target species. There are toxicities published for a variety of fish species (Table 4-1). However, many species do not have published toxicities and thus require further research to determine the toxicity of rotenone to these species. Generally, the toxicity reported in the literature is the LC 50,

which is the concentration that will kill 50% of the populations in a specified time; often these values are reported with temperature, water hardness, or pH all of, which may have an effect on toxicity (Meadows 1973; Marking and Bills 1976; Wujtewicz et al. 1997). Fisheries scientists will want to apply a concentration that kills the entire target species (LC 100) so will need to apply a dose greater than LC 50. Future research on toxicity of rotenone should report LC 99 or LC 100 values in addition to LC 50 values because LC 99 and LC 100 values are more applicable to the use of rotenone. Ideally, fisheries scientists will be able to select a toxicity that affects the target species without affecting the non-target species; however, it is unlikely that managers will be able to find a concentration that results in 100% mortality of the target species with no mortality of non-target species. For example, to achieve 100% mortality of grass carp in a Florida Lake, the concentration applied resulted of 40% mortality in largemouth bass (Figure 4-2) (Colle et al. 1978).

Managers attempting to apply this technique need to take into account logistical constraints. Mixing and uniform application are important considerations for any rotenone treatment (Krumholz 1948). With low-dose-rotenone applications, these considerations are even more important because of the small amounts being applied. Rotenone applied on the water's surface can penetrate to between 4.6 and 7.6 m if there is no stratification (Foye 1956). Meaning that if there is stratification or if the waterbody is deeper than 7.6 m rotenone will need to be pumped down into the water column in order to get a uniform application.

Fisheries scientists also need to consider season when planning low-dose applications. As water temperature increases so does the detoxification rate of rotenone (Siegler and Pillsbury 1946; Gilderhus et al. 1988; Finlayson et al. 2000). In the case of low-dose-rotenone applications, fisheries scientists need to consider the exposure time in addition to the concentration applied. As exposure time increases, the lethal concentration decreases. For example, 3 h LC 50 for green sunfish is  $19.45 \pm 1.45$   $\mu\text{g/L}$  as compared to the 96 h LC 50 of  $7.05 \pm 0.69$   $\mu\text{g/L}$  (Figure 4-3) (Marking and Bills 1976). If fisheries scientists apply at lower water temperatures, they can use a lower dose because exposure time increases. If fisheries scientists apply rotenone at a higher water temperature, they will need to apply a higher dose because the rotenone will detoxify quicker and exposure time will be shorter.

The development of tolerance to rotenone is something that fisheries scientists need to consider if prior applications have occurred in a waterbody. Rotenone is also a pesticide used in agriculture, and agricultural pests such as Mexican bean beetle (*Epilachna varivestis*) can become resistant to rotenone after repeated application (Brett and Brubaker 1955). Fish can develop resistance to heavy metal pollution such as has been observed with methyl mercury and killifish (*Fundulus heteroclitus*) in several New York creeks (Weis et al. 1981). Researchers have also documented resistance to rotenone in a number of fish species. Orciari (1979) observed up to 7-fold increases in rotenone tolerance of golden shiner (*Notemigonus crysoleucas*) from a pond that managers had treated with rotenone six times when compared to golden shiner from untreated ponds

(Figure 4-4). Orciari (1979) also observed approximately a two-fold increase in rotenone tolerance when comparing golden shiner from a pond that managers had treated once to golden shiner from untreated ponds (Figure 4-4). In Mississippi, researchers discovered resistant populations of mosquito fish (*Gambusia affinis*) that had twice the tolerance for rotenone compared to non-resistant populations. The researchers suspected that these populations developed resistance to rotenone following exposure to organochlorine insecticides (Fabacher 1972). If the initial low-dose rotenone application does not eradicate the targeted population, future applications may need to be at increasingly greater concentrations and the effects on non-target species may change if different species develop tolerances at different rates. Further research on the development of rotenone resistance in fish and whether this resistance differs by species should be conducted before low-dose rotenone applications are carried out on a large scale.

Based on our assessment, low doses of rotenone applied to reservoirs may be an effective method for reducing abundance of white perch or other superabundant fish, depending on rotenone tolerance. Low doses of rotenone however, are unlikely to be a one-time solution to superabundant fish populations and may ultimately lead to rotenone resistant fish. In our case, we did not eliminate white perch from the waterbody; thus, population monitoring needs to continue and managers will likely need to take further actions to control abundance in the future. To allow for use of this management technique to control other superabundant populations, managers need further information on the chemical tolerances of other species.

## References

- Amberg, J. J., T. M. Schreier, and M. P. Gaikowski. 2012. Molecular responses differ between sensitive silver carp and tolerant bighead carp and bigmouth buffalo exposed to rotenone. *Fish Physiology and Biochemistry* 38:1379-1391.
- Becker, G. C. 1983. *Fishes of Wisconsin*. The University of Wisconsin Press, Madison, Wisconsin.
- Bettoli, P. W., and M. J. Maceina. 1996. Sampling with toxicants. Pages 303-333 in B. R. Murphy, and D. W. Willis, editors. *Fisheries techniques*, 2nd edition. American Fisheries Society, Bethesda, Maryland.
- Bills, T. F., J. J. Rach, and L. L. Marking. 1988. Toxicity of rotenone to developing rainbow trout. U.S. Fish and Wildlife Service, Investigations in fish control 93, Washington, D.C.
- Bowers, C. C. 1955. Selective poisoning of gizzard shad with rotenone. *The Progressive Fish -Culturist* 17:134-135.
- Brett, C. H. and R. W. Brubaker. 1955. Rotenone resistance in the Mexican bean beetle. *Journal of Economic Entomology* 48:343.
- Chizinski, C. J., K. L. Pope, G. R. Wilde. 2010. A modeling approach to evaluate potential management actions designed to increase growth of white perch in a high-density population. *Fisheries Management and Ecology* 17:262-271.
- Colle, D. E., J. V. Shireman, R. D. Gasaway, R. L. Stetler, and W. T. Haller. 1978. Utilization of selective removal of grass carp (*Ctenopharyngodon idella*) from and 80-hectare Florida lake to obtain a population estimate. *Transactions of the American Fisheries Society* 107:724-729.
- Fabacher, D. L. 1972. Rotenone tolerance in mosquitofish. *Environmental Pollution*. 3:139-141.
- Finlayson, B. J., R. A. Schnick, R. L. Cailteux, L. DeMong, W. D. Horton, W. McClay, C. W. Thompson, and G. W. Tichacek. 2000. Rotenone use in fisheries management: administrative and technical guidelines manual. American Fisheries Society, Bethesda, Maryland.
- Foye, R. E. 1956. Reclamation of potential trout ponds in Maine. *The Journal of Wildlife Management* 20:389-398.



- Gilderhus, P. A., V. K. Dawson, and J. L. Allen. 1988. Deposition and persistence of rotenone in shallow ponds during cold and warm seasons. U.S. Fish and Wildlife Service, Investigations in fish control 95, Washington, D.C.
- Gosch, N. J. C. 2008. Predation as a mechanism for the control of white perch: an investigation of food habits in two Nebraska reservoirs. Master's thesis. University of Nebraska Lincoln.
- Harris, J. L. 2006. Impacts of the invasive white perch on fish assemblage of Kerr Reservoir, Virginia. Master's Thesis. Virginia Polytechnic Institute and State University, Blacksburg.
- Hergenrader, G. L., and Q. P. Bliss. 1971. The white perch in Nebraska. Transactions of the American Fisheries Society 100:734-738.
- Hodkin, C. E. 2001. Population characteristics and food habits of white perch (*Morone americana*) in Branched Oak Lake, Nebraska. Master's Thesis. University of Nebraska Lincoln.
- Krumholz, L. A. 1948. The use of rotenone in fisheries research. The Journal of Wildlife Management 12:305-317.
- Lazur, A., S. Early, J. M. Jacobs. 2006. Acute toxicity of 5% rotenone to northern snakehead. North American Journal of Fisheries Management 26:628-630.
- Libey G. S., and L. E. Holland. 1980. The use of periodic light applications of rotenone as a management technique for small impoundments. Purdue University Water Resources Research Center. Technical Report 132. West Lafayette, Indiana.
- Madenjian, C. P., R. L. Knight, M. T. Bur, and J. L. Forney. 2000. Reduction in recruitment of white bass in Lake Erie after invasion of white perch. Transactions of the American Fisheries Society 129:1340-1353.
- Marking, L. L., and T. D. Bills. 1976. Toxicity of rotenone to fish in standardized laboratory tests. United States Department of the Interior Fish and Wildlife Service. Investigations in Fish Control 72. Washington D.C.
- Marking, L. L., and T. D. Bills. 1981. Sensitivity of four carp to selected fish toxicants. North American Journal of Fisheries Management 1:51-54.
- Meadows, B. S. 1973. Toxicity of rotenone to some species of coarse fish and invertebrates. Journal of Fish Biology 5:155-163.
- NDEQ (Nebraska Department of Environmental Quality). 2001. Total maximum daily load for Pawnee Reservoir-Lancaster County, Nebraska. Nebraska Department of Environmental Quality, Lincoln.

- Orciari, R. D. 1979. Rotenone resistance of golden shiners from a periodically reclaimed pond. *Transactions of the American Fisheries Society* 108:641-645.
- Pope, K. L., M. L. Brown, W. G. Duffy, and P. H. Michaletz. 2001. A caloric-based evaluation of diet indices for largemouth bass. *Environmental Biology of Fishes* 61:329-339.
- Schaeffer, J. S., and F. J. Margraf. 1987. Predation on fish eggs by white perch, *Morone americana* in western Lake Erie. *Environmental Biology of Fishes* 18:77-80.
- Siegler, H. R., and H. W. Pillsbury. 1946. Use of derris to reclaim ponds for game fish. *The Journal of Wildlife Management* 10:308-316.
- Smith, M. W. 1940. Copper sulfate and rotenone as fish poisons. *Transactions of the American Fisheries Society* 69:141-157.
- Wahl, D. H., and R. A. Stein. 1988. Selective predation by three esocids: the role of prey behavior and morphology. *Transactions of the American Fisheries Society* 117:142-152.
- Weis, J. S., P. Weis, M. Heber, and S. Vaidya. 1981. Methylmercury tolerance of killifish (*Fundulus heteroclitus*) embryos from a polluted vs non-polluted environment. *Marine Biology* 65:283-287.
- Wisner, R. J. 2004. Glenn Flint Lake gizzard shad selective 2004 fish management report. Fisheries Section Indiana Department of Natural Resources Division of Fish and Wildlife.
- Wong, R. K., R. L. Noble, J. R. Jackson, and S. V. Horn. 1999. white perch invasion of B. Everett Jordan Reservoir, North Carolina. *Proceedings of the Annual Conference of Southeastern Association of Fish and Wildlife Agencies* 52:162-169.
- Wujtewicz, D., B. R. Petrosky, D.L. Petrosky. 1997. Acute toxicity of 5% non-synergized emulsifiable rotenone to white river crayfish *Procambarus acutus* and white perch *Morone americana*. *Journal of the World Aquaculture Society* 28:249-259.
- Zuerlein, G. 1981. The white perch in Nebraska. Nebraska Technical Series No. 8, Lincoln.

Table 4-1. Species-specific rotenone toxicity estimates with standard error if available as reported in the literature; (\* rough estimates of LC 100).

