

**EVALUATION OF CURRENT MANAGEMENT STRATEGIES FOR THE NEW RIVER, VIRGINIA,  
MUSKELLUNGE FISHERY: MODELING THE EFFECT OF ALTERNATIVE HARVEST REGULATIONS  
AND HABITAT SELECTION**

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The purpose of this research was to evaluate current management strategies for the New River, Virginia, muskellunge *Esox masquinongy* fishery, which is the premier muskellunge fishery in the state. The primary objectives were to evaluate potential benefits and angler support for more restrictive harvest regulations and to quantify habitat selection at multiple spatial scales. A secondary objective was to develop an alternative procedure for testing differences in muskellunge condition from relative weight  $W_r$  data that incorporates uncertainty regarding the accuracy of the standard weight equation and that is based on derived statistical properties of the  $W_r$  index. Abundance of memorable-length ( $\geq 1,070$  mm) muskellunge was predicted to increase with minimum length limits of 914, 1,016, and 1,143 mm. Although yield per recruit would decline under a 1,143-mm minimum length limit, it was predicted to remain fairly stable at length limits of 914 and 1,016 mm due to fast growth rates of young fish. Even though most anglers defined trophy muskellunge to be in excess of 1,016 mm, angler support for length limits in excess of 1,000 mm was low. Habitat variables that were most strongly related to muskellunge habitat selection were measures of patch shape complexity and water depth. Increased river discharge was found to significantly affect muskellunge habitat use and selection, with fish abandoning deeper open-water habitats and moving to shallower areas closer to the shoreline during periods of high discharge. As for the secondary objective, a new statistical test ( $R$ -test) was developed that can be used to test for differences in  $W_r$  between and within fish stocks. Comparison with other statistical tests indicated that the  $R$  test provides more conservative results than traditional statistical procedures, and that substantial variability in standard weight equations will make it more difficult to detect statistical differences. Management recommendations for the New River muskellunge fishery include increasing the minimum length limit to approximately 965 to 1,067 mm and limiting the stocking of muskellunge only to those areas with sufficient juxtaposition of shallow- and deep-water habitat patches.

## **DEDICATION**

This dissertation is dedicated to the memory of my grandfather, Clifford Foreng, who passed away while I was working towards my doctoral degree. Some of my fondest childhood moments were spent with him fishing for Devils Lake, North Dakota, walleye. Although my time in Virginia lessened the time I could spend with him, his encouragement when I was a child helped lead me into this field.

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## TABLE OF CONTENTS

<b>ABSTRACT</b> .....	ii
<b>DEDICATION</b> .....	iii
<b>FUNDING SOURCES</b> .....	iv
<b>ACKNOWLEDGEMENTS</b> .....	v
<b>LIST OF FIGURES</b> .....	ix
<b>LIST OF TABLES</b> .....	xiii
<b>INTRODUCTION</b> .....	1
<b>STUDY SITE</b> .....	8
<b>CHAPTER 1: STATISTICAL PROPERTIES OF THE RELATIVE WEIGHT (<math>W_r</math>) INDEX AND AN ALTERNATIVE PROCEDURE FOR TESTING <math>W_r</math> DIFFERENCES BETWEEN GROUPS</b> .....	11
<b>ABSTRACT</b> .....	11
<b>INTRODUCTION</b> .....	12
<b>METHODS</b> .....	13
<i>Model Specification</i> .....	13
<i>Derivation</i> .....	15
<i>Estimation and Test Comparison</i> .....	17
<b>RESULTS</b> .....	20
<i>Derivation</i> .....	20
<i>Estimation and Test Comparison</i> .....	21
<b>DISCUSSION</b> .....	24
<i>Statistical Properties of <math>W_r</math></i> .....	24
<i>Statistical Testing of <math>W_r</math> Data</i> .....	26
<b>MANAGEMENT IMPLICATIONS</b> .....	28
<b>CHAPTER 2: THE NEW RIVER, VIRGINIA, MUSKELLUNGE FISHERY: POPULATION DYNAMICS, HARVEST REGULATION MODELING, AND ANGLER ATTITUDES</b> .....	37
<b>ABSTRACT</b> .....	37
<b>INTRODUCTION</b> .....	38
<b>STUDY SITE</b> .....	40
<b>METHODS</b> .....	40
<i>Data Collection</i> .....	40
<i>Data Analyses</i> .....	43
<b>RESULTS</b> .....	47
<i>Muskellunge Population Dynamics</i> .....	47
<i>Angler Attitudes</i> .....	52
<i>Alternative Length Limit Evaluations</i> .....	56
<b>DISCUSSION</b> .....	57
<i>New River Muskellunge Population Dynamics</i> .....	57
<i>Angler Attitudes</i> .....	62
<i>Alternative Harvest Regulations</i> .....	64
<b>MANAGEMENT IMPLICATIONS/CONCLUSIONS</b> .....	66
<b>CHAPTER 3: ESTIMATING TOTAL ERROR IN LOCATING RADIOTELEMETRY TRANSMITTERS BY HOMING IN A RIVERINE ENVIRONMENT</b> .....	86
<b>ABSTRACT</b> .....	86
<b>INTRODUCTION</b> .....	86
<b>METHODS</b> .....	88
<b>RESULTS</b> .....	90
<b>DISCUSSION</b> .....	91
<b>CHAPTER 4: MULTI-SCALE HABITAT SELECTION BY MUSKELLUNGE IN A SOUTHEASTERN U.S. WARMWATER RIVER</b> .....	100
<b>ABSTRACT</b> .....	100
<b>INTRODUCTION</b> .....	101
<b>STUDY AREA</b> .....	102
<b>METHODS</b> .....	103
<i>Transmitter Implantation and Tracking Methodology</i> .....	103

<i>Habitat Variable Measurement and Mapping</i> .....	104
<i>Verification of Habitat Map Accuracy</i> .....	108
<i>Home Range Delineation</i> .....	109
<i>Muskellunge Habitat Selection</i> .....	110
<i>Effect of River Discharge on Habitat Use and Selection</i> .....	114
<b>RESULTS</b> .....	116
<i>Macro-Scale Habitat Selection</i> .....	117
<i>Micro-Scale Habitat Selection</i> .....	119
<i>Effect of River Discharge on Habitat Use and Selection</i> .....	121
<b>DISCUSSION</b> .....	123
<b>CONCLUSIONS/MANAGEMENT RECOMMENDATIONS/FUTURE INVESTIGATIONS</b> .....	155
<b>SUMMARY</b> .....	160
<b>LITERATURE CITED</b> .....	164
<b>APPENDIX 1: TECHNICAL DESCRIPTION OF DERIVATION RESULTS</b> .....	182
<b>APPENDIX 2: SAS PROGRAMMING CODE FOR THE R TEST</b> .....	189
<b>APPENDIX 3: VARIANCE-COVARIANCE ESTIMATES OF <math>W_s</math> EQUATION PARAMETERS FOR 58 SPECIES AND PURPOSEFUL HYBRIDS</b> .....	195
<b>APPENDIX 4: SAS CODE FOR FINDING VARIANCE AND COVARIANCE ESTIMATES OF <math>W_s</math> EQUATION PARAMETERS</b> .....	199
<b>APPENDIX 5: GENERALIZED ADDITIVE MODELING RESPONSE CURVES FOR WINTER AND SUMMER MICRO-LEVEL HABITAT SELECTION PROBABILITY FUNCTIONS FOR THOSE HABITAT VARIABLES WITHOUT CONSISTENT PATTERNS ACROSS MUSKELLUNGE</b> .....	203
<b>VITA</b> .....	207



## LIST OF FIGURES

Figure 1.	Comparison of predicted fish weights when weight is extrapolated for all populations used to construct the $W_s$ equation for muskellunge versus the fish weight where extrapolation is restricted only to the length categories from which fish were originally sampled. The horizontal lines are used to compare the variability in fish weights that result from unrestricted versus restricted extrapolation.....	7
Figure 2.	Location of the New River in Virginia and its subdivision into upper, middle, and lower sections.....	10
Figure 1.1.	Predicted weight versus length relationships for muskellunge (top left; Neumann and Willis 1994), walleye Sander vitreus (top right; Murphy et al. 1990), and black crappie (bottom; Neumann and Murphy 1991) for the populations used to determine $W_s$ for each species.....	33
Figure 1.2.	Scatterplot of length versus weight for the muskellunge (top left), largemouth bass (Smoots Pond – top right; Big Pond – bottom left), and black crappie (bottom right) electrofishing samples.....	34
Figure 1.3.	Plots of $W_r$ expectations (black dots) $\pm$ 2 SE (connected lines; $SE = \sqrt{\text{Var}}$ ) for the muskellunge (top left), largemouth bass (Smoots Pond - top right; Big Pond – bottom left), and black crappie (bottom right) length-weight data.....	35
Figure 1.4.	An illustration of the conditionality of $W_r$ on fish length. Rather than being generated from a common distribution, the $W_r$ data are generated by a unique distribution for each fish length under study. The straight line indicates a trend in mean $W_r$ that might be found for a sample of fish and how $W_r$ might be distributed around such a mean. Although the distributions are depicted as equally shaped and normal, this is only for illustrative purposes and is not meant to imply that this is the true nature of $W_r$ distributions.....	36
Figure 2.1.	Map of the New River in southwestern Virginia and specific locations of sites (e.g., dams, sampling areas) mentioned in the text.....	74
Figure 2.2.	Length-frequency histograms and size structure indices (PSD = proportional stock density; proportion of fish $\geq$ 510 mm that also are $\geq$ 760 mm, RSD = relative stock density; proportion of fish $\geq$ 510 mm that also are $\geq$ 970 mm (RSD-P), $\geq$ 1,070 mm (RSD-M), and $\geq$ 1,270 mm (RSD-T)) for muskellunge captured among different years and method of capture.....	75
Figure 2.3.	Pairwise age-bias plots calculated for the three readers. Each plot indicates the mean age and associated 95% confidence interval for the ages assigned by one reader relative to the ages assigned by another reader. The 1:1 equivalence (dashed line) is also indicated on each graph.....	76
Figure 2.4.	Scatterplot comparison of cleithrum age estimates to sectioned pelvic fin ray estimates for 21 muskellunge ranging in length from 593 to 1,230 mm. A slight Y-direction jitter has been applied to the data points to prevent overlap. The dashed line represents a perfect agreement between the estimates.....	77
Figure 2.5.	Predicted versus actual length-at-age data for two von Bertalanffy growth models fit to the age data. The top panel shows predicted versus actual length-at-age data for a von Bertalanffy growth model where all six parameters were estimated (solid dots and line = females; open dots and dashed line = males). The lower panel shows predicted versus actual length-at-age data for the von Bertalanffy growth model where $L_\infty$ for the sexes was selected based on available data. Coefficients for each growth equation are shown on the graphs.....	78
Figure 2.6.	Catch curves fit to the $\log_e$ catch at age data. Based on the plots, it was believed that muskellunge fully recruited to the sampling gear at age 1. The top panel shows the catch curve and resulting estimate of $Z$ fitted to all of the age data. The lower panel shows catch curves and the associated estimates of $Z$ fitted individually to fish ages 1 to 4 and to fish ages 4 and higher.....	79

Figure 2.7. Estimated monthly instantaneous fishing mortality rates (top panel) and instantaneous natural mortality (lower panel) for the New River. Each graph shows the estimated mortalities for models where the rates were allowed to vary monthly (dotted lines), quarterly (solid line), or to be constant (dashed line). ..... 80

Figure 2.8. Number of days per year that New River anglers indicated they fished for muskellunge..... 81

Figure 2.9. Length of muskellunge considered a “trophy” (bottom) and minimum harvestable lengths (top) identified by non-, occasional, moderately-dedicated, and dedicated muskellunge anglers. The percent of anglers that specified all muskellunge would be released are under the category marked C&R (catch and release). ..... 82

Figure 2.10. Percent expected changes in the number of memorable length ( $\geq 1,070$  mm) muskellunge in the New River muskellunge fishery with the implementation of a 914-mm (top-left), 1,016-mm (top-right), and 1,143-mm (bottom) minimum length limit. Current annual mortality rate estimates ( $cm$  = conditional natural mortality;  $cf$  = conditional fishing mortality) are denoted on the graphs with an “X”. ..... 83

Figure 2.11. Percent expected changes in the number of harvested fish from the New River muskellunge fishery with the implementation of a 914-mm (top-left), 1,016-mm (top-right), and 1,143-mm (bottom) minimum length limit. Current annual mortality rate estimates ( $cm$  = conditional natural mortality;  $cf$  = conditional fishing mortality) are denoted on the graphs with an “X”. ..... 84

Figure 2.12. Expected yield per recruit (YPR) changes of the New River muskellunge fishery with the implementation of a 914-mm (top-left), 1,016-mm (top-right), and 1,143-mm (bottom) minimum length limit. Current annual mortality rate estimates ( $cm$  = conditional natural mortality;  $cf$  = conditional fishing mortality) are denoted on the graphs with an “X”. ..... 85

Figure 3.1. Illustration of the relative influence of locating and mapping error on total error where telemetered fish position is recorded as a two-dimensional (X,Y) attribute..... 94

Figure 3.2. Top and side profile of a completed transmitter anchor. .... 95

Figure 3.3. Polar plots of recorded test transmitter positions in relation to original mapped positions. Distance units for each polar plot are in m. The arrows on the polar plots indicate the direction of river flow at that particular site..... 96

Figure 3.4. Rose diagram for the azimuth angular deviations in the weekly location estimates of the test transmitter anchors relative to the original mapped locations. On each diagram, the mean angular deviation is indicated by the black line running from the center of each diagram. The arc extending from this line at the edge of the diagram represents the upper and lower 95% confidence interval..... 97

Figure 3.5. Boxplots of distance error for each test transmitter and GPS receiver type. The asterisks indicate outliers, which are data points lying 1.5 times the inter-quartile range beyond the upper or lower quartiles. .... 98

Figure 3.6. Time-series plot of distance error combined across GPS receiver type for each test transmitter. .... 99

Figure 4.1. The 17-km study reach and its location in the New River where muskellunge habitat selection was evaluated..... 140

Figure 4.2. Scatterplots showing fish longitudinal location in the study reach (RKM) in relation to day of the year. The plots on the top row show fish that exhibited clear transition between summer and winter home ranges. The plots on the middle row show less clear transitions, while the plots on the bottom row show no clear transition between summer and winter home ranges. .... 141

Figure 4.3. Frequency histogram of median river discharge measurements for the 12-hours prior to each muskellunge location estimate. Locations associated with high and low discharges were classified based on the overall median (solid vertical line:  $\bar{x} = 45.3$  m<sup>3</sup>/s) of the discharge measurements. .... 142

Figure 4.4.	Response curves for the landscape pattern and composition metrics (PARA_MN: mean of the perimeter-area ratio distribution, SHAPE_CV: coefficient of variation of the shape index distribution, SHAPE_MN: mean of the shape index distribution, SHDI: Shannon's diversity index of patch classes) that comprised the AIC-selected model for the winter-macro-level habitat selection probability function fit by generalized additive modeling. The vertical axes, expressed in logits, indicate the relative influence of each habitat variable on predicted probability of habitat use based on partial residuals. Dashed lines represent two standard error bands. ....	143
Figure 4.5.	Response curves for the landscape pattern and composition metrics (ED10: edge density of vegetated habitats ranging in depth from 1 to 2 m; PARA_RA: range of the perimeter-area ratio distribution; PLAND11: percentage of the landscape consisting of vegetated habitats ranging in depth from 2 to 3 m) that comprised the AIC-selected model for the summer-macro-level habitat selection probability function fit by generalized additive modeling. The vertical axes, expressed in logits, indicate the relative influence of each habitat variable on predicted probability of habitat use based on partial residuals. Dashed lines represent two standard error bands. ....	144
Figure 4.6.	Scatterplot of model-average coefficient estimates in relation to fish length for the habitat variables included in the winter habitat selection probability functions. The solid lines on the figures are least-squares linear regression lines fit to the coefficient-fish length relationships. The dashed lines are reference lines (slope = 0).....	145
Figure 4.7.	Response curves of habitat selection probability functions to mean depth for those fish in which mean depth was among the variables included in the AIC-selected generalized additive model for winter. The vertical axes, expressed in logits, indicate the relative influence on probability of habitat use predictions based on partial residuals. Dashed lines represent two standard error bands. Lengths of fish when first equipped with transmitters are shown on each graph. ....	146
Figure 4.8.	Response curves of habitat selection probability functions to nearest distance to the 1- to 2-m depth contour for those fish in which this habitat variable was among those included in the AIC-selected generalized additive model for winter. The vertical axes, expressed in logits, indicate the relative influence on predictions of probability of habitat use based on partial residuals. Dashed lines represent two standard error bands. Lengths of fish when first equipped with transmitters are shown on each graph. ....	147
Figure 4.9.	Scatterplot of model-average coefficient estimates in relation to fish length for the habitat variables included in the summer habitat selection probability functions. The solid lines on the figures are least-squares linear regression lines fit to the coefficient-fish length relationships. The dashed lines are reference lines (slope = 0).....	148
Figure 4.10.	Response curves of habitat selection probability functions to mean depth for those fish in which this habitat variable was among those included in the AIC-selected generalized additive model for summer. The vertical axes, expressed in logits, indicate the relative influence on predictions of probability of habitat use based on partial residuals. Dashed lines represent two standard error bands. Lengths of fish when first equipped with transmitters are shown on each graph. ....	149
Figure 4.11.	Comparisons of mean coefficient estimates ( $\pm$ 95% bootstrap confidence intervals) between low and high discharges for winter habitat selection probability functions. ....	150
Figure 4.12.	Comparisons of response curves for the winter habitat selection probability functions fit by generalized additive modeling for fish locations associated with low and high river discharges. The vertical axes, expressed in logits, indicate the relative influence on predictions of probability of habitat use for each of the habitat variables based on partial residuals. Dashed lines represent two standard error bands.....	151
Figure 4.13.	Comparisons between mean coefficient estimates ( $\pm$ 95% bootstrap confidence intervals) of summer habitat selection probability functions calculated for low and high discharges. ....	152