Species	Temperature (C°)	LC 50 (µg/L)					Source
		1 h	3 h	6 h	24 h	96 h	
Crucian carp ( <i>Carassius carassius</i> )	11	-	-	-	360.00 (-)	-	Meadows 1973
Goldfish ( <i>Carassius auratus</i> )	12	-	-	-	-	24.85 (2.17)	Marking and Bills 1976
Black bullhead ( <i>Ameiurus melas</i> )	12	-	-	-	33.25 (3.80)	19.45 (2.32)	Marking and Bills 1976
Juvenile northern snakehead ( <i>Channa argus</i> )	24	-	-	-	<75.00 (-)	-	Lazur et al. 2006
Channel catfish ( <i>Ictalurus punctatus</i> )	12	-	70.50 (6.91)	42.00 (3.14)	20.00 (4.23)	8.20 (0.66)	Marking and Bills 1976
Roach ( <i>Rutilus rutilus</i> )	10	-	-	40.00 (-)	-	-	Meadows 1973
Fathead minnow ( <i>Pimephales promelas</i> )	12	-	-	59.50 (6.96)	20.00 (2.78)	7.10 (0.69)	Marking and Bills 1976
Mosquito fish ( <i>Gambusia affinis</i> )	-	-	-	-	17.00 (-)	-	Fabacher 1972
Green sunfish ( <i>Lepomis cyanellus</i> )	12	-	19.45 (1.45)	16.60 (2.12)	10.90 (0.54)	7.05 (0.69)	Marking and Bills 1976
Largemouth bass ( <i>Micropterus salmoides</i> )	12	-	25.70 (1.66)	18.00 (1.40)	10.00 (1.76)	7.10 (0.69)	Marking and Bills 1976
White perch ( <i>Morone americana</i> )	-	-	-	-	<7.50 (-)	-	Wujewicz et al. 1997
Bluegill ( <i>Lepomis macrochirus</i> )	12	-	21.20 (2.27)	16.80 (2.32)	7.45 (0.64)	7.05 (0.20)	Marking and Bills 1976
Grass carp ( <i>Ctenopharyngodon idella</i> )	12	-	-	-	-	4.26 (0.23)	Marking and Bills 1981
Smallmouth bass ( <i>Micropterus dolomieu</i> )	12	-	13.85 (1.48)	8.25 (-)	4.66 (0.20)	3.95 (0.21)	Marking and Bills 1976
Yellow perch ( <i>Perca flavescens</i> )	12	-	7.50 (0.61)	6.70 (0.36)	4.60 (0.30)	3.50 (0.26)	Marking and Bills 1976
Common carp ( <i>Cyprinus carpio</i> )	12	-	-	13.50 (0.41)	4.20 (0.23)	2.50 (0.22)	Marking and Bills 1976
White sucker ( <i>Catostomus commersoni</i> )	12	-	31.50 (4.54)	11.90 (1.33)	3.60 (0.20)	3.40 (0.36)	Marking and Bills 1976
Coho salmon ( <i>Oncorhynchus kisutch</i> )	12	-	17.90 (-)	7.60 (1.20)	3.58 (0.21)	3.10 (0.18)	Marking and Bills 1976
Golden shiner ( <i>Notemigonus crysoleucas</i> )	20	-	-	-	3.51 (0.24)	-	Orciari 1979
Rainbow trout ( <i>Oncorhynchus mykiss</i> )	12	-	8.75 (0.38)	4.35 (-)	3.45 (0.33)	2.30 (0.34)	Marking and Bills 1976
Longnose sucker ( <i>Catostomus catostomus</i> )	12	-	19.40 (1.43)	10.90 (1.96)	3.36 (0.39)	2.85 (0.13)	Marking and Bills 1976
Silver carp ( <i>Hypophthalmichthys molitrix</i> )	12	-	-	-	-	2.79 (0.43)	Marking and Bills 1981
Chinook salmon ( <i>Oncorhynchus tshawytsch</i> )	12	-	10.60 (1.05)	7.80 (0.48)	2.45 (0.12)	1.85 (0.08)	Marking and Bills 1976
Bowfin ( <i>Amia calva</i> )	12	-	7.05 (0.69)	5.30 (0.60)	2.88 (0.18)	1.50 (0.16)	Marking and Bills 1976
Brook trout ( <i>Salvelinus fontinalis</i> )	12	-	7.05 (0.43)	3.99 (0.27)	2.35 (0.12)	2.22 (0.08)	Marking and Bills 1976
Bighead carp ( <i>Hypophthalmichthys nobilis</i> )	12	-	-	-	-	2.19 (0.22)	Marking and Bills 1981
Northern Pike ( <i>Esox lucius</i> )	12	-	9.05 (0.54)	2.91 (0.14)	2.25 (0.35)	1.65 (0.16)	Marking and Bills 1976
Lake trout ( <i>Salvelinus namaycush</i> )	12	-	2.50 (0.29)	1.42 (0.19)	1.35 (0.18)	1.35 (0.18)	Marking and Bills 1976
Atlantic salmon ( <i>Salmo salar</i> )	12	-	3.08 (0.21)	2.00 (0.16)	1.75 (0.13)	1.08 (0.15)	Marking and Bills 1976
Walleye ( <i>Sander vitreus</i> )	12	-	6.75 (0.82)	2.62 (0.14)	0.83 (0.04)	-	Marking and Bills 1976
Rudd ( <i>Scardinius erythrophthalmus</i> )	20	125.00 (-)	-	-	-	-	Meadows 1973
Gudgeon ( <i>Gobio gobio</i> )	20	25.00 (-)	-	-	-	-	Meadows 1973

Table 4-2. Generalized N-mixture models ranked with AIC used to model white perch abundance on Pawnee Reservoir, Nebraska prior to (pre) and following (post) a low-dose rotenone treatment during November 2013 (K: number of model parameters, AIC: Akaike Information Criterion score,  $\Delta$ AIC: difference between AIC score for the specified model and for the top model, AICwt: AIC weight, cumwt: cumulative AIC weight). Count data were collected with a consumer grade sonar unit used in conjunction with vertically set gillnets (SN) in waters with total depths  $\geq 2$  m and a boat electrofisher (EF) used to electrify points in water with total depths  $< 2$  m. In each model,  $\lambda$  is abundance,  $\gamma$  is recruitment,  $\Omega$  is apparent survival, and p is detection probability. The covariates in the models are depth (D), slope (S), sampling period (P), and shoreline habitat (H).

Period	Gear	Model	K	AIC	$\Delta$ AIC	AICwt	cumwt
Pre	SN	$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: D	20	1468	0	1.00	1.00
		$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: D	17	1607	139	0.00	1.00
		$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: P	19	1741	273	0.00	1.00
		$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1	5	2729	1261	0.00	1.00
	EF	$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: D*P	23	838	0	1.00	1.00
		$\lambda$ : S, $\gamma$ : S+P, $\Omega$ : S+P, p: P	15	921	83	0.00	1.00
		$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1	5	1098	260	0.00	1.00
Post	SN	$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: P	32	1070	0	1.00	1.00
		$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: D	25	1128	58	0.00	1.00
		$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: P	29	1146	76	0.00	1.00
		$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: D	28	1210	140	0.00	1.00
		$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1	5	2569	1499	0.00	1.00
	EF	$\lambda$ : S, $\gamma$ : S+P, $\Omega$ : S+P, p: P	21	341	0	1.00	1.00
		$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1	5	360	19	0.00	1.00

Table 4-3. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass in Pawnee Reservoir, Nebraska during 2013. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: June 17, category B: July 25, category C: September 9, category D: October 8). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model.

Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 1.56	0.14	- 11.34	<0.001
	Depth	- 0.81	0.11	- 7.51	<0.001
	Slope 2	0.08	0.24	0.33	0.742
$\gamma$	Intercept	3.80	0.07	52.31	<0.001
	Period B	- 0.70	0.10	- 6.86	<0.001
	Period C	- 1.19	0.11	- 10.92	<0.001
	Depth	- 0.28	0.07	- 4.31	<0.001
	Slope 2	- 0.90	0.10	- 8.58	<0.001
	Period B*Depth	- 0.91	0.10	- 9.42	<0.001
	Period C*Depth	0.11	0.12	0.91	0.362
$\Omega$	Intercept	- 4.12	0.82	- 5.00	<0.001
	Period B	- 45.12	35.99	- 1.25	0.210
	Period C	- 9.95	1.86	- 5.36	<0.001
	Depth	0.16	0.08	1.87	0.061
	Slope 2	3.31	0.81	4.07	<0.001
	Period B*Depth	- 70.03	52.03	- 1.35	0.178
	Period C*Depth	- 8.51	1.62	- 5.26	<0.001
p	Intercept	3.83	0.33	11.60	<0.001
	Depth	3.85	0.25	15.50	<0.001
Dispersion		1.50	0.32	4.68	<0.001

Table 4-4. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass in Pawnee Reservoir, Nebraska during 2013. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), and Period (the period in, which sampling took place; category A: June 17, category B: July 25, category C: September 9, category D: October 8). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were.



Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 0.29	0.26	- 1.13	0.257
	Depth	- 0.79	0.21	- 3.77	<0.001
$\gamma$	Intercept	1.51	0.23	6.72	<0.001
	Period B	- 26.30	6.57	- 4.00	<0.001
	Period C	- 4.99	1.62	- 3.09	0.002
	Depth	1.49	0.31	4.86	<0.001
	Period B*Depth	- 16.68	3.73	- 4.47	<0.001
	Period C*Depth	- 4.58	1.03	- 4.44	<0.001
$\Omega$	Intercept	1.06	0.56	1.89	0.059
	Period B	2.62	1.26	2.09	0.037
	Period C	1.71	11.71	0.15	0.884
	Depth	1.76	0.41	4.26	<0.001
	Period B*Depth	3.38	1.66	2.04	0.041
	Period C*Depth	29.66	203.01	0.15	0.884
p	Intercept	- 0.83	0.45	- 1.84	0.066
	Depth	0.58	0.38	1.54	0.124
	Period B	1.04	0.43	2.45	0.014
	Period C	1.38	0.44	3.11	0.002
	Period D	- 0.60	0.65	- 0.92	0.355
	Period B*Depth	- 2.47	0.58	- 4.28	<0.001
	Period C*Depth	- 3.55	0.64	- 5.52	<0.001
	Period D*Depth	- 4.64	1.42	- 3.26	0.001
Zero-inflation		- 0.27	0.37	- 0.73	0.465

Table 4-5. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass in Pawnee Reservoir, Nebraska during 2014. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: May 2, category B: May 14, category C: May 21, category D: June 20, category E: September 18, category F: October 7). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model.

Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 3.62	0.24	- 15.02	<0.001
	Depth	0.28	0.14	1.98	0.048
	Slope 2	- 0.03	0.24	- 0.11	0.912
$\gamma$	Intercept	1.47	0.51	2.87	0.004
	Period B	1.10	0.53	2.09	0.037
	Period C	1.38	0.52	2.68	0.007
	Period D	- 9.14	5.56	- 1.65	0.100
	Period E	- 0.06	0.53	- 0.11	0.911
	Depth	0.44	0.28	1.59	0.112
	Slope 2	- 0.12	0.07	- 1.70	0.089
	Period B*Depth	0.25	0.29	0.86	0.392
	Period C*Depth	- 0.17	0.28	- 0.62	0.534
	Period D*Depth	5.26	3.22	1.63	0.103
	Period E*Depth	- 0.83	0.31	- 2.72	0.006
$\Omega$	Intercept	11.80	6.44	1.84	0.066
	Period B	- 23.40	11.04	- 2.12	0.034
	Period C	188.00	98.87	1.90	0.057
	Period D	100.70	567.61	0.18	0.859
	Period E	- 22.30	10.96	- 2.04	0.042
	Depth	- 12.40	6.06	- 2.05	0.040
	Slope 2	10.00	4.58	2.18	0.029
	Period B*Depth	10.50	6.15	1.70	0.089
	Period C*Depth	272.60	140.79	1.94	0.053
	Period D*Depth	- 81.70	452.98	- 0.18	0.857
	Period E*Depth	13.00	6.06	2.15	0.031
p	Intercept	- 1.72	0.24	- 7.29	<0.001
	Period B	2.02	0.41	4.99	<0.001
	Period C	12.47	238.00	0.05	0.958
	Period D	1.98	0.27	7.34	<0.001
	Period E	- 0.99	0.27	- 3.63	<0.001
	Period F	19.08	23800.00	0.00	0.999
Dispersion		1.90	0.61	3.13	0.002

Table 4-6. Parameter estimates for generalized N-mixture model used to estimate white perch abundance and biomass in Pawnee Reservoir, Nebraska during 2014. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), and Period (the period in, which sampling took place; category A: May 2, category B: May 14, category C: May 21, category D: June 20, category E: September 18, category F: October 7). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were.

Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 0.52	0.49	- 1.08	0.282
	Slope 2	- 1.30	0.39	- 3.37	0.001
$\gamma$	Intercept	- 2.88	1.55	- 1.86	0.063
	Period B	3.24	68.21	0.05	0.962
	Period C	1.34	1.64	0.82	0.414
	Period D	- 5.21	27.20	- 0.19	0.848
	Period E	3.70	1.66	2.23	0.026
	Slope 2	1.25	0.74	1.68	0.092
$\Omega$	Intercept	- 9.58	59.70	- 0.16	0.873
	Period B	- 9.25	86.70	- 0.11	0.915
	Period C	- 11.52	57.20	- 0.20	0.840
	Period D	- 0.52	19.30	- 0.03	0.979
	Period E	3.60	67.30	0.05	0.957
	Slope 2	13.30	61.90	0.21	0.830
p	Intercept	0.53	0.95	0.56	0.576
	Period B	- 1.62	0.91	- 1.77	0.076
	Period C	- 3.68	71.11	- 0.05	0.959
	Period D	0.14	2.52	0.06	0.954
	Period E	3.31	32.05	0.10	0.918
	Period F	- 4.62	1.31	- 3.52	<0.001
Zero-inflation		0.93	0.42	2.20	0.028

Table 4-7. Generalized N-mixture models ranked with AIC used to model gizzard shad abundance on Pawnee Reservoir Nebraska prior to a low-dose rotenone treatment during November 2013 (K: number of model parameters, AIC: Akaike Information Criterion score,  $\Delta$ AIC: difference between AIC score for the specified model and for the top model, AICwt: AIC weight, cumwt: cumulative AIC weight). Count data were collected with a consumer grade sonar unit (SN) used in conjunction with vertically set gillnets in waters with total depths of 2 m or more and a boat electrofisher (EF) used to shock points in water with total depths less than 2 m. In each model,  $\lambda$  is abundance,  $\gamma$  is recruitment,  $\Omega$  is apparent survival, and p is detection probability. The covariates in the models are depth (D), slope (S), sampling period (P), and shoreline habitat (H).