Figure 4.14. Comparisons of response curves for the summer habitat selection probability functions fit by generalized additive modeling for fish locations associated with low and high river discharges. The vertical axes, expressed in logits, indicate the relative influence on predictions of probability of habitat use for each of the habitat variables based on partial residuals. Dashed lines represent two standard error bands..... 153

Figure 5.1 Comparison of real-time river discharge measurements for the New River when water is released from Claytor Hydroelectric Dam according to a run-of-river and hydropeaking release schedule. The horizontal line on each graph demarks the discharge measurement used to distinguish between low and high discharges in the habitat selection assessment for muskellunge..... 159

## LIST OF TABLES

TABLE 1.1	Parameter estimates used for the calculations of expectation, variance, and covariance for the muskellunge, largemouth bass (LMB* = Smoots Pond; LMB** = Big Pond), and black crappie $W_r$ data.....	30
TABLE 1.2	Overall and multiple comparison test results for testing no difference in $W_r$ among the length categories for the muskellunge, largemouth bass (LMB* = Smoots Pond; LMB** = Big Pond), and black crappie samples. All tests were conducted at $P_\alpha = 0.10$ . For the multiple comparison procedures, length categories that were found to be significantly different and how they differed are indicated (PS = pre-stock, S = stock-quality, Q = quality-preferred, P = preferred-memorable; NS = no significant difference in any of the length categories were found; “-“ = no multiple comparison procedure conducted).....	31
TABLE 1.3	Test results for testing the hypothesis of no difference in $W_r$ between the largemouth bass samples.....	32
TABLE 2.1	Total numbers of muskellunge captured and seen while electrofishing at the twelve sites sampled on the middle and lower sections of the New River from 2000 to 2003. The median number of muskellunge captured per electrofishing hour and the median number of muskellunge seen per electrofishing hour for the 12 sites also are displayed.....	69
TABLE 2.2	Observed TL changes of marked and recaptured muskellunge by tag type and sex versus length changes that were predicted using sex-specific von Bertalanffy growth equations. Growth equations were calculated using age estimates from pelvic fin ray sections.....	70
TABLE 2.3	Candidate models for estimating instantaneous fishing ( $F$ ) and natural ( $M$ ) mortality rates for the New River muskellunge telemetry data. The models differed as to whether the mortality rates remained constant or were allowed to vary quarterly or monthly. Candidate models are sorted according to the Akaike Information Criterion $AIC_c$ for each model. Also shown is the $\Delta AIC_c$ , which is the difference in each models $AIC_c$ from the minimum model $AIC_c$ , the relative likelihood of each model, the Akaike weight, which is the relative likelihood of each model, and the mortality estimates associated with each model. The model-average estimates of fishing and natural mortality are found by the summation of each model's mortality estimates multiplied by the Akaike weights of that model. The scaled estimates of mortality are the model-average estimates scaled to a yearly basis, as opposed to a 19-month time frame.....	71
TABLE 2.4	Response of angler subgroups to questions asked during a creel survey conducted on the New River in 2002 regarding the muskellunge fishery. Anglers that stated they had no opinions regarding the muskellunge fishery were excluded from the analysis.....	72
TABLE 2.5	Response of angler subgroups as to whether harvest regulations for New River muskellunge should be changed. Anglers with no opinions regarding regulation changes were combined with anglers that did not believe regulations needed to be changed. The suggested size limited proposed by the angler subgroups is a weighted average of the mean size limit suggested by anglers that wanted a higher limit and the mean size limit suggested by anglers that wanted a lower limit.....	73
TABLE 4.1.	Cross-validation classification accuracies for identifying substrate type with the reference hydroacoustic database via canonical discriminant analysis. Cells along the diagonal are the percent of substrate types correctly identified, while the off-diagonal values are the percent of habitat types incorrectly classified.....	130
TABLE 4.2.	Description of habitat components for each of the patch classes used in the macro-level habitat selection assessment.....	131
TABLE 4.3.	Landscape pattern and composition metrics included in the macro-level habitat selection assessment for muskellunge in the New River and a brief description of each metric. ...	132
TABLE 4.4.	Information concerning the 42 muskellunge implanted with radiotelemetry transmitters and the duration that tracking was conducted.....	133
TABLE 4.5.	Test statistics ( $t$ -stat.) and $P$ -values (winter $df = 11$ , summer $df = 19$ ) from the initial tests for differences between landscape pattern and composition metrics defined within muskellunge home ranges and within randomly identified areas for the summer and winter macro-level habitat selection assessment.....	135

TABLE 4.6.	Coefficient estimates for the landscape pattern and composition metrics included in the macro-level habitat selection models. Coefficients are the AIC model-average estimates of the metrics. Also shown are the lower (LCL) and upper 95% confidence limits (UCL) for the coefficients, which were estimated by bootstrapping. See Table 4.3 for a description of the metrics. ....	137
TABLE 4.7.	Coefficient estimates and 95% confidence limits for the habitat variables used in determining the micro-level habitat selection probability functions. Estimates were calculated by averaging the AIC model-average coefficient estimates across all telemetered muskellunge. Confidence limits are based on a student's-t distribution. The number of telemetered muskellunge among which coefficients were averaged are shown for each season. ....	138
TABLE 4.8.	Average correlation coefficients and the upper (UCL) and lower (LCL) 95% confidence limits relating muskellunge use of winter and summer habitat variables to median river discharge for the 12-hr period before fish were located. The number of telemetered muskellunge among which coefficients were averaged are shown for each season. ....	139

## INTRODUCTION

The muskellunge *Esox masquinongy* is a primarily piscivorous fish species whose native range is restricted to the St. Lawrence, Mississippi, Ohio, and Tennessee River drainages of North America (Crossman 1978). Due to its popularity as a sportfish, though, muskellunge have been propagated and stocked throughout much of North America (Crossman 1986). In the southern United States, muskellunge have been introduced into waterbodies in Alabama, Arkansas, Georgia, Kentucky, North Carolina, South Carolina, Tennessee, Virginia, and West Virginia (USGS 2004a). Some of the most productive muskellunge fisheries in southern U.S. regions are riverine stocks, which may be linked to cooler water temperatures in these environments during the summer than in neighboring lacustrine environments. Nevertheless, there has been very little research conducted that has explicitly addressed muskellunge biology and ecology in southern warmwater rivers [notable exceptions include Parsons (1959), Miles (1978), Axon and Kornman (1986), and Monaghan and Borawa (1988)]. This resulting lack of regional knowledge complicates management of southern riverine muskellunge stocks. Although questions addressed elsewhere (e.g., northern latitude lakes and rivers) are relevant, the degree to which findings are transferable to southern stocks is questionable (Leftwich et al. 1997). Southern rivers offer muskellunge a unique environment in terms of thermal conditions, prey availability, and system productivity that may affect growth, mortality, recruitment, and habitat use (Miles 1978; Harrison and Hadley 1979; Brewer 1980). If research results are applied without regard to the potential differences between geographical regions, fishery biologists responsible for managing southern riverine muskellunge stocks may find themselves ill-equipped for addressing management problems that may arise (Hanson et al. 1986).

In Virginia, muskellunge fisheries are managed primarily for the production of trophy fish and secondarily for forage fish control [J. A. Williams, Virginia Department of Game and Inland Fisheries (VDGIF), personal communication] through stocking and through minimum length and creel limit regulations. Stocked fish are obtained as eggs, which are cultured at VDGIF's Buller Fish Hatchery Station in Marion, Virginia. Sources for eggs have included Kentucky, Minnesota, Pennsylvania, Virginia, and Wisconsin brood fish (C. D. Stickle, VDGIF, personal communication). Muskellunge are stocked when approximately 100 mm [this and all lengths reported herein are total length (TL) measurements].

Several rivers and lakes in Virginia are stocked on a rotating priority system – waterbodies not stocked the previous year are given higher priority than those that were stocked. Statewide harvest of muskellunge is regulated by a 762-mm minimum length limit and a 2-fish/day creel limit.

The stocking of muskellunge in Virginia has created several quality fisheries. Since 1990, 936 citation size ( $\geq 1,016$  mm or  $\geq 6.8$  kg) muskellunge from 20 reservoirs, lakes, and rivers have been registered through Virginia's Angler Recognition Program (VARP; VDGIF, unpublished data). Nearly 70% of registered citations have been from three systems; New River, James River, and Smith Mountain Lake. Approximately 45% of all VARP-registered citation muskellunge captured since 1990 have been from the New River, making the New River the state's top trophy-producing fishery during this time period. The current state-record muskellunge (20.4 kg) was caught from the New River in 1989.