Gear	Model	K	AIC	$\Delta$ AIC	AICwt	cumwt
SN	$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: D*P	20	1058	0	1.00	1.00
	$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: D*P	17	1112	54	0.00	1.00
	$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1	5	1346	288	0.00	1.00
EF	$\lambda$ : D, $\gamma$ : D*P, $\Omega$ : D*P, p: D*P	23	483	0	1.00	1.00
	$\lambda$ : D+H, $\gamma$ : D*P+H, $\Omega$ : D*P+H p: D+P	30	517	34	0.00	1.00
	$\lambda$ : D+S, $\gamma$ : D*P+S, $\Omega$ : D*P+S, p: D	20	520	37	0.00	1.00
	$\lambda$ : 1, $\gamma$ : 1, $\Omega$ : 1, p: 1	5	549	66	0.00	1.00
	$\lambda$ : S, $\gamma$ : S+P, $\Omega$ : S+P, p: P	15	551	68	0.00	1.00

Table 4-8. Parameter estimates for generalized N-mixture model used to estimate gizzard shad abundance and biomass in Pawnee Reservoir, Nebraska during 2013. We collected data using a combination of sonar and vertical gillnets. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), and Period (the period in, which sampling took place; category A: June 17, category B: July 25, category C: September 9, category D: October 8). This model also included dispersion parameter that is a measure of how much overdispersion the model allowed relative to a Poisson model.

Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 2.77	0.20	- 13.71	<0.001
	Depth	- 0.76	0.16	- 4.91	<0.001
	Slope 2	0.08	0.33	0.26	0.799
$\gamma$	Intercept	2.28	0.17	13.49	<0.001
	Period B	- 0.48	0.20	- 2.40	0.016
	Period C	- 0.89	0.27	- 3.34	<0.001
	Depth	0.15	0.10	1.48	0.1390
	Slope 2	1.15	0.15	7.50	<0.001
	Period B*Depth	- 0.09	0.15	- 0.61	0.545
	Period C*Depth	0.07	0.19	0.39	0.70
$\Omega$	Intercept	- 1.96	0.40	- 4.88	<0.001
	Period B	4.42	0.83	5.32	<0.001
	Period C	2.07	0.50	4.17	<0.001
	Depth	1.53	0.26	5.99	<0.001
	Slope 2	- 2.07	0.42	- 4.93	<0.001
	Period B*Depth	- 3.01	0.59	- 5.11	<0.001
	Period C*Depth	- 1.73	0.37	- 4.65	<0.001
p	Intercept	0.62	0.17	3.57	<0.001
	Depth	0.49	0.18	2.68	0.007
Dispersion		0.83	0.32	2.61	0.009



Table 4-9. Parameter estimates for generalized N-mixture model used to estimate gizzard shad abundance and biomass in Pawnee Reservoir, Nebraska during 2013. We collected data using a boat electrofisher. In the model,  $\lambda$  is site and time specific abundance (log scale),  $\gamma$  is site and time specific recruitment (log scale),  $\Omega$  is site and time specific apparent survival (logit scale), and  $p$  is site and time specific detection probability (logit scale). Covariates were Depth (the mean depth of cells), Slope (mean bottom slope in a cell; category 1:  $<1\%$  slope, category 2:  $\geq 1\%$  slope), Shore (whether or not a cell was adjacent to shore and whether or not that shore had rip rap; category 1: offshore, category 2: adjacent to shore, category 3: adjacent to rip-rapped shore), and Period (the period in, which sampling took place; category A: June 17, category B: July 25, category C: September 9, category D: October 8). This model contains a zero-inflation term, which provided a measure of how zero inflated the data were.

Component	Variable	Estimate	SE	Z	p
$\lambda$	Intercept	- 0.59	0.23	- 2.53	0.012
	Depth	- 0.36	0.30	- 1.22	0.222
$\gamma$	Intercept	- 1.21	0.96	- 1.27	0.206
	Period B	0.70	1.06	0.66	0.509
	Period C	1.21	1.04	1.16	0.245
	Depth	1.82	0.89	2.05	0.040
	Period B*Depth	- 1.90	1.02	- 1.86	0.063
	Period C*Depth	- 0.54	1.11	- 0.49	0.627
$\Omega$	Intercept	- 1.63	0.46	- 3.57	<0.001
	Period B	- 231.51	6823.12	- 0.03	0.973
	Period C	2.84	1.55	1.84	0.066
	Depth	2.31	0.82	2.82	0.005
	Period B*Depth	329.95	9700.55	0.03	0.973
	Period C*Depth	- 1.61	1.54	- 1.05	0.294
p	Intercept	- 1.52	0.31	- 4.90	<0.001
	Depth	0.00	0.39	- 0.01	0.994
	Period B	4.09	1.20	3.41	0.001
	Period C	2.72	1.56	1.74	0.082
	Period D	13.98	8.99	1.56	0.120
	Period B*Depth	- 5.13	1.41	- 3.63	<0.001
	Period C*Depth	- 1.91	1.17	- 1.63	0.103
	Period D*Depth	- 21.85	13.13	- 1.66	0.096
Zero-inflation		- 1.22	0.49	- 2.52	0.012

Table 4-10. Daily observed mortality of non-target fish species counted along seven, 10-m sections of shoreline 2, 3, 5, and 7 days post low-dose rotenone application on Pawnee Reservoir, Nebraska.

Species	Days post treatment			
	2	3	5	7
Common carp ( <i>Cyprinus carpio</i> )	39	164	19	86
Freshwater drum ( <i>Aplodinotus grunniens</i> )	129	39	31	29
White crappie ( <i>Pomoxis annularis</i> )	20	8	2	3
Bluegill ( <i>Lepomis macrochirus</i> )	9	4	2	1
Channel catfish ( <i>Ictalurus punctatus</i> )	1	2	1	0
Flathead catfish ( <i>Pylodictis olivaris</i> )	1	0	1	1
Golden shiner ( <i>Notemigonus crysoleucas</i> )	0	0	0	0
Black bullhead ( <i>Ameiurus melas</i> )	0	2	0	0
Walleye ( <i>Sander vitreus</i> )	1	0	0	0
Black crappie ( <i>Pomoxis nigromaculatus</i> )	0	0	0	0
Green sunfish ( <i>Lepomis cyanellus</i> )	1	0	0	0
Bigmouth buffalo ( <i>Ictiobus cyprinellus</i> )	0	0	0	1

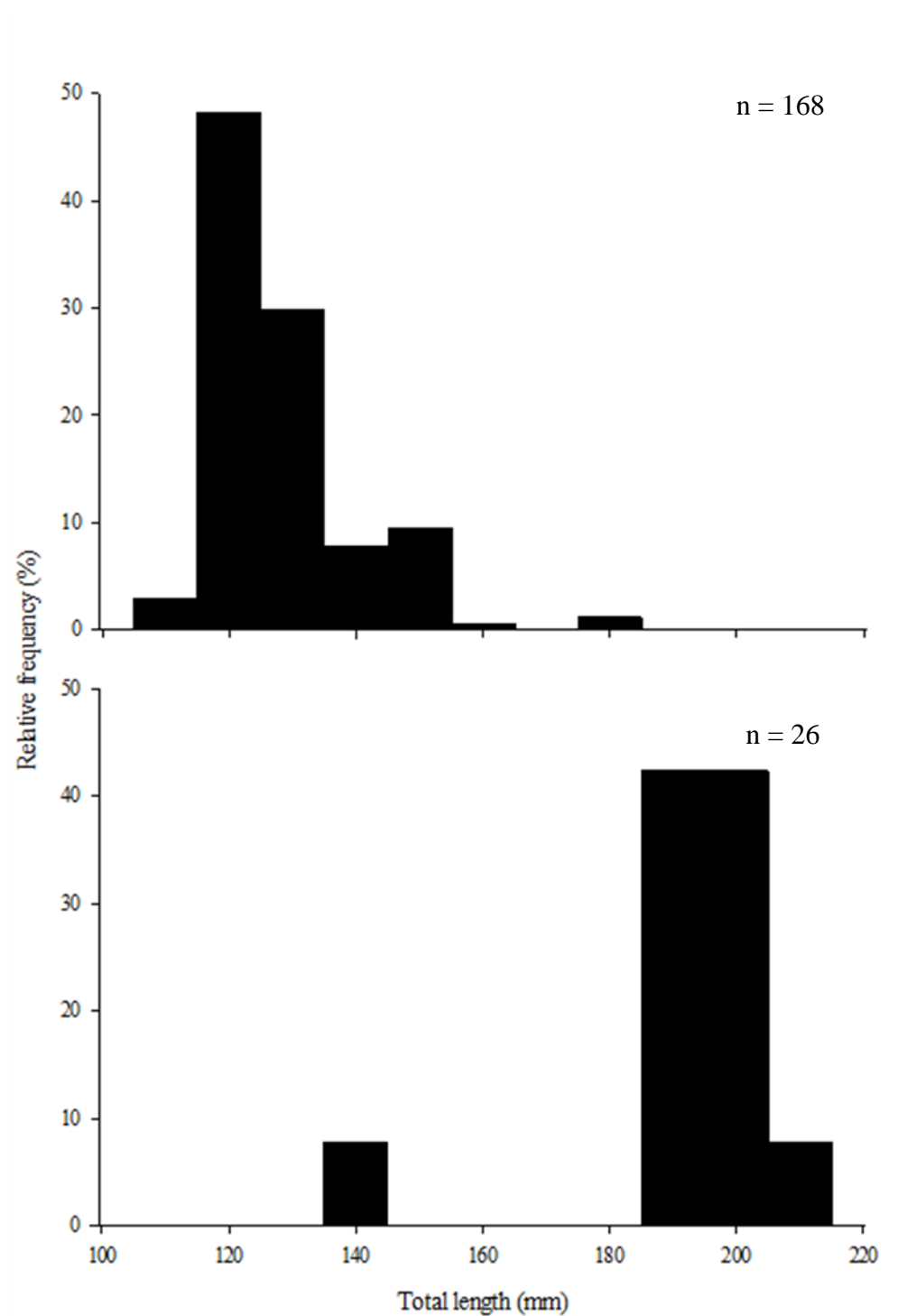


Figure 4-1. Length distributions of white perch captured in Pawnee Reservoir, Nebraska with a boat electrofisher and vertical gillnets during September 2013 (top) and September 2014 (bottom).

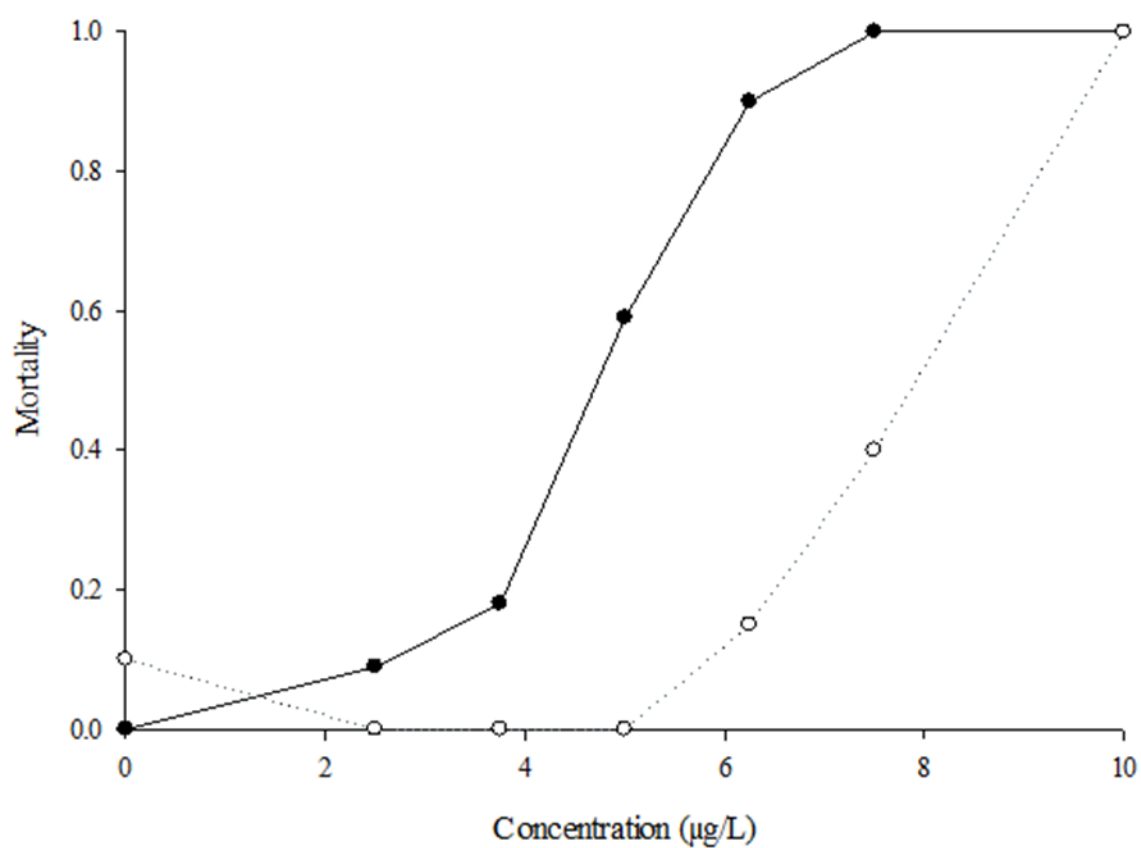


Figure 4-2. Observed mortality of grass carp (●) and largemouth bass (○) from a Florida Lake over a 24-h period as a function of rotenone concentrations (Colle et al. 1978).