Despite the high quality muskellunge fishery that has been established on the New River, there are several areas of research needed that, when met, would be useful for optimizing management of the muskellunge fishery. One area of research concerns the application of the relative weight ( $W_r$ ) index (Wege and Anderson 1978) to the management of muskellunge populations. The  $W_r$  index is a widely used measure of physiological condition in fisheries management (Blackwell et al. 2000). The  $W_r$  index is calculated as

$$W_r = \frac{W}{W_s} \cdot 100,$$

where  $W$  is the observed weight of a fish and  $W_s$  is a species- and length-specific standard weight that is considered to represent what a fish in better-than-average condition would weigh (Murphy et al. 1991). Although conceptually simple, the use of the  $W_r$  index in fisheries management is controversial, with some researchers promoting its use (Murphy et al. 1991; Blackwell et al. 2000) and other researchers suggesting alternative measures (Packard and Boardman 1988; Cone 1989; Jakob et al. 1996).

One of the areas in which application of the  $W_r$  index is controversial concerns appropriate methods for analyzing  $W_r$  data (Cone 1989). Relative weight data frequently are analyzed using traditional parametric or nonparametric statistical tests, such as analysis of variance (ANOVA) or the Kruskal-Wallis test (Blackwell et al. 2000). However, for such tests to provide reliable results regarding differences in  $W_r$  among groups,  $W_r$  data must satisfy several theoretical assumptions. One assumption



that is shared by both parametric and nonparametric statistical tests of location is that of independent and identically distributed (i.i.d.) data (Neter et al. 1996; Hollander and Wolfe 1999). When the i.i.d. assumption is violated, statistical tests such as ANOVA and the Kruskal-Wallis test frequently yield more liberal results, meaning that it is easier to conclude that differences exist among groups (Carroll and Pearson 2000). Although empirical distributions of  $W_r$  data frequently are tested to assess assumptions of normality (Murphy et al. 1990; Hyatt and Hubert 2001), the statistical properties of the  $W_r$  index from a model standpoint have not been rigorously evaluated. Consequently, we cannot be sure that the  $W_r$  index indeed generates i.i.d. data; thus, testing of  $W_r$  data with traditional statistical procedures may in fact lead to false conclusions (Cone 1989).

Although the benefits of studying the analytical appropriateness of  $W_r$  data would not be limited to just one species, I believe that such research would be of particular benefit for muskellunge management for several reasons. Muskellunge standard weights are predicted from a  $W_s$  equation that was developed with length-weight data from 45 populations distributed throughout 16 U.S. states (Neumann and Willis 1994). The  $W_s$  equation for muskellunge was developed using the regression-line-percentile (RLP) technique, which involves extrapolation of the population length-weight data to a length traditionally equal to the world-record length for the species (Murphy et al. 1990). This extrapolation is conducted regardless of the lengths of fish used in the original length-weight relationship development. The justification for the extrapolation of the length-weight relationships is to prevent a few populations from biasing the final  $W_s$  equation (Murphy et al. 1990). While it may indeed prevent a few populations from biasing the final  $W_s$  equation, extrapolation also may result in substantial variability in predicted weights for fish of longer lengths. Of the populations used to construct the  $W_s$  equation for muskellunge, only 11% of the population length-weight datasets had fish measurements at lengths  $\geq 1,270$  mm, and plots of predicted weight versus length indeed confirm substantial variability in fish weight at longer lengths (Figure 1). The maximum fish weight predicted is 67.7 kg, which is more than twice the current world record for the species (Diana 1996). Standard weight equations are calculated directly from the extrapolated weights (actually from statistics of the extrapolated weights); thus, high variability in fish weights should lead to greater uncertainty as to the accuracy of the  $W_s$  equation. When empirical  $W_r$  data are analyzed with standard methods, the uncertainty associated with  $W_s$  equations is ignored.

Considering that  $W_r$  data may be used as a basis for evaluating management decisions, incorporation of  $W_s$  equation variability within a testing framework may help prevent improper management decisions from being made, particularly for those species where there may be reason to suspect substantial variability associated with  $W_s$  equations (e.g., muskellunge).

The second area of research that I believe would be helpful with managing the New River muskellunge population concerns an evaluation of the effectiveness of the current harvest regulations. Although liberal harvest regulations were once a fairly common approach to managing muskellunge fisheries (Carlander et al. 1978; Graff 1986), fishery management agencies have enacted more restrictive harvest regulations as muskellunge fishing has increased in popularity (Simonson and Hewett 1999). In northern regions (e.g., Wisconsin and Ontario), minimum length limits as high as 1,254 to 1,371 mm now are used to protect muskellunge from harvest and to allow female muskellunge an opportunity to spawn (Simonson and Hewett 1999; OMNR 2003). Further, with the realization that systems differ in their potential to produce trophy fish, fishery biologists have begun formulating management strategies for individual systems rather than managing on a statewide or province-wide basis. Nearly 20% of Wisconsin muskellunge fisheries are managed with harvest regulations that are different from the statewide regulation (Simonson and Hewett 1999).

While the liberal harvest regulation that is enforced on the New River may indeed be justified under certain conditions (e.g., slow growth rates resulting from intraspecific and/or interspecific competition for food resources, physiological inability to reach large sizes due to thermal intolerance), the low minimum length limit also may limit the recreational opportunity of the muskellunge fishery. Muskellunge in rivers frequently grow at fast rates early in life (Harrison and Hadley 1979); thus, fish can reach exploitable sizes in only a few years and fish may be harvested before having a chance to spawn or to add a significant amount of biomass. Low minimum length limits also may encourage harvest by novice anglers, who sometimes identify a "trophy" fish based on current regulations (Wingate 1986). This tendency towards harvesting muskellunge in the New River by novice anglers also may be exacerbated by the scarcity of private muskellunge angling clubs (e.g., Muskies, Inc.) in southern regions. Such groups often promote voluntary release of muskellunge both within the club as well as to the general angling public (Gasbarino 1986). As a result of these factors (i.e., early fast growth rates and potential for

high harvest), the enactment of more conservative harvest regulations for the New River may prove beneficial in increasing the abundance of “trophy” fish.

A third area of research that would be beneficial from a management standpoint concerns assessment of muskellunge habitat use and selection. Little research concerning this aspect of muskellunge ecology has been conducted in southern U.S. warmwater rivers. The stocking rate for Virginia rivers is based on a single, large-scale habitat variable, pool surface area. Although muskellunge frequently are collected in pools (Parsons 1959; Miles 1978; Brewer 1980; Axon and Kornman 1986), pools typically are sampled to the exclusion of other habitat types. Even if muskellunge preferentially use pool habitats, fish also may also select smaller-scale habitats based on characteristics such as depth, width, gradient, and amount of large woody debris within pools (Parsons 1959; Miles 1978; Brewer 1980; Axon and Kornman 1986). Thus, basing stocking rates on a habitat variable such as pool surface area may lead to stocking rates that either exceed or underestimate muskellunge carrying capacity.

A better understanding of muskellunge habitat use in warmwater rivers would assist in the development of a standardized sampling protocol for the species. Such a sampling protocol for riverine muskellunge populations currently does not exist, which has led to collection efforts that vary substantially even when similar sampling methodologies are employed. For example, Monaghan and Borawa (1988) used boat electrofishing to collect muskellunge in the French Broad River (North Carolina) by sampling exclusively behind large woody debris piles and reported an electrofishing catch rate of 4.7 fish per electrofishing hour. Conversely, Kornman (1999) used boat electrofishing to collect muskellunge from the Little Sandy River and Salt Lick Creek (Kentucky) by sampling along pool shorelines and reported an electrofishing catch rate of 0.9 fish per electrofishing hour. Based solely on catch rates, one might be tempted to conclude that the system sampled by Monaghan and Borawa (1988) had a muskellunge population that was  $\approx 5$  times greater in abundance than the system studied by Kornman (1999). However, this conclusion would only be valid if the catchability, or the fraction of a fish stock which is caught by a defined unit of fishing effort (Ricker 1975), was constant. Because the habitats that were sampled differed between the two studies, muskellunge catchability differed between the studies as well. As a result, there is virtually no basis for drawing any conclusions regarding abundance differences between the systems (Bonar and Hubert 2002). The development of a standardized sampling protocol

for muskellunge would permit broad spatio-temporal comparisons of sampling results and would allow management decisions to be made at spatial and temporal scales much larger than what currently is possible.