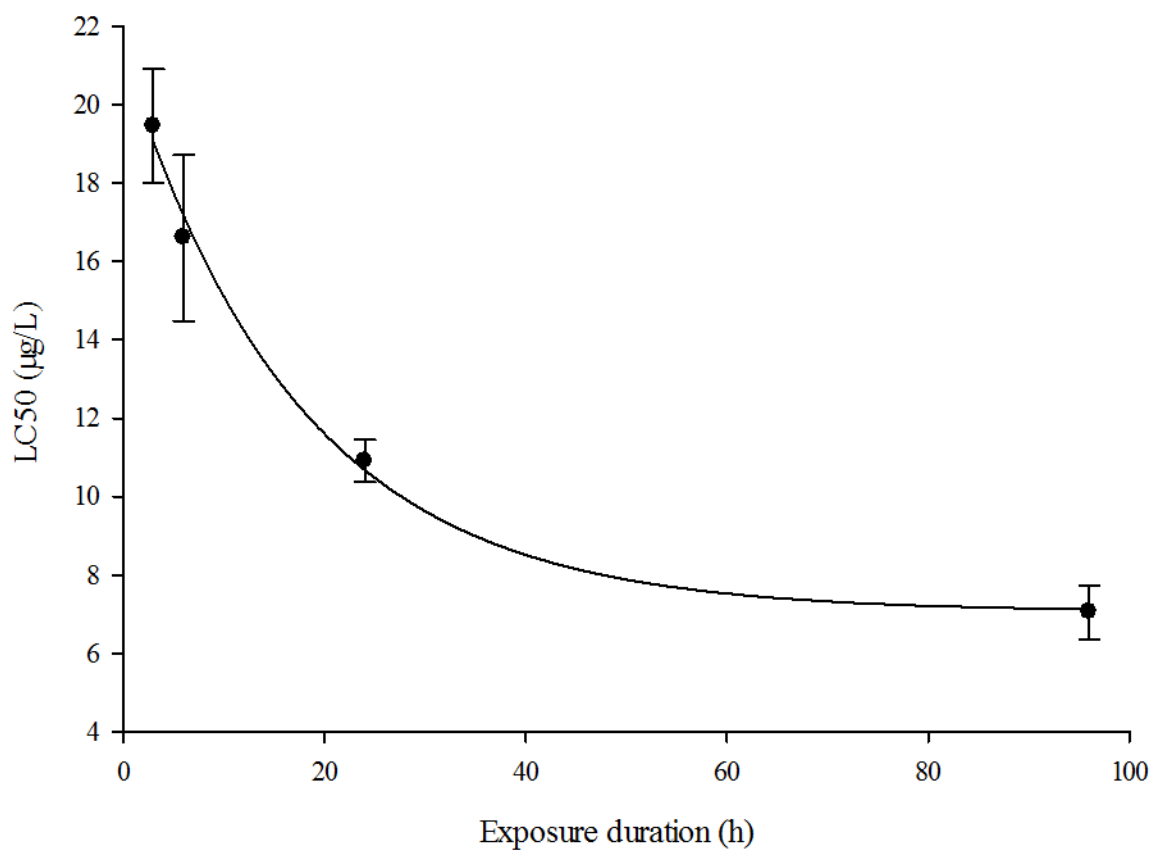


Figure 4-3. Rotenone toxicity (LC 50  $\mu\text{g/L}$ ) as a function of exposure time for green sunfish in a laboratory setting (Marking and Bills 1976).

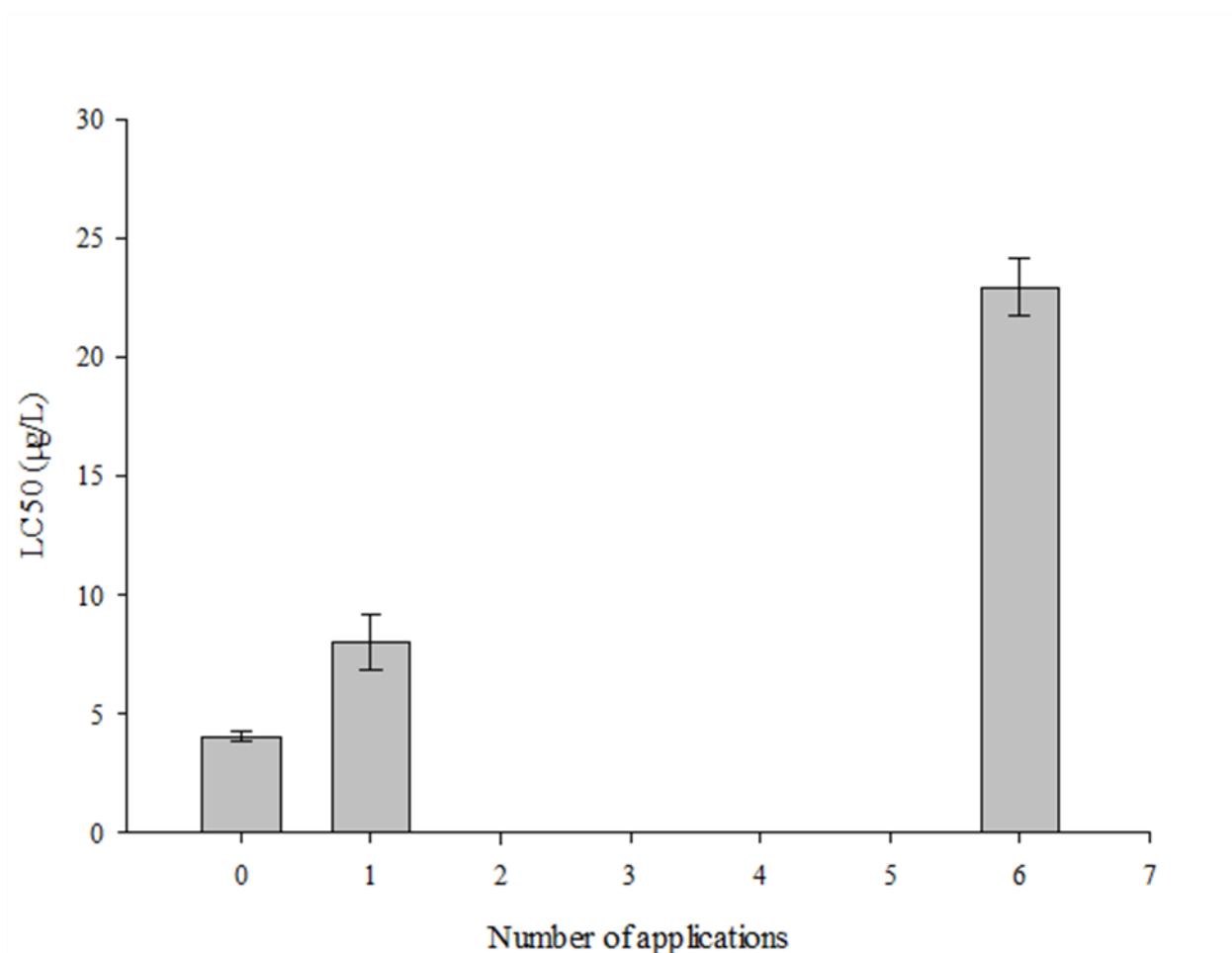


Figure 4-4. Rotenone resistance (48 h LC 50 with standard error) of golden shiner in Connecticut ponds increasing with repeated applications of rotenone between 1957 and 1974 (Orciari 1979).

## Chapter 5 Conclusions, management recommendations, and research needs

Our research provided information to guide white perch (*Morone americana*) and gizzard shad (*Dorosoma cepedianum*) management in eastern Nebraska reservoirs. In these systems, Chizinski et al. (2010) prescribed a removal of 90% of the white perch biomass to increase white perch maximum size by 50%. Based on our estimates of the white perch population size in Branched Oak Lake, managers need to remove approximately 40,500 kg or 1,000,000 white perch from this system to achieve a 50% increase in maximum size. During 2013 in Pawnee Reservoir, approximately 39,341 kg or 1,430,000 white perch would have needed to be removed. However, the removal target assumed no change in gizzard shad abundance; it may be possible to get the 50% increase in white perch maximum size with less than a 90% reduction in biomass by also reducing gizzard shad biomass.

The advantage of the abundance data over relative abundance data is that the abundance values can be used directly to set control targets, whereas relative abundance values are more difficult to use in setting control targets because they are not directly translatable to a number of fish. Also, relative abundance is susceptible to hyperstability, which may mask changes in true abundance, because abundance estimates account for catchability in most cases, they are generally resistant to this. One disadvantage of abundance estimators in relation to relative abundance is that it takes much longer to collect the data.



Ideally, managers could target aggregations of these species rather than the entire waterbody. The overall pattern in spatial distributions of white perch and gizzard shad in eastern Nebraska reservoirs was that in general both species occupied deep water ( $> 4$  m) in the spring, dispersed in the summer, and then move back into deep water ( $> 4$  m) late in the fall. However, there was a large amount of noise in this pattern. White perch and gizzard shad are most aggregated late in the fall and early in the spring. The aggregations occur in the lower reaches of the reservoir in water  $> 4$  m deep. These aggregations cover large areas of the reservoirs making them difficult to target. From late spring until early fall, they disperse throughout the reservoir. However, our models have a lot of uncertainty in predicting spatial distributions.

With information on how many white perch we need to remove and information on how white perch distribute spatially, the next step is to determine the best control method. The size of these populations limits us to methods that remove large numbers of fish per unit effort, taking methods such as fyke netting off the table. To date, predator management efforts have not lead to sufficient reductions in abundance; alone, this method is inadequate. A targeted approach such as a commercial seine may be applicable because white perch do appear to aggregate during the early spring and late fall. However, these aggregations cover large areas making them difficult to target. The low-dose-rotenone application on Pawnee Reservoir lead to an 83% reduction in white perch abundance and eliminated or nearly eliminated gizzard shad from the waterbody. This type of approach has the benefit of not needing to be targeted, but may be logistically difficult to accomplish on a waterbody the size of Branched Oak Lake. Also, further research is needed on fish developing resistance to this chemical. If fish do

develop resistance, subsequent low-dose-rotenone applications will need to use greater concentrations of rotenone. A combined approach with commercial seines or rotenone followed by predator management is the most likely to be effective. Regardless to the method used, it is unlikely that white perch or gizzard shad will be eliminated from these systems permanently so managers will need to repeat control efforts to achieve management goals.

### **Management needs**

1. *Clear objectives for white perch management designed from a system standpoint.*

White perch control efforts need a clear objective. The present objective is to increase angler trips to Branched Oak Lake back to levels seen in the 1980s. This objective is good in that it provides a target; however, I believe it has some shortcomings. First, I do not believe that the target of increasing angling to 1980s levels is realistic. The landscape has changed such that anglers now have more waterbodies to go to distributing effort. Second, the objective does not take into account angler specialization. Branched Oak Lake currently provides unique angling opportunities within the Salt Valley to target hybrid striped bass (*Morone chrysops* x *Morone saxatilis*) and large flathead catfish (*Pylodictis olivaris*). Controlling white perch may increase the number of anglers for species such as bluegill (*Lepomis macrochirus*), but those gains may come with a loss of wiper and flathead catfish angling opportunities.

2. *Thorough evaluation of any management actions taken on white perch.*

Evaluations of any management actions are important because they provide an opportunity to learn so that we are more effective in the future. Evaluation is particularly

important for white perch management because it is unlikely that they will be permanently eliminated from the Salt Valley. I recommend that an adaptive management approach be adopted for white perch control. This would involve first developing clear measureable objectives for management. Then collecting data to assess the state of the population specifically related to the objective prior to taking a management action. A management action should then be taken. Following the management action data on the state of the population should again be collected, this data should then be compared back to the data collected prior to the management action to determine the effect of the action. The information on the effect of the management action should then be used to improve future management actions.

### 3. *Develop Action thresholds.*

It is unlikely that white perch will ever be eliminated from the Salt Valley; control efforts will likely need to be repeated. Managers should develop some measurable population thresholds to determine when it is necessary to conduct further control efforts. These thresholds could include some form of growth metric, condition metric, or relative abundance. Monitoring efforts then need to focus on measuring the selected metric to determine when it is necessary to carry out control efforts on that population.

## **Research questions**

### 1. *What ecological mechanisms drive the patterns in white perch and gizzard shad distributions that we observed?*

Our research documented shifts in white perch and gizzard shad distributions seasonally (Chapter 3). However, we did not explore the mechanisms behind or the ecological

consequences of these distributions. An understanding of the mechanisms behind these distributions would improve our understanding of their consequences and improve our ability to predict distributions in other waterbodies.

2. *What will the effects of white perch control efforts be on other fisheries in the same waterbodies?*

Hybrid striped bass and flathead catfish were introduced as part of white perch control efforts in Branched Oak Lake. These species now provide angling opportunities in this waterbody and rely on white perch and gizzard shad as their prey base. White perch control efforts may lead to declines in these fish populations by reducing their prey base. Research should be conducted to determine if there is a way to control white perch populations without crashing these fisheries.

3. *What are the effects of white perch on angler use of the Salt Valley and what will the effects of white perch control efforts be on angler use in the Salt Valley?*

The ultimate goal of white perch control efforts is to increase the number of angler trips to waterbodies such as Branched Oak Lake by improving the sportfishery. However, we do not have a good understanding of how white perch populations affect angler use of the Salt Valley or how control efforts will affect angler distribution. If the goal of white perch control efforts is increased angler trips, an understanding of these relationships would benefit control efforts.

4. *How can we apply the methods for estimating abundance described in chapter 2 to lotic systems?*

We were able to apply the method we described in Chapter 2 to estimate abundance superabundant populations in reservoirs. However, superabundant fish populations also exist in lotic systems. An example of this are asian carp (*Hypophthalmichthys spp.*) populations found in rivers. Lotic environments present a challenge to our method because in many cases the gears we employed such as gillnets and the point electrofishing approach we used will not be effective because of flowing water. The modeling approach we used would be applicable to these habitats if the data could be collected. A new sampling scheme should be designed to collect data that can be used in generalized N-mixture models.

5. *What determines if a fish population becomes superabundant?*

Through our research we have defined a superabundant fish population (Chapter 2) and explored some of the ecological interactions between superabundant fish populations (Chapter 3). A next step in furthering our understanding of these populations would be to gain a better understanding of what factors lead to the formation of these populations. We know that events such as species invasions and predator removals can play a part. However, some species tend to be more prone to becoming superabundant; an understanding of what makes these species prone to superabundance and what local conditions contribute to this would allow us to better predict and prevent the formations of these populations.

6. *What is the toxicity of rotenone to fish species?*

In chapter 4, we evaluated the use of low-dose-rotenone applications to control white perch. The application we evaluated resulted in a large reduction in white perch abundance in this system. To effectively carry out this type of control effort a knowledge of species specific rotenone tolerance is necessary. Some rotenone tolerances have been published (see Marking and Bills 1976). However, these concentrations are generally concentrations that will kill 50% of the populations (LC 50); estimates of LC 99s would be much more useful for applications in fisheries. Also, the list of species for which toxicities have been published is far from complete. Future research to expand the number of species with published rotenone toxicities would allow for a broader use of low-dose-rotenone applications to control superabundant fish populations.

7. *What species of fish can develop resistance to rotenone, and what is the mechanism behind this resistance?*

The low-dose-rotenone application that we evaluated (Chapter 4) did not eliminate the superabundant fish from the waterbody; future control efforts and possibly future applications of rotenone may be needed. There is some evidence that fish can develop a resistance to rotenone either through repeated exposure (Orciari 1979) or possibly through exposure to other pesticides (Fabacher 1972). Research on this phenomenon is limited in terms of the species that can be developed resistance and the mechanism by which they develop resistance.

## Conclusions

There are five crucial pieces of information needed to understand and manage superabundant fish populations. First, we need to know what superabundant fish populations are. We define superabundant fish populations as populations of organisms that are abundant and for which traditional means estimating abundance are ineffective (Chapter 2). With a definition, we can now begin to categorize fish populations to aid in understanding their ecology and effective management.

Second, we need to understand how large these populations are. Methods commonly used in fisheries to estimate population size are ineffective on these populations because they are so large. We described a new method to estimate the sizes of superabundant fish populations and applied it to superabundant fish populations in eastern Nebraska Reservoirs (Chapter 2). With information on abundance, we can set management objectives, evaluate management actions, and gain a better understanding of the ecology of these populations.

Third, we need an understanding of the ecology of these populations. Even basic ecological information such as diet and spatial distribution can provide insight into the mechanisms behind the superabundant populations. We estimated the spatio-temporal distributions of superabundant fish populations in eastern Nebraska reservoirs and compared these distributions between species (Chapter 3). With this information, we can also provide guidance for management efforts.

Fourth, we need an understanding of management and sampling options. There are many different approaches to reducing fish abundance, each with benefits and drawbacks — there is no one perfect management technique for all scenarios. For

example, the large abundance of white perch in eastern Nebraska reservoirs makes removal with fyke nets or gillnets ineffective, but because of the low tolerance of this species to rotenone, low doses of rotenone may provide an effective control method. Managers need to select the best option for a given situation.

Fifth, we need information on the effectiveness of management actions. Assessment of management actions is crucial to effective long-term management. Without assessment, we cannot learn from previous management actions to make future actions more effective. We assessed a low-dose-rotenone application designed to control superabundant fish populations in a Nebraska reservoir (Chapter 4). The knowledge we gained through this assessment can be used to improve future control efforts in these systems.

Superabundant populations of organisms currently present us with serious challenges to management. Our knowledge about these populations is limited, which hampers our ability to manage them. A better understanding of these populations will allow us to more effectively monitor and manage them if necessary for the good of our natural resources and their users.



## References

- Chizinski, C. J., K. L. Pope, G. R. Wilde. 2010. A modeling approach to evaluate potential management actions designed to increase growth of White Perch in a high-density population. *Fisheries Management and Ecology* 17:262-271.
- Fabacher, D. L. 1972. Rotenone tolerance in mosquitofish. *Environmental Pollution*. 3:139-141.
- Marking, L. L., and T. D. Bills. 1976. Toxicity of rotenone to fish in standardized laboratory tests. United States Department of the Interior Fish and Wildlife Service. *Investigations in Fish Control* 72. Washington D.C.
- Orciari, R. D. 1979. Rotenone resistance of golden shiners from a periodically reclaimed pond. *Transactions of the American Fisheries Society* 108:641-645.

## **Appendix A. Diel distribution of white perch and gizzard shad in a flood-control reservoir**

Aquatic organisms live in a 3-dimensional environment in which they can shift their distribution. Aquatic organisms can move closer to or further from shore, as Gibson et al. (1998) described for the fish community in a bay on the coast of Sweden. In addition to being able to move in to shore, aquatic organisms in lotic environments can move up and down stream; many species of sturgeon migrate within river systems to reach spawning grounds (Auer 1996). Organisms can also move vertically in many lentic systems, as was observed in kokanee salmon (*Oncorhynchus nerka*) in some lakes and reservoirs (Finnell and Reed 1969).

Fish do not always move independently, but may move in response to other organisms. Some species such as grass carp (*Ctenopharyngodon idella*) can alter environmental conditions by modifying habitat structure (Dibble and Kovalenko 2009) resulting in possible changes in spatial distribution of other species. Other species may force changes in the spatial distribution of a fish species by changing resource availability through competition (Taniguchi and Nakano 2000) or by changing risk across the habitat through predation (He and Kitchell 1990). Further, if one species gains benefits from another or competes for resources, their distributions may shift together. When populations are large and their distributions change in conjunction with each other, this may result in large spatial shifts in fish biomass over relatively short temporal scales.

White perch (*Morone americana*), an invasive species in U.S.A. Midwestern waterbodies (Zuerlein 1981), and gizzard shad (*Dorosoma cepedianum*) can be extremely

abundant in Midwestern reservoirs and may share a common food resource possibly resulting in distributions that change in conjunction with each other if distributions of their food change. In some Nebraskan waterbodies white perch constituted greater than 90% of all fish caught in samples in certain years (Hodkin 2001) on top of already large populations of gizzard shad. In these waterbodies white perch consume cladocera and diptera larvae year-round and other seasonally available items (Gosch et al. 2010). Gizzard shad consume zooplankton such as cladocera when they are available in sufficient numbers, and when zooplankton are not available in sufficient numbers they filter detritus (Yako et al. 1996; Maynard et al. 2002). Based on similarities in the diet of the two species there is reason to believe that the distributions of these two species will change with each other. Zooplankton are known to exhibit shifts in distribution over diel cycles, particularly shifts in vertical distribution (Ringelberg 1995), which could lead to a shift in fish biomass over a diel cycle in systems that contain white perch and gizzard shad.

The spatial distribution of fish biomass is unknown in systems containing both white perch and gizzard shad. A better understanding of how the spatial distribution of fish biomass changes temporally would provide a starting point for further research on the interactions between white perch and gizzard shad. My goal was to describe how fish spatial distribution changed over a diel cycle in an eastern Nebraska flood-control reservoir. My objective was to estimate spatial distribution of fish during four periods (dawn, day, dusk, and night) within a diel cycle.

## Methods

### Study Site

Branched Oak Lake is a polymictic flood-control reservoir with an area of 728 ha located approximately 24 km northwest of Lincoln, Nebraska in the Salt Creek Watershed. Oak Creek and Middle Oak Creek flow into the reservoir forming two reservoir arms. Our study was limited to the south arm of the reservoir. Fish species present in the reservoir include white perch, gizzard shad, walleye (*Sander vitreus*), freshwater drum (*Aplodinotus grunniens*), hybrid striped bass (*Morone chrysops* x *Morone saxatilis*), bluegill (*Lepomis macrochirus*), green sunfish (*Lepomis cyanellus*), largemouth bass (*Micropterus salmoides*), black crappie (*Pomoxis nigromaculatus*), white crappie (*Pomoxis annularis*), flathead catfish (*Pylodictis olivaris*), channel catfish (*Ictalurus punctatus*), blue catfish (*Ictalurus furcatus*), brook silverside (*Labidesthes sicculus*), common carp (*Cyprinus carpio*), and striped bass (*Morone saxatilis*).

### Sampling Design

Diel sampling was conducted using a combination of sonar, vertical gillnets, and a boat electrofisher. Sampling took place during four periods; daylight hours (1100-1500), nighttime hours (2300-0300), at sunrise (2 hours before sunrise to 2 hours after sunrise), and at sunset (2 hours before sunset to 2 hours after sunset). We characterized the spatial distribution of the fish community during each period using all of the gears. Three separate samples (one sample a week) were collected between the 11 - 29 August 2014.

### **Approach Water Depths > 2 m**

We sampled sonar transects organized in a box pattern that we established on the reservoir in water depths >2 m (Figure A-1) (Murphy and Willis 1996). The corner where each sampling event began and the direction of sampling were randomly selected for each period within a sampling event. We collected sonar data using a Lowrance<sup>®</sup> HDS-9 Gen2 Touch sonar operating at 200 kHz. We used a frequency of 200 kHz because it resulted in the best separation between fish targets and large amounts of noise observed in the water column. To estimate the field of view for this sonar frequency we jigged ping-pong balls, an object sometimes used to calibrate sonars (Dahl and Mathisen 1983) spaced at 1 m intervals along a weighted line at distance increments of 0.5 m from the transducer and observing what ping-pong balls were visible at each distance increment. We estimated the field of view to be approximately 60° based on the results of this test. Data were collected along the transect; the boat was navigated at speeds between 4.8 and 8.0 km/h. We saved sonar logs for later analysis.

Prior to running the sonar transect, four vertical gillnets each made up of 19-mm bar mesh monofilament netting were set along the long axis of the reservoir (Figure A-1) to evaluate whether large numbers of fish were moving into the top two meters of the water column where they would not be visible with sonar. 19-mm bar mesh nets were used because the time constraints limited the number of nets that could be set to four and because based on previous sampling, this size of net captured the most fish. Gillnets were 2-m wide and 10-m high constructed based on the designs described by Lackey (1968) and Kohler et al. (1979). At each site, the gillnet was unrolled such that approximately 0.5 m of excess net was let out then the side ropes were secured to the

float and the net was anchored in place. Following the sonar sampling we retrieved each net and recorded the vertical position of each fish in the net to the nearest meter.