Against this background, the specific research objectives for this dissertation are to:

- 1) Derive the statistical properties of the  $W_r$  index and formulate an alternative testing procedure that can accommodate i.i.d. violations when testing  $W_r$  differences between muskellunge length classes and populations.
- 2) Investigate the demographic characteristics of the New River muskellunge fishery and predict the effect that alternative harvest regulations might have on the production of trophy fish.
- 3) Develop a method for anchoring radiotelemetry transmitters in a riverine environment and quantify error associated with locating transmitters through homing and recording their position using two GPS receiver types.
- 4) Model spatio-temporal habitat selection of muskellunge in a 17-km reach of the New River.

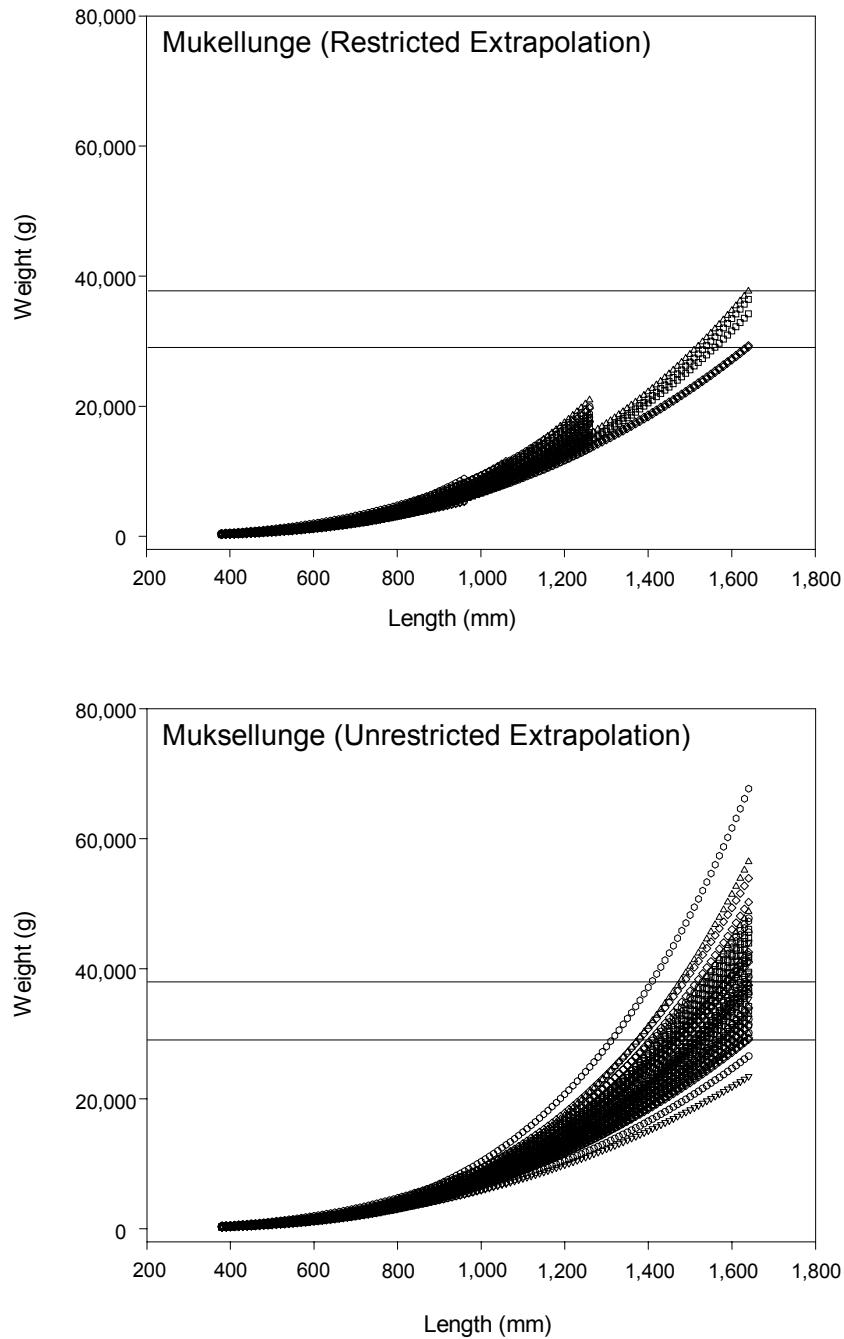


Figure 1. Comparison of predicted fish weights when weight is extrapolated for all populations used to construct the  $W_s$  equation for muskellunge versus the fish weight where extrapolation is restricted only to the length categories from which fish were originally sampled. The horizontal lines are used to compare the variability in fish weights that result from unrestricted versus restricted extrapolation.

## STUDY SITE

The New River originates in northwest North Carolina and flows northward through southwest Virginia into West Virginia (Figure 2). The New River originates from both a north and south fork. The confluence of the forks is 2 km east of Weavers Ford, NC. After the forks merge, the New River flows 6 river kilometers (rkm) before entering Virginia. The Virginia portion of the New River is 245 rkm in length and drains approximately 8,000 km<sup>2</sup> of primarily crop and grazing land. The river basin lies within two Virginia physiographic provinces, the Ridge and Valley and the Southern Blue Ridge Mountain Province. The West Virginia portion of the New River is 127 rkm in length. The New River merges with the Gauley River near Anstead, West Virginia to form the Kanawha River, which eventually flows into the Ohio River near Point Pleasant, West Virginia.

Compared to other drainages in Virginia and the eastern United States as a whole, the New River drainage has a fairly low number of native aquatic fish species (Jenkins and Burkhead 1993). Only 46 freshwater fish species are believed to be native to the drainage; 42 other species have been introduced (Jenkins and Burkhead 1993). Stocking of muskellunge in the New River was initiated by VDGIF in 1963. Although muskellunge are native to both the Ohio and Kanawha Rivers (Crossman 1978; Miles 1978), naturalized expansion of muskellunge into the New River possibly was prevented by Kanawha Falls, a waterfall located 3 rkm below the convergence of the New and Gauley Rivers. Kanawha Falls is believed to have played a major role in isolating the New River from other rivers in the Ohio River drainage and to have led to a high rate of endemism for fishes of the New River drainage (Jenkins and Burkhead 1993).

The Virginia portion of the New River is impounded by five dams: Buck, Byllesby, Claytor, Fields, and Fries Dams (Figure 2). All of these dams are capable of generating hydroelectric power, although the generating capacity of Fields and Fries Dam is fairly limited (< 5 megawatt capacity). Buck, Byllesby, and Claytor Dams are owned and operated by American Electric Power. The power generating capacities of these dams range from 10 (Buck Dam) to 76 megawatts (Claytor Dam). River flows in the lower section of the New River are heavily dependent on water release from Claytor Dam. From approximately mid-April to mid-October, Claytor Dam is operated on a "run-of-the river" release schedule to protect spawning habitat for fish in the upstream impoundments (J. A. Williams, VDGIF, personal

communication). During the rest of the year, Claytor Dam is operated on a hydropeaking release schedule.

Muskellunge currently are stocked in two sections of the New River, from the North Carolina/Virginia border to Fries Dam (upper section) and from Claytor Dam to the Virginia/West Virginia border (lower section). Approximately 1,000 muskellunge are stocked in the upper section and 4,000 are stocked in the lower section each year. Stocking of muskellunge from Fries Dam to Claytor Dam (middle section) was discontinued in 1994 because of possible detrimental effects to the walleye *Sander vitreus* fishery in this section of the river (J. A. Williams, VDGIF, personal communication).