### **Approach Water Depths $\leq 2$ m**

We electrofished in waters with depths of  $\leq 2$  m where sonar transects would not be effective to assess fish distribution. In total 10 samples were collected during each period, 1 in each of 10 zones. Prior to sampling, we randomly selected the centers of each zone in open-water areas and in areas with submerged trees in areas with water depths  $\leq 2$  m based on the availability of each habitat. We defined each zone as the area within a 100-m radius of the center point with depth  $\leq 2$  m. Within each zone, we randomly selected 4 points with a minimum spacing of 24 m so that electric fields did not overlap (Figure A-1) (Burkhardt and Gutreuter 1995). In an attempt to minimize bias between diel sampling events we standardized power density to differences in conductivity (Temple 2009).

During each period, we randomly selected the zone and point within the zone where sampling would begin and the direction sampling would proceed. We sampled each point once during a complete set of diel data collection. During a sampling event, we electrified the point for 60 seconds and collected all fish using a dip net. At each site, we tallied the total number of fish by species and then released fish.

### **Analysis**

Sonar data were analyzed to determine if there were large lateral or longitudinal shifts in fish distribution in water with depths  $>2$  m. The sonar transect was divided into 300-m segments and images of each segment were extracted. We used ImageJ to analyze

the extracted images (Abramoff, et al. 2004). Images were first filtered using a threshold filter with parameters based on test images of ping-pong balls and dispersed fish. To identify targets we used the particle analysis function in the software with parameters estimated from test images of ping-pong balls and dispersed fish. We overlaid the image with lines denoting the depth layers (2.1-4.0 m, 4.1-6.0 m, and > 6.0 m) and targets were counted separately within each depth layer. When fish were in schools too tightly packed for the particle analyzer to separate, they were counted visually if there was enough separation to distinguish individuals, or if there was not enough separation to distinguish individuals and the school was separated from large patches of noise, the area occupied by the school was measured and divided by midpoint of the range of the target size parameters to estimate the number of fish in the school. When there was not adequate separation between individuals in the school and no separation from noise, we estimated the number of fish in the school visually based on distinct fish visible in the image and the size of the school. We then analyzed the data using geostatistical analyst tools in ArcMap 10 (ESRI 2012) for each depth within the four periods. Prior to running the analysis we created semivariograms to better understand spatial dependency in the data. We also assessed the data for trends, and checked for outliers. We detected global trends in the data, we removed these trends in the kriging process using first or second order polynomials to produce more accurate maps, the order or polynomial used in the trend removal was determined based on diagnostic plots generated before the data were analyzed (Table A-1). One outlier was removed from the data prior to analysis because it was characteristic of a relatively small habitat and not representative of the general

habitat of the area. We visually compared spatial distributions to determine if there were lateral or longitudinal shifts.

Data from the sonar and vertical gillnets were analyzed to determine if there were any vertical shifts in distribution. Counts from the sonar were compared between periods within each depth layer (2.1-4.0 m, 4.1-6.0 m, and > 6.0 m) using generalized linear models for data with a negative binomial distribution blocked by sampling event ( $\alpha = 0.05$ ). Counts for gillnets were compared between periods within depth layers using generalized linear models for data with a negative binomial distribution with repeated measures ( $\alpha = 0.05$ ). We carried out the analysis in R version 3.1.2 (R Development Core Team 2014) using the package MASS (Venables and Ripley 2002).

Data from the boat electrofisher were analyzed to determine if there were any shifts in fish distribution into or out of water with total depths of < 2 m. Catches were compared between periods using a generalized-linear-mixed model for data with a negative binomial distribution for multiple occasions blocked by habitat type ( $\alpha = 0.05$ ). We carried out the analysis in R version 3.1.2 (R Development Core Team 2014) using the package lme4 (Bates et al. 2014).

## Results

During the three weeks of sampling, we collected sonar data for 10 out of the possible 12 periods, which we used to assess if there were changes in fish distribution laterally and longitudinally within the sample site. During the first week of sampling, we collected sonar data during all four periods. We observed increasing densities of fish from up reservoir to down reservoir, but no differences across the four periods in this sample (Figure A-2, A-3, and A-4). During the second and third weeks of sampling, we



collected sonar data during dawn, day, and dusk; we did not collect a night sample either week due to thunderstorms. We observed the same trend in density as the first sample with no lateral or longitudinal differences across the sampling periods in both the second and third samples (Figures A-2, A-3, and A-4).

Based on our analysis there was only weak evidence that there were significant movements of fish into or out of habitats with depths  $< 2$  m. We captured significantly more fish in these habitats at dusk than at dawn (Table A-2). However, there were no significant differences in catch between any other periods (Table A-2).

Based on our assessment of the sonar and vertical gillnet data there were likely shifts in fish vertical distribution across diel cycles. Across all three-depth layers, we detected significantly more fish at dawn and during the day than at dusk or during the night (Table A-3). We detected significantly more fish at dawn in the 2.1-4.0 m depth layer than during the day, but there were no significant differences in the numbers of fish detected between dawn and day for either of the other two depth layers. There were no significant differences in the number of fish detected between dusk and night in any of the depth layers (Table A-3). Gillnet data could only be assessed for the two uppermost depth layers (0.0-2.0 m and 2.1-4.0 m) due to data limitations for the two deeper layers (4.1-6.0 m and  $>6$  m). In the uppermost depth layer (0.0-2.0 m) there were no significant differences in catch across periods (Table A-4). In the second depth layer (2.1-4.0 m) we captured significantly more fish during the day than at night, but there were no significant differences for any other periods (Table A-4).

## Discussion

The distribution of fish in Branched Oak Lake did not change in the lateral or longitudinal dimensions over diel cycles during August 2014. Based on the sonar data and the data collected by the boat electrofisher there was not strong evidence for substantial onshore to offshore movements of fish during our sampling. There were vertical changes in distribution during our sampling. Based on our sonar data fish appear to move out of water depths greater than 2 meters at dusk and then return at dawn. We captured significantly greater numbers of fish between 2.1 and 4.0 m during the day than during the night corroborating our finding (Table A-4). Our gillnets did not detect any significant change in the numbers of fish present in the top 2 m of the water column.

We detected significant decreases in the numbers of fish in depths  $> 2$  m, but did not detect any significant increases in the numbers of fish in any other areas; there are several possible reasons that could explain this. One possibility is that the decrease detected by the sonar was a false positive; this is unlikely because the change was detected across all three depth layers, appears to be consistent through the three weeks of sampling, and was corroborated in the 2.1-4.0 depth layer where we had sufficient gillnet data to make comparisons. Another possibility is that the fish moved into water with depths  $< 2$  m and we did not detect the change with our boat electrofisher. Researchers have documented that electrofishing catchability is greater at night than during the day so it is possible that our results are biased (Murphy and Willis 1996). In this case, we should have captured more fish at night and been more likely to detect an increase in abundance in water with depths  $< 2$  m, thus it is improbable that large numbers of fish moved into these habitats. We only sampled the south arm of the reservoir, so it is

possible that the fish moved to the north arm of the reservoir at night and then returned to the south arm at dawn; this is unlikely because the habitat is similar between the two arms such that there is little incentive for fish to migrate between arms, they may however, move back and forth at random. The final possibility is that fish moved into the top 2 m of the water column at night and we did not detect the difference with our gillnets. We believe that this is the most likely explanation; catches in passive gears such as gillnets can be highly variable (Murphy and Willis 1996) and our sample size was small because we were only able to collect one night sample - the combination of these factors limited our statistical power.

We observed a distribution shift that differs from what has been documented in the literature for white perch and gizzard shad. White perch typically move into shallow water at night to feed and then move back to deeper water during the day in waters along the east coast of the U.S.A. (Webster 1943; McGarth and Austin 2009). Gizzard shad distributions are similar between day and night in Lake Texoma (Vondracek and Degan 1995). In other systems white perch predominately eat benthos along with fish eggs, but in Branched Oak Lake zooplankton are large components of white perch diet (Zuerlein 1981; Schaeffer and Margraf 1987; Gosch et al. 2010). Gizzard shad prefer to consume zooplankton when enough are available (Yako et al. 1996; Maynard et al. 2002). During our sampling we observed a large amount of what appeared to be noise that moved up in the water column at dusk and then moved back down at dawn. We suspect that this may have been large numbers of zooplankton going through diel-vertical migration, a movement well documented for these organisms (Ringelberg 1995); this may be what caused the distribution shift we observed.

Our study provided insight into the movement of fish over diel cycles in a system containing superabundant white perch and abundant gizzard shad, but was not able to determine the movement of specific species over this time scale. Further research, specifically into how each species distributes over this time scale would provide insight into interactions between white perch and gizzard shad and their influence on aquatic systems. Research of this nature would also further our understanding of how superabundant fish populations behave and how they interact within fish communities, improving our ability to manage them and our understanding of their effects on fish communities.

## References

- Abràmoff, M. D., P. J. Magalhães, and S.J. Ram. 2004. Image processing with ImageJ. Biophototics International. Available: <http://igitur-archive.library.uu.nl/med/2011-0512-200507/ImageJ.pdf> (August 2013).
- Auer, N.A. 1996. Importance of habitat and migration to sturgeons with emphasis on lake sturgeon. *Canadian Journal of Aquatic Science* 53:152-160.
- Bates D., M. Maechler, B.M. Bolker, and S. Walker. 2014. lme4: linear mixed-effects models using Eigen and S4.” ArXiv e-print; submitted to *Journal of Statistical Software*, <http://arxiv.org/abs/1406.5823>.
- Burkhardt, R. W., and S. Gutreuter. 1995. Improving electrofishing catch consistency by standardizing power. *North American Journal of Fisheries Management* 15:375-381.
- Dahl, P.H. and O.A. Mathisen. 1983. Measurement of fish target strength and associated directivity at high frequencies. *Journal of the Acoustic Society of America* 73:1205-1210.
- Dibble, E.D. and K. Kovalenko. 2009. Ecological impact of grass carp: a review of the available data. *Journal of Aquatic Plant Management* 47:1-15.
- ESRI, 2012. ArcGIS help library. ESRI, Redlands, California. Available: <http://help.arcgis.com/en/arcgisdesktop/10.0/help/> (February 2013).
- Finnell, L.M. and E.B. Reed. 1969. The diel vertical movements of kokanee salmon, *Oncorhynchus nerka*, in Grandy Reservoir, Colorado. *Transactions of the American Fisheries Society* 98:245-252.
- Gibson, R.N., L. Pihl, M.T. Burrows, J. Modin. H. Wennhage, and L. A. Nickell. 1998. Diel movements of juvenile plaice *Pleuronectes platessa* in relation to predators, competitors, food availability and abiotic factors on a microtidal nursery ground. *Marine Ecology Progress Series* 165:145-159.
- Gosch, N.J.C., J.R. Stittle, and K.L. Pope. 2010. Food habits of stunted and non-stunted white perch *Morone americana*. *Journal of Freshwater Ecology* 25:31-36.
- He, X. and J.F. Kitchell. 1990. Direct and indirect effects of predation on a fish community: a whole-lake experiment. *Transactions of the American Fisheries Society* 119:825-835.
- Hodkin, C.E. 2001. Population characteristics and food habits of white perch (*Morone americana*) in Branched Oak Lake, Nebraska. Master’s Thesis. University of Nebraska Lincoln.
- Kohler, C. C., J. J. Ney, and A. A. Nigro. 1979. Compact, portable vertical gill net system. *The Progressive Fish-Culturist* 41:34-35.

- Lackey, R. T. 1968. Vertical gill nets for studying depth distribution of small fish. Transactions of the American Fisheries Society 97:296-299.
- Maynard, H.S., M.J. Vanni, and T.E. Wissing. 2002. Biomass dependent diet shifts in omnivorous gizzard shad: implications for growth, food web, and ecosystem effects. Transactions of the American Fisheries Society 131:40-50.
- McGrath, P., and H.A. Austin. 2009. Site fidelity, home range, and tidal movements of white perch during the summer in two small tributaries of the York River, Virginia. Transactions of the American Fisheries Society 138:966-974.
- Murphy, B. R., and D. W. Willis, editors. 1996. Fisheries techniques, 2nd edition. American Fisheries Society, Bethesda, Maryland.
- R Development Core Team. 2014. R: a language for statistical computing, USA:R Foundation for Statistical Computing. Available: [www.R-project.org](http://www.R-project.org) (January 2015)
- Ringelberg, J. 1995. Changes in light intensity and diel vertical migration: a comparison of marine and freshwater environments. Journal of the Marine Biological Association of the United Kingdom 75:15-25.
- Schaeffer, J.S., and F.J. Margraf. 1987. Predation on fish eggs by white perch, *Morone americana* in western Lake Erie. Environmental Biology of Fishes 18:77-80.
- Temple, A. J. 2009. An Introduction to Electrofishing with Power v1.4. U.S. Fish and Wildlife Service National Conservation Training Center. Available: <http://electrofishing.net/2009/09/electrofishing-with-power-v141/> (June 2013).
- Taniguchi, Y. and S. Nakano. 2000. Condition-specific competition: implications for the altitudinal distribution of stream fishes. Ecology 81:2027-2039.
- Venables, W. N. and B. D. Ripley. 2002 Modern Applied Statistics with S. Fourth Edition. Springer, New York.
- Vondracek, B., and D.J. Degan. 1995. Among- and within-transect variability in estimates of shad abundance made with hydroacoustics. North American Journal of Fisheries Management 15:933-939.
- Webster, D.A. 1943. Food progression in young white perch *Morone americana* (Gmelin) from Bantam Lake, Connecticut. Transactions of the American Fisheries Society 72:136-144.
- Yako, L.A., J.M. Dettmers, and R.A. Stein. 1996. Feeding preferences of omnivorous gizzard shad as influenced by fish size and zooplankton density. Transactions of the American Fisheries Society 125:753-759.
- Zuerlein, G. 1981. The white perch in Nebraska. Nebraska Technical Series No. 8.