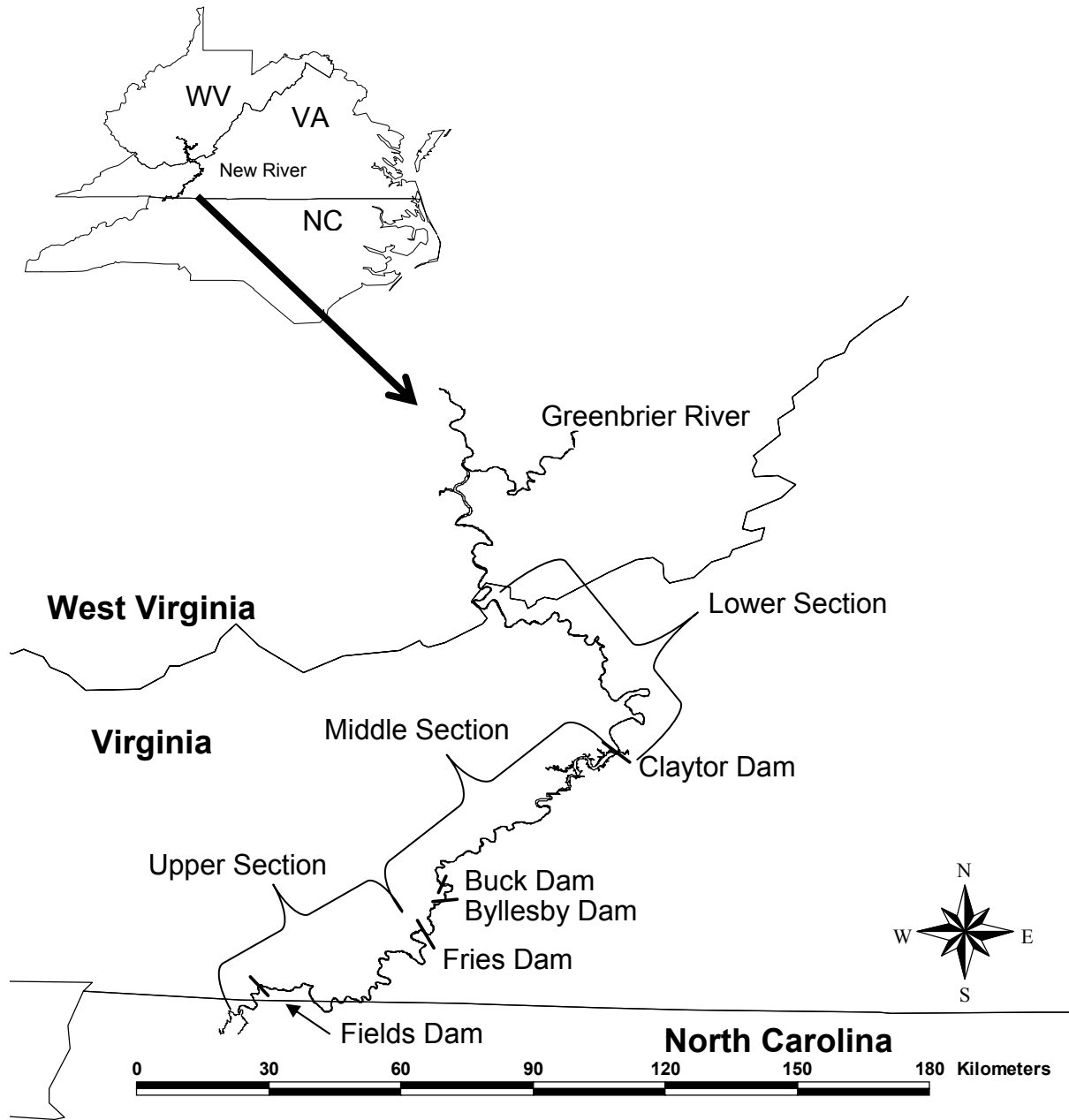


Figure 2. Location of the New River in Virginia and its subdivision into upper, middle, and lower sections.



## CHAPTER 1: STATISTICAL PROPERTIES OF THE RELATIVE WEIGHT ( $W_r$ ) INDEX AND AN ALTERNATIVE PROCEDURE FOR TESTING $W_r$ DIFFERENCES BETWEEN GROUPS

### ABSTRACT

Fishery managers commonly test for differences in relative weight ( $W_r$ ) between or within populations using standard parametric or nonparametric statistical tests. However, the statistical properties of the  $W_r$  index have not been studied; consequently, we cannot be certain that  $W_r$  data satisfy the theoretical assumptions upon which many standard tests are based. In particular, we do not know if  $W_r$  data are independent and identically distributed (i.i.d.), which is an assumption made by most standard statistical tests and which can increase the Type-I error rate of a statistical test when the assumption is violated. I derived approximations to the expectation, variance, and covariance of the  $W_r$  index using the Delta method and estimated these parameters for muskellunge *Esox masquinongy*, largemouth bass *Micropterus salmoides*, and black crappie *Pomoxis nigromaculatus* sample data. Additionally, I devised a likelihood ratio test ( $R$  test) that tests for differences in  $W_r$  between groups and which does not assume i.i.d. data. I applied the  $R$  test to the sample data and compared the results to those obtained using traditional statistical tests. The statistical properties of the  $W_r$  index were conditionally dependent on fish length. This conditionality prevented the covariance from equaling zero across an entire fish sample, thus  $W_r$  data inherently will be correlated. For the sample data, parameter estimates increased with fish length and typically were inflated above realistic  $W_r$  values. This bias was attributed to variability in sample length-weight data. Traditional statistical tests were more liberal than the  $R$  test in declaring statistical significance when testing differences in  $W_r$  between groups. Based on my derivations, I conclude that  $W_r$  data will violate an i.i.d. assumption to some extent. Because the Type-I error rate of traditional statistical tests increases when applied to non-i.i.d. data, I recommend that the  $R$  test be used when testing  $W_r$  data.

## INTRODUCTION

Relative weight ( $W_r$ ; Wege and Anderson 1978) is a commonly used index for assessing the physiological condition of fish (Blackwell et al. 2000). The  $W_r$  index is calculated as

$$W_r = \frac{W}{W_s} \cdot 100 \quad (1)$$

where  $W$  is the observed weight of a fish and  $W_s$  is the standard weight for a fish of the same length.

Although several methods have been proposed (Wege and Anderson 1978; Willis 1989; Murphy et al. 1990), the regression-line-percentile (RLP) technique developed by Murphy et al. (1990) is the recommended procedure for developing  $W_s$  equations (Murphy et al. 1991; Blackwell et al. 2000). The RLP technique uses length-weight data from populations across the species range to predict fish weight at 1-cm length intervals. The RLP technique then fits a simple linear regression equation to the 75th percentile of predicted weights by fish length. The parameter estimates from this final regression can then be used to predict length-specific  $W_s$  values. The 75th percentile is used as the standard for the RLP technique because it is believed that managing fish populations to attain average condition is not a typically desired management goal (Murphy et al. 1991).

In practice, fishery managers often use sample  $W_r$  data to test whether condition differs between or within fish populations. Typically, a Student's- $t$  distribution is used to model  $W_r$  data, and analysis of variance (ANOVA) or a Student's- $t$  test is used to test whether  $W_r$  differs among groups, to compute confidence intervals around mean  $W_r$  estimates, or to estimate sample size required to achieve a desired level of precision around mean  $W_r$  estimates (Murphy et al. 1990; Hyatt and Hubert 2001). Sample  $W_r$  distributions frequently are leptokurtic, so parametric tests are believed to provide conservative results when testing  $W_r$  differences among groups (Murphy et al. 1990). Analysis of variance and the Student's- $t$  test also are robust to departures from normality (Neter et al. 1996) so test results are only slightly affected when sample  $W_r$  distributions deviate from normality (Murphy et al. 1990). Blackwell et al. (2000) suggested that a nonparametric statistical test, such as the Wilcoxon rank sum or Kruskal-Wallis test, could be used to test for differences in  $W_r$  among groups when the assumptions of parametric tests were violated.

One assumption shared by both parametric and nonparametric statistical tests of location is the assumption of independent and identically distributed (i.i.d.) observations (Neter et al. 1996; Hollander and Wolfe 1999). Although ANOVA and the Student's-*t* test are robust to departures from normality, these procedures are not robust to a departure from the i.i.d. assumption and violations can seriously affect inferences from both procedures (Neter et al. 1996). This is true for the nonparametric tests as well (Hollander and Wolfe 1999). Consequently, before parametric or nonparametric statistical tests are used with  $W_r$  data, the statistical properties (i.e., expectation, variance, and covariance) of the  $W_r$  index should first be derived to determine whether the i.i.d. assumption can be met. Gutreuter in Springer et al. (1990) previously derived the expectation of  $W_r$ , but the variance and covariance of the index have not been determined to my knowledge. The purpose of this study was to derive the statistical properties of the  $W_r$  index and to formulate an alternative testing procedure that could accommodate i.i.d. violations when testing  $W_r$  differences among groups.

## METHODS

### *Model Specification*

I began by assuming a random sample  $i = 1, \dots, n$  of fish of lengths  $L_i$ . I assumed that fish lengths were measured without error so  $L_i$  was treated as a fixed variable throughout this study. Typically, fish weight is modeled as a function of length using the allometric growth model. Either an additive or multiplicative error structure can be assumed with this model depending on whether or not variability in fish weight is constant with length (Quinn and Deriso 1999). Because variability in fish weight typically increases with length, I believed that a multiplicative error structure was the appropriate assumption. This model can be stated as

$$W_i = \alpha^* L_i^{\beta^*} 10^{\varepsilon_i^*} \quad (2)$$

where  $W_i$  is the observed weight of fish  $i$  which is of length  $L_i$ ,  $\alpha^*$  and  $\beta^*$  are model parameters, and

$\varepsilon_i^*$  is the random error associated with fish  $i$ . I used the power function  $10^{\varepsilon_i^*}$  in equation (2) rather than

the typical exponential function  $e^{\varepsilon_i^*}$  because it is more common for fishery managers to use  $\log_{10}$  transformation as opposed to  $\log_e$  transformation with length-weight data (Anderson and Neumann 1996). I assumed that the random errors in equation (2) were i.i.d. with expectation 0 and variance  $\sigma_w^2$ , which are standard assumptions for this model (Quinn and Deriso 1999).

In order to identify the underlying model for  $W_s$ , I constructed scatter plots of predicted weight versus length for the populations used in the RLP technique to determine  $W_s$  for three species with published  $W_s$  equations (Figure 1.1). The variance in predicted weight for these three species increased with fish length. Consequently, I believed that the allometric growth model with a multiplicative error structure was the most appropriate model for  $W_s$ . This model can be stated as

$$W_{s_i} = \alpha L_i^\beta 10^{\varepsilon_i} \quad (3)$$

where  $W_{s_i}$  is the standard weight for a fish of the same length as the  $i$ -th fish,  $\alpha$  and  $\beta$  are parameters of the standard weight model with  $\alpha$  and  $\beta$  not necessarily equal to  $\alpha^*$  and  $\beta^*$  from equation (2), and  $\varepsilon_i$  is the random error associated with the standard weight for a fish of the same length as the  $i$ -th fish with  $\varepsilon_i$  not necessarily equal to  $\varepsilon_i^*$  from equation (2). I again used the power function  $10^{\varepsilon_i}$  in equation (3) because of the history of using  $\log_{10}$  transformation with  $W_s$  data as opposed to  $\log_e$  transformation (Murphy et al. 1990). I assumed that the random errors in equation (3) were i.i.d. with expectation 0 and variance  $\sigma_x^2$  with  $\sigma_x^2$  not necessarily equal to  $\sigma_w^2$ .

Because  $W_s$  typically is found as a predicted value from a  $W_s$  equation (Anderson and Neumann 1996), the calculation of a length-specific  $W_s$  value can be considered as

$$\hat{W}_{s_i} = \hat{\alpha} L_i^{\hat{\beta}} \quad (4)$$

where  $\hat{W}_{s_i}$  is the predicted standard weight for a fish of the same length as the  $i$ -th fish and  $\hat{\alpha}$  and  $\hat{\beta}$  are the estimates of the model parameters in equation (3) and so are random variables. Based upon these model formulations, the  $W_r$  index can be rewritten more explicitly as

$$W_{r_i} = \frac{W_i}{\hat{W}_{s_i}} \cdot 100 = \frac{W_i}{\hat{\alpha} L_i^{\hat{\beta}}} \cdot 100, \quad (5)$$

where  $W_{r_i}$  is the relative weight of fish  $i$ .

### Derivation

To derive the statistical properties of the allometric growth model,  $W_s$ , and  $W_r$ , I used the Delta ( $\delta$ ) method. The  $\delta$  method is a technique for finding the approximate expressions for the statistical properties of a function of one or more random variables based on a Taylor series expansion of that function (Kendall and Stuart 1969). The  $\delta$  method is particularly useful for nonlinear functions of random variables as exact solutions for these functions may not be mathematically tractable. The approximations to the expectations of the allometric growth model,  $W_s$ , and  $W_r$  were found by expanding the functions with a second-order Taylor series approximation and applying the expectation operator (Kendall and Stuart 1969). The approximations to the variances and covariances of the functions were found using only first-order Taylor series expansions (Kendall and Stuart 1969). The variances were found by subtracting the squared approximate expectations of the functions from the approximate expectations of the square of the functions (Hoel et al. 1971). The covariances between two random variables were found by subtracting the products of the approximate expectations of the random variables from the approximate expectations of the products of the random variables (Hoel et al. 1971).

### Alternative Testing Procedure

Because most statistical tests of location assume i.i.d. data, I needed to devise an alternative testing procedure that could accommodate non-i.i.d. data when testing for differences among  $k$  groups. Using linear models theory (McCullagh and Nelder 1989), I formulated the statistic

$$R = \frac{(\hat{\boldsymbol{\mu}}_1 - \hat{\boldsymbol{\mu}}_0)^T \hat{\mathbf{V}}^{-1} (\hat{\boldsymbol{\mu}}_1 - \hat{\boldsymbol{\mu}}_0)}{k - 1} \quad (6)$$

where  $\hat{\boldsymbol{\mu}}_1$  is an  $n \times 1$  vector of group means  $\left( \hat{\boldsymbol{\mu}}_1^T = \begin{bmatrix} \hat{\mu}_1 \cdots \hat{\mu}_1 & \cdots & \hat{\mu}_k \cdots \hat{\mu}_k \\ n_1 \times 1 & & n_k \times 1 \end{bmatrix} \right)$ ,  $\hat{\boldsymbol{\mu}}_0$  is an  $n \times 1$  vector with

all elements equal to the overall group mean  $(\hat{\boldsymbol{\mu}}_0^T = [\hat{\mu}_{..} \cdots \hat{\mu}_{..}])$ ,  $\hat{\mathbf{V}}$  is the estimated  $n \times n$  variance-covariance matrix for the individual observations in the groups being tested,  $k$  is the total number of groups being tested,  $n_k$  is the number of observations in each group, and  $n$  is the total number of

observations ( $n = n_1 + \dots + n_k$ ). If we assume that the data being tested are distributed normally with expectation  $\mu$  and variance  $\mathbf{V}$ , then  $R$  is distributed approximately as an  $F$  distribution with  $k-1$  and  $n-k$  degrees of freedom (McCullagh and Nelder 1989).

Using the  $R$  statistic, I devised a likelihood ratio test, which I refer to as an  $R$  test, for testing the global hypothesis of no difference in mean  $W_r$  among  $k$  groups. The  $R$  test is conducted as follows. First, the maximum likelihood estimates of the mean  $W_r$  for each group and the overall mean  $W_r$  are substituted into the vectors  $\hat{\mu}_1$  and  $\hat{\mu}_0$ , respectively. The maximum likelihood estimates of the mean  $W_r$  for each group can be found using the equation

$$\hat{\mu}_k = (\mathbf{X}^T \hat{\mathbf{V}}^{-1} \mathbf{X})^{-1} \mathbf{X}^T \hat{\mathbf{V}}^{-1} \mathbf{y} \quad (7)$$

where  $\mathbf{X}$  is the following  $n \times k$  matrix

$$\mathbf{X} = \begin{bmatrix} \mathbf{1}_{n_1 \times 1} & \mathbf{0}_{n_1 \times 1} & \cdots & \mathbf{0}_{n_1 \times 1} & \mathbf{0}_{n_1 \times 1} \\ \mathbf{0}_{n_2 \times 1} & \mathbf{1}_{n_2 \times 1} & \ddots & \mathbf{0}_{n_2 \times 1} & \mathbf{0}_{n_2 \times 1} \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \mathbf{0}_{n_{k-1} \times 1} & \mathbf{0}_{n_{k-1} \times 1} & \ddots & \mathbf{1}_{n_{k-1} \times 1} & \mathbf{0}_{n_{k-1} \times 1} \\ \mathbf{0}_{n_k \times 1} & \mathbf{0}_{n_k \times 1} & \cdots & \mathbf{0}_{n_k \times 1} & \mathbf{1}_{n_k \times 1} \end{bmatrix}$$

with  $\mathbf{1}$  and  $\mathbf{0}$  being vectors of indicated size with all elements equal to 1 or 0, respectively,  $\hat{\mathbf{V}}$  is the  $n \times n$  variance-covariance matrix of the  $W_r$  data for the fish sample of interest,  $\mathbf{y}$  is the  $n \times 1$  vector of the  $W_r$  observations, and  $\hat{\mu}_k$  is the  $k \times 1$  vector of mean  $W_r$  for the  $k$  groups (i.e.,  $\hat{\mu}_k^T = [\hat{\mu}_1 \ \cdots \ \hat{\mu}_k]$ ). The maximum likelihood estimate of the overall mean  $W_r$  ( $\hat{\mu}_{..}$ ) can be found using the equation

$$\hat{\mu}_{..} = (\mathbf{1}^T \hat{\mathbf{V}}^{-1} \mathbf{1})^{-1} \mathbf{1}^T \hat{\mathbf{V}}^{-1} \mathbf{y} \quad (8)$$

where  $\mathbf{1}$  is an  $n \times 1$  vector with all elements equal to 1. By substituting the individual groups and overall mean  $W_r$  in for the elements of  $\hat{\mu}_1$  and  $\hat{\mu}_0$ ,  $R$  can be found. If  $R$  is greater than  $F_{k-1, n-k, 1-P_\alpha}$  where  $P_\alpha$  is the desired experiment-wise error rate, the global null hypothesis of no differences in mean  $W_r$  among the  $k$  groups would be rejected in favor of the alternative hypothesis that at least one pair of the groups differ.