Table A-1. The order of polynomial used to remove global trends and mean prediction error for universal kriging analysis carried out using geostatistical analyst tools in ArcGIS10 to assess changes in fish spatial distribution in Branched Oak Lake during diel cycles between August 11 and 29 of 2014. Data were collected using a consumer grade sonar unit.

Sample	Period	Depth layer (m)					
		2.1-4.0		4.1-6.0		>6	
		Order of trend removal	Mean prediction error	Order of trend removal	Mean prediction error	Order of trend removal	Mean prediction error
1	Dawn	2	-0.026	1	0.153	1	0.037
	Day	2	-0.143	1	-0.172	1	-0.082
	Dusk	2	0.184	1	-0.028	2	0.016
	Night	2	0.058	1	-0.023	1	-0.020
2	Dawn	2	-0.011	1	0.035	2	-3.085
	Day	2	-0.016	1	-0.044	1	-0.030
	Dusk	2	-0.108	1	-0.049	2	0.016
3	Dawn	2	0.424	1	-0.162	2	0.004
	Day	2	0.316	0	-0.025	2	3.540
	Dusk	2	-0.020	0	0.022	2	-0.034

Table A-2. Comparisons of the number of fish captured with a boat electrofisher between periods over diel cycles in Branched Oak Lake, Nebraska from August 11 to 29, 2014.

Analyses were carried out using generalized linear models for data with negative binomial distribution.

Period comparison	t	df	p
Dawn v. day	-1.322	105	0.186
Dawn v. dusk	-2.946	105	0.003
Dawn v. night	-1.803	105	0.071
Day v. dusk	1.832	105	0.067
Day v. night	0.708	105	0.479
Dusk v. night	-0.188	105	0.271



Table A-3. Results of comparisons of number of fish targets identified using consumer-grade sonar between periods within depth layers. Data were collected between August 11 and 29, 2014 in Branched Oak Lake, Nebraska. Analyses were carried out using generalized linear models for data with negative binomial distribution.

Depth layer (m)	Period comparison	df	t	p
2.1-4.0	Dawn v. day	360	2.019	0.044
	Dawn v. dusk	360	- 3.192	0.001
	Dawn v. night	360	- 11.945	<0.001
	Day v. dusk	362	4.896	<0.001
	Day v. night	362	9.917	<0.001
	Dusk v. night	362	1.060	0.289
4.1-6.0	Dawn v. day	242	1.445	0.148
	Dawn v. dusk	242	- 2.826	0.005
	Dawn v. night	242	- 7.296	<0.001
	Day v. dusk	244	4.076	<0.001
	Day v. night	244	6.623	<0.001
	Dusk v. night	244	- 0.364	0.716
>6.0	Dawn v. day	136	0.470	0.639
	Dawn v. dusk	136	- 2.102	0.036
	Dawn v. night	136	- 3.315	0.001
	Day v. dusk	138	2.575	0.010
	Day v. night	138	3.208	0.001
	Dusk v. night	138	- 0.714	0.475

Table A-4. Results of comparisons of number of fish captured with vertical gillnets in the top 4 meters of the water column between periods. Data were collected between August 11 to 29, 2014 in Branched Oak Lake, Nebraska. Analyses were carried out using generalized linear models for data with negative binomial distribution.

Depth layer (m)	Period comparison	df	t	p
0.0-2.0	Dawn v. day	32	-0.503	0.615
	Dawn v. dusk	32	1.404	0.160
	Dawn v. night	32	0.204	0.838
	Day v. dusk	34	-1.895	0.058
	Day v. night	34	-1.027	0.304
	Dusk v. night	34	1.281	0.200
2.1-4.0	Dawn v. day	32	0.133	0.894
	Dawn v. dusk	32	-0.194	0.846
	Dawn v. night	32	0.000	1.000
	Day v. dusk	34	0.333	0.739
	Day v. night	34	1.974	0.048
	Dusk v. night	34	1.449	0.147

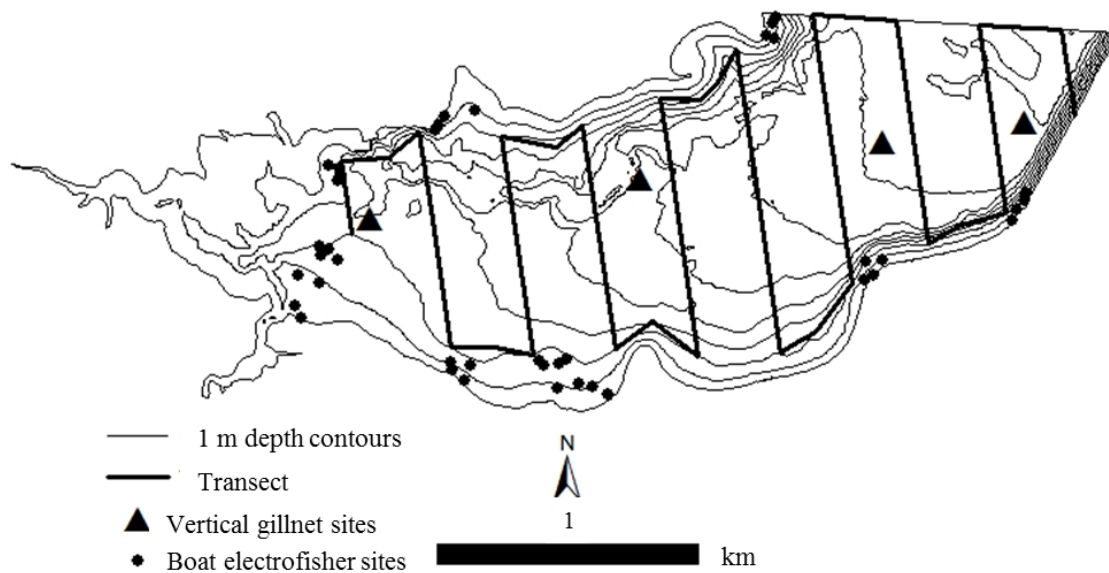


Figure A-1. Sampling used to estimating changes in fish spatial distribution in Branched Oak Lake, Nebraska over diel cycles between August 11 and 29, 2014.

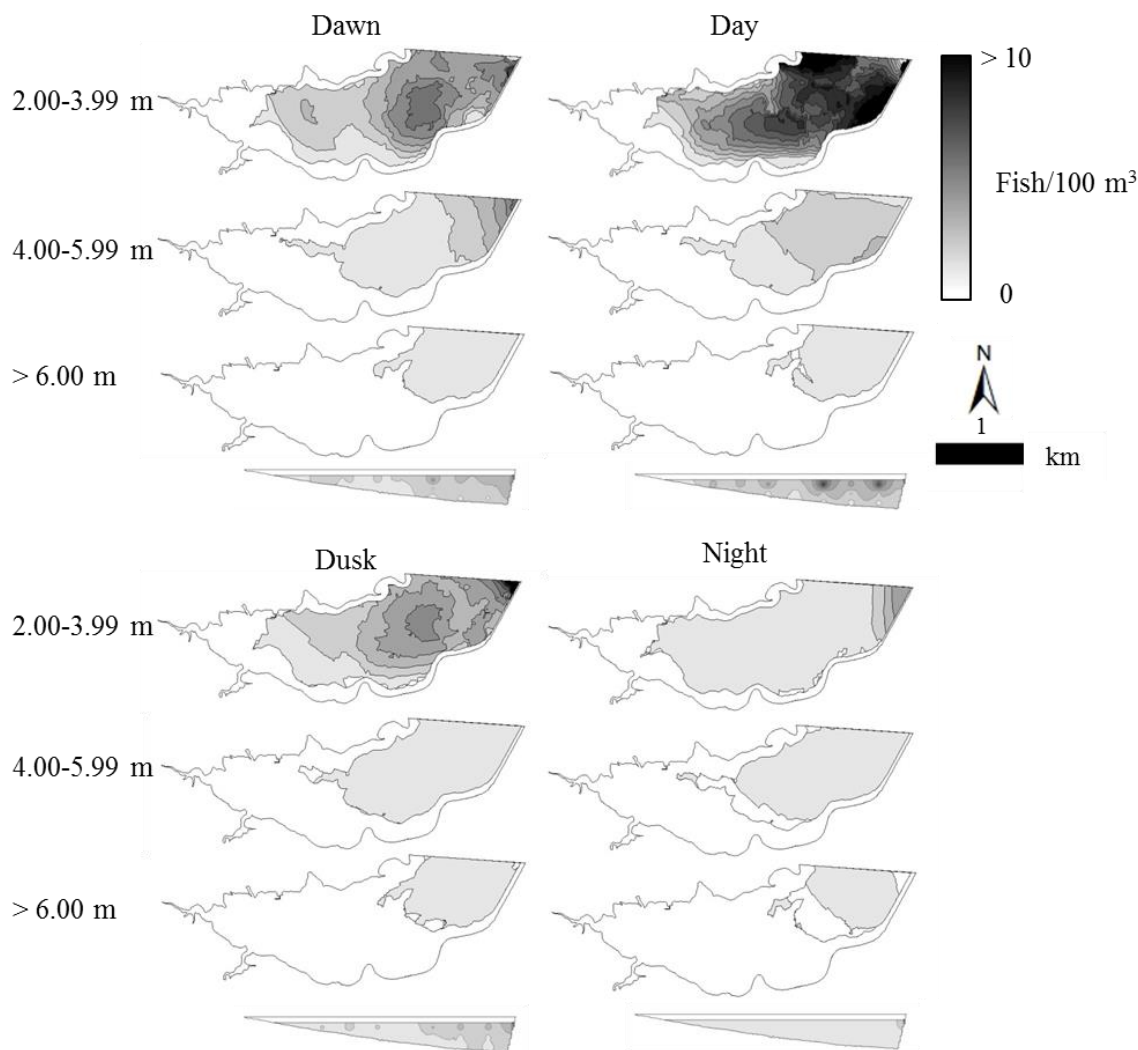


Figure A-2. Fish distribution during four periods (dawn 2 h before to 2 h after sunrise, day 11:00-15:00, dusk 2 h before to 2 h after sunset, night 23:00-03:00) in three depth layers of Branched Oak Lake, Nebraska during the week of August 11, 2014. Data were collected using a consumer grade sonar unit and maps were generated using universal kriging.

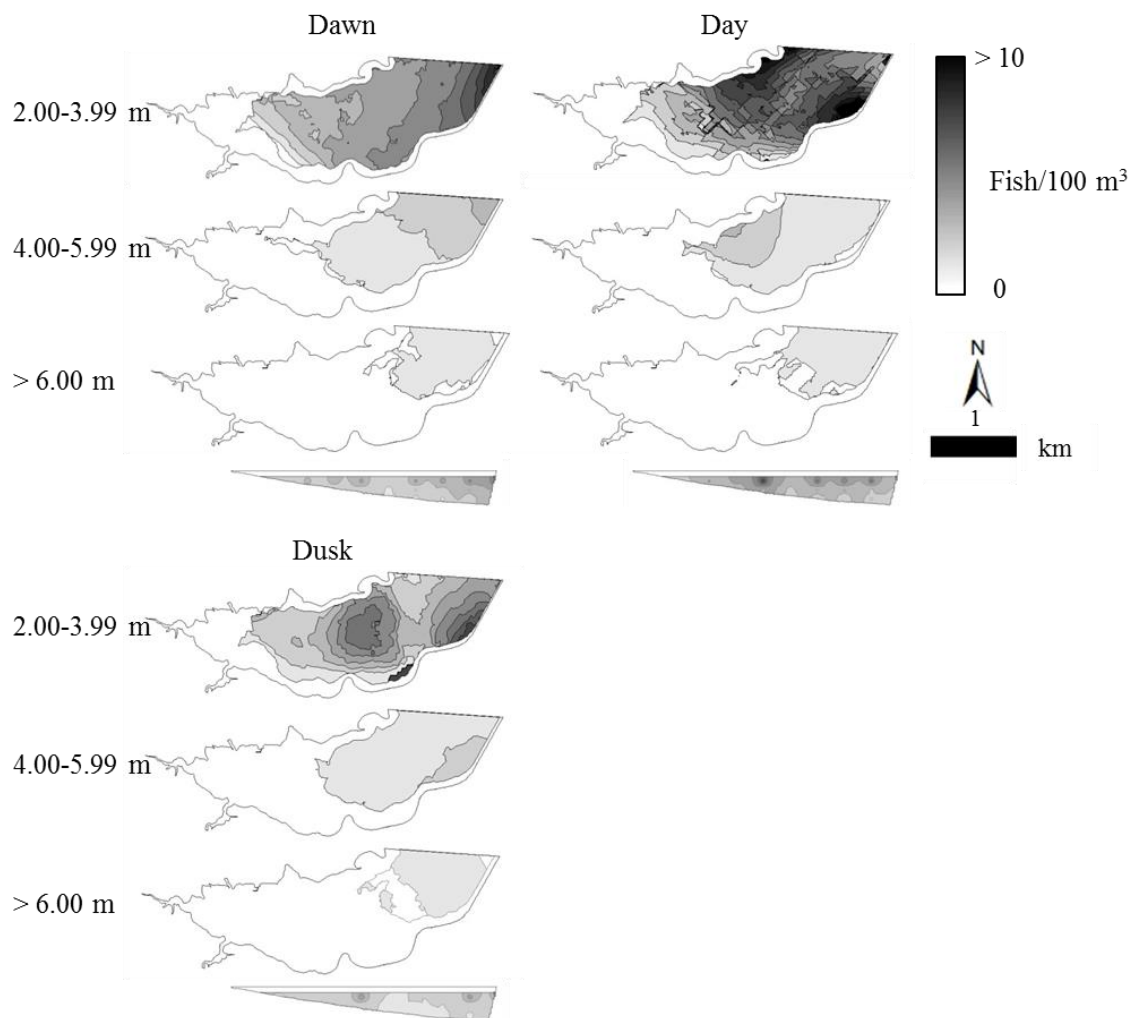


Figure A-3. Fish distribution during three periods (dawn 2 h before to 2 h after sunrise, day 11:00-15:00, and dusk 2 h before to 2 h after sunset) in three depth layers of Branched Oak Lake, Nebraska during the week of August 18, 2014. Data were collected using a consumer grade sonar unit and maps were generated using universal kriging.

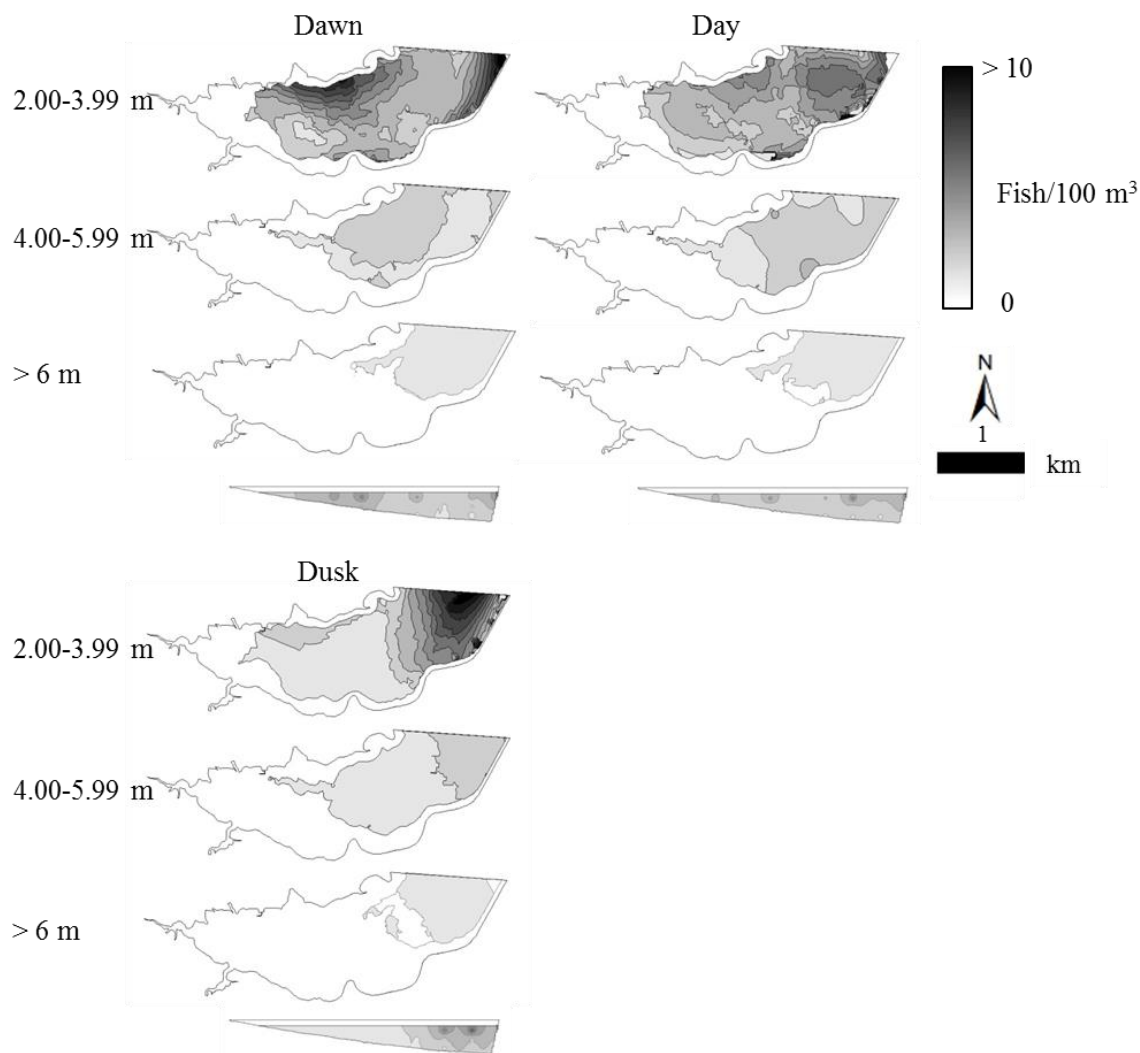


Figure A-4. Fish distribution during three periods (dawn 2 h before to 2 h after sunrise, day 11:00-15:00, and dusk 2 h before to 2 h after sunset) in three depth layers of Branched Oak Lake, Nebraska during the week of August 25, 2014. Data were collected using a consumer grade sonar unit and maps were generated using universal kriging.

## **Appendix B. Striped bass condition and diet**

### **Introduction**

In an attempt to reduce white perch (*Morone americana*) abundance in Branched Oak Lake, the Nebraska Game and Parks Commission stocked striped bass (*Morone saxatilis*). Striped bass were selected for stocking because they are a predator of white perch in their native range and because they tend to consume smaller prey (Walters and Austin 2003; Gosch 2008). In October 2013, 8,000 striped bass were stocked at a total length of 76 mm along with 2,400 striped bass at a total length of 89 mm. During May 2014, 8,524 striped bass were stocked at a total length of 203 mm. Our goal was to evaluate these stockings in terms of striped bass condition and diet.

### **Methods**

We recorded any striped bass captured during 2014 on Branched Oak Lake while sampling to estimate abundance (Chapter 2) and to estimate how fish distributions changed over diel cycles (Appendix A) we recorded any striped bass captured. In addition to this sampling, we electrofished specifically for striped bass during June 2014, September 2014, and April 2015. The Nebraska Game and Parks Commission also electrofished for striped bass during April 2015. This sampling was conducted during daylight hours using a boat electrofisher and targeted at areas low in the reservoir near water > 4 m deep such as the jetties on the bay mouths and the face of the dam. We also set gillnets during April 2014 and August 2014. These nets were made up of fish 10-m monofilament panels, two 19-mm bar mesh panels and one each of 25-, 32-, and 38-mm

bar mesh panels; all panels were 2-m high and were arranged in a random sequence. During April 2014, two gillnets were set in water > 7 m deep low in the reservoir to target aggregations of white perch and gizzard shad; these nets were retrieved 24 h after setting. During August 2014, 13 gillnets were set to specifically target striped bass; these nets were distributed throughout the reservoir and 7 were set as floating gillnets by attaching buoys to the float line at 5-m intervals thereby keeping the float line within 15 cm of the water's surface; these nets were retrieved 1-2 h after setting.

When striped bass were captured, total length (mm) and mass (g) were recorded in the field. Striped bass were then frozen and returned to the laboratory. In the laboratory, the fish were thawed and we removed the stomach from each fish. All items in the stomach were removed and all fish contained in striped bass stomachs were identified to species if possible. Relative weight was calculated for each fish (Brown and Murphy 1991).

## **Results and discussion**

In total, we captured 12 striped bass (Table B-1). Three striped bass were captured in vertical gillnets during July 2014, one striped bass was captured in a standard set gillnet during August 2014 (Table B-1), and eight striped bass were captured electrofishing along the jetties at the bay mouths during September (Table B-1). In addition to the striped bass that we captured, the Nebraska Game and Parks Commission captured two striped bass in standardized gillnets and two in standardized frame nets during October. We captured the most striped bass by electrofishing the jetties at the bay mouths during September.



Condition of striped bass captured was poor with relative weights ranging from 58 to 87 (Table B-2). Relative weight of fish captured decreased from July through September then slightly increased from September to October (Table B-2). Seven of the 16 (44%) fish examined had empty stomachs. Two striped bass had small amounts of digested material in their stomachs (Table B-2). Three striped bass contained fish material that could not be identified (Table B-2). Four striped bass contained gizzard shad (*Dorosoma cepedianum*) (Table B-2). Thus some of the stocked striped bass grew to a size where they were able to consume young of the year gizzard shad by October. No white perch were identified in any of the striped bass stomachs.

Future research should focus on understanding striped bass ecology in Branched Oak Lake as it relates to the effect on the white perch population. Survival of the stocked striped bass should be assessed to determine the best manner in which to stock them and to determine if they can survive long term in this system. Prey selection and bioenergetics data would be beneficial for determining if white perch are a substantial portion of striped bass diet in Branched Oak Lake and to predict their effect on the white perch population in this waterbody. Finally, an understanding of how striped bass spatially distribute in this system would allow us to determine what habitats are critical for the success of this species in this system and what the carrying capacity of this system is in terms of striped bass. Once we understand this, we may be able to manipulate the habitat to increase the carrying capacity for striped bass possibly with greater effects on the white perch population in Branched Oak Lake.

Table B-1. Sampling effort (N) and catch of striped bass (*Morone saxatilis*) in Branched Oak Lake, Nebraska. Sampling gears were vertical gillnets (VG; number of sets), a boat electrofisher (EF; seconds of on time), and horizontal gillnets (GN; number of sets).

Month	Gear	N	Striped bass
April 2014	VG	96	0
	EF	3540	0
	GN	2	0
June 2014	EF	-	0
July 2014	VG	96	3
	EF	4320	0
August 2014	GN	13	1
	EF	6600	0
September 2014	EF	4575	8
October 2014	VG	66	0
	EF	4500	0
November 2014	VG	30	0
April 2015	EF	9771	0

Table B-2. Length, weight, relative weight ( $W_r$ ), and gut content information for striped bass (*Morone saxatilis*) captured in Branched Oak Lake, Nebraska during 2014. Effort consisted of 288, 1-2 h vertical gillnet sets (VG), 15, 1-24 h horizontal gillnet sets (GN), and 26,731 seconds of electrofishing (EF) during 2014. Fish from October were captured in Nebraska Game and Parks Commission standardized gillnets and trapnets (TN).

Parameters for estimating relative weight from Brown and Murphy 1991.

Month	Gear	Length (mm)	Weight (g)	$W_r$	Stomach
July	VG	201	87	87	4 spinal columns
	VG	174	57	88	Empty
	VG	161	45	87	1 gizzard shad 1 spinal column
August	GN	193	56	63	Empty
September	EF	261	150	68	1 unidentified fish
	EF	246	135	73	1 spinal column
	EF	252	139	70	Empty
	EF	263	157	70	Empty
	EF	246	135	73	Empty
	EF	199	64	66	Empty
	EF	230	100	66	Small amount digested material
	EF	248	122	65	Small amount digested material
October	GN	282	216	78	2 gizzard shad 1 spinal column
	GN	274	220	86	2 gizzard shad
	TN	271	196	79	1 gizzard shad
	TN	250	112	58	Empty

## References

- Brown, M. L., and B. R. Murphy. 1991. Standard weights ( $W_s$ ) for striped bass, white bass, and hybrid striped bass. *North American Journal of Fisheries Management* 11:451-467.
- Gosch, N. J. C. 2008. Predation as a mechanism for the control of white perch: an investigation of food habits in two Nebraska reservoirs. Master's thesis. University of Nebraska Lincoln.
- Walters, J. F., and H. M. Austin. 2003. Diet composition of large striped bass (*Morone saxatilis*) in Chesapeake Bay. *Fishery Bulletin* 101:414-423.