When testing for no differences among  $k$  groups with tests of location, post-hoc procedures typically follow when the global null hypothesis is rejected. Most traditional multiple comparison procedures cannot accommodate data that are not i.i.d. so I needed an alternative post-hoc testing

procedure. The testing procedure I devised uses linear contrasts to make multiple pairwise comparisons. A single pairwise comparison is specified with the statistic

$$R_l = (\mathbf{c}_l^T \hat{\boldsymbol{\mu}}_k)^T \cdot \left( \mathbf{c}_l^T (\mathbf{X}^T \hat{\mathbf{V}}^{-1} \mathbf{X})^{-1} \mathbf{c}_l \right) \cdot (\mathbf{c}_l^T \hat{\boldsymbol{\mu}}_k) \quad (9)$$

where  $\hat{\boldsymbol{\mu}}_k$ ,  $\hat{\mathbf{V}}$ , and  $\mathbf{X}$  are as previously defined,  $\mathbf{c}_l$  is a  $k \times 1$  vector with two row elements of the vector equal to 1 and -1 and the other  $k-2$  elements equal to 0, and  $l = 1 \dots g$  with  $g$  equal to the total number of possible pairwise comparisons. As an example, if we had a total of 5 groups and were to test whether  $W_r$  of group 2 differed from group 4,  $\mathbf{c}_l$  would be a  $5 \times 1$  vector with the second and fourth row element equal to 1 and -1, respectively, and the remaining elements equal to 0 (i.e.,  $\mathbf{c}_l^T = [0 \ 1 \ 0 \ -1 \ 0]$ ). The null hypothesis of no difference in mean  $W_r$  between two groups would be rejected if  $R_l$  was greater than  $F_{1, n-k, 1-P_\alpha^B}$ , where  $P_\alpha^B = P_\alpha/g$  is the Bonferroni corrected experiment-wise error rate (Neter et al. 1996).

### Estimation and Test Comparison

Length-weight data for muskellunge *Esox masquinongy*, largemouth bass *Micropterus salmoides*, and black crappie *Pomoxis nigromaculatus* were used to calculate  $W_r$  and the estimates of its statistical properties and to compare my suggested testing procedure to traditional parametric and nonparametric statistical tests. Data were from fish samples collected by boat electrofishing on the New River (muskellunge; T. Brenden, unpublished data), Smoots Pond (largemouth bass; T. Copeland, Virginia Polytechnic Institute and State University, unpublished data), Big Pond (largemouth bass; T. Brenden, unpublished data), and Rural Retreat Lake (black crappie; J. Copeland, Virginia Department of Game and Inland Fisheries, unpublished data) in Virginia. Relative weight data for each of the populations were tested for differences among length categories with ANOVA, Kruskal-Wallis, and the  $R$  test. Although Kruskal-Wallis tests for no difference in median  $W_r$  while the  $R$  test and ANOVA tests for no difference in mean  $W_r$ , the approximate symmetry of many sample  $W_r$  distributions (Murphy et al. 1990; Hyatt and Hubert 2001) make these tests approximately equivalent with respect to the hypotheses being tested. Length-categories for each of the species were defined using the length-categorization system of

Gabelhouse (1984). The largemouth bass data were tested for an overall difference in  $W_r$  between the two populations using the Student's- $t$ , Wilcoxon rank sum, and  $R$  test. The  $R$  test was conducted as previously described. ANOVA, Kruskal-Wallis, Wilcoxon rank sum, and Student's- $t$  tests were conducted using standard methodology. Tukey's and Steel-Dwass-Critchlow-Fligner two-sided all-treatment (SDCF; Hollander and Wolfe 1999) multiple comparison procedures were used as post-hoc tests following ANOVA and the Kruskal-Wallis test, respectively. All statistical tests were conducted with  $P_\alpha = 0.10$ .

Before the  $R$  statistic could be calculated, several parameters from the model formulations needed to be estimated. The parameters for the allometric growth model for each of the fish samples were estimated using simple linear regression after  $\log_{10}$  transformation of the length-weight data (Myers 1990). Because the length-weight data were  $\log_{10}$  transformed, estimates of  $\log_{10} \alpha^*$  were obtained as opposed to estimates of  $\alpha^*$ . Median-unbiased estimates of  $\alpha^*$  were found by the following method

$$\hat{\alpha}^* = 10^{\left( \log_{10} \hat{\alpha}^* \right)} \quad (10)$$

where  $\log_{10} \hat{\alpha}^*$  was the intercept parameter from the simple linear regression analysis (Quinn and Deriso 1999). The estimates of  $\sigma_w^2$  were the residual mean squared errors from each of the estimation procedures.

The RLP technique parameter estimates of the  $W_s$  equation for muskellunge, largemouth bass, and black crappie were obtained from Neumann and Willis (1994), Henson (1991), and Neumann and Murphy (1991), respectively. Because the RLP technique uses  $\log_{10}$  transformed length-weight data, this estimation procedure yields estimates of  $\log_{10} \alpha$  as opposed to estimates of  $\alpha$ . As with equation (10), estimates for  $\alpha$  were found using the method

$$\hat{\alpha} = 10^{\left( \log_{10} \hat{\alpha} \right)} \quad (11)$$

where  $\log_{10} \hat{\alpha}$  is the intercept parameter from the RLP technique (Quinn and Deriso 1999). The RLP technique estimate of  $\beta$  did not need to be adjusted. I assumed that the RLP technique gave unbiased estimates of  $\alpha$  and  $\beta$ , although this assumption was not tested.



One problem with the RLP technique is that it does not give reliable estimates of the variances and covariance of  $\log_{10}\hat{\alpha}$  and  $\hat{\beta}$ , because by fitting the final regression to the 75th percentile of predicted fish weights it disregards much of the variability in predicted fish weight. The procedure is similar to fitting a regression to the average of data instead of to the original observations, a consequence of which is an underestimation of the true variability around the regression line (Quinn and Deriso 1999). I used bootstrapping (Efron 1979) to find more reliable estimates of the variances and covariance of the RLP estimates. I obtained the parameter estimates of the length-weight relationships from the populations that were used in the original  $W_s$  equation development and selected with replacement a sample equal in size to the original number of populations. I then applied the RLP technique to this bootstrap sample of length-weight relationship parameter estimates. This procedure (sampling with replacement of the parameter estimates and application of the RLP technique) was repeated 1,000 times, which resulted in bootstrap distributions for the RLP estimates of  $\log_{10}\alpha$  and  $\beta$ . These distributions were then used to find the variances and covariance of the RLP estimates of  $\log_{10}\alpha$  and  $\beta$ . The variance estimate of  $\hat{\beta}$  equaled the sample variance of the bootstrap estimates of  $\beta$ . The variance of  $\hat{\alpha}$  and the covariance of  $\hat{\alpha}$  and  $\hat{\beta}$ , which were found using the  $\bar{\delta}$  method, equaled

$$Var(\hat{\alpha}) = \hat{\alpha}^2 Var_B \left( \log_{10} \hat{\alpha} \right) (\log_e 10)^2 \quad (12)$$

and

$$Cov(\hat{\alpha}, \hat{\beta}) = \hat{\alpha} Cov_B \left( \log_{10} \hat{\alpha}, \hat{\beta} \right) \log_e 10 \quad (13)$$

where  $Var_B \left( \log_{10} \hat{\alpha} \right)$  and  $Cov_B \left( \log_{10} \hat{\alpha}, \hat{\beta} \right)$  were the sample variance of the bootstrap estimates of  $\log_{10}\alpha$

and the sample covariance of the bootstrap estimates of  $\log_{10}\alpha$  and  $\beta$ .

## RESULTS

## Derivation

Technical descriptions of the statistical property results obtained by the  $\delta$  method are presented in Appendix 1. For brevity, I report only the findings for the properties of  $W_r$ . The approximate expectation and variance of  $W_r$  equaled

$$E(W_{r_i}) \approx \left( \frac{\alpha^* L_i^{\beta^*}}{\alpha L_i^\beta} \cdot 100 \right) + \frac{\sigma_W^2 (\alpha^* L_i^{\beta^*} \log_e 10)^2}{2} \left( \frac{100}{\alpha L_i^\beta} \right) + \text{Var}(\hat{\alpha}) \cdot \left( \frac{(\alpha^* L_i^{\beta^*}) \cdot 100}{\alpha^3 L_i^\beta} \right) + \frac{\text{Var}(\hat{\beta})}{2} \cdot \left( \frac{(\alpha^* L_i^{\beta^*}) (\log_e L_i)^2 \cdot 100}{\alpha L_i^\beta} \right) + \text{Cov}(\hat{\alpha}, \hat{\beta}) \cdot \left( \frac{(\alpha^* L_i^{\beta^*}) (\log_e L_i) \cdot 100}{\alpha^2 L_i^\beta} \right) \quad (14)$$

and

$$\text{Var}(W_{r_i}) \approx \sigma_W^2 (\alpha^* L_i^{\beta^*} \log_e 10)^2 \left( \frac{100}{\alpha L_i^\beta} \right)^2 + \text{Var}(\hat{\alpha}) \cdot \left( \frac{\alpha^* L_i^{\beta^*} 100}{\alpha^2 L_i^\beta} \right)^2 + \text{Var}(\hat{\beta}) \cdot \left( \frac{\alpha^* L_i^{\beta^*} \log_e L_i 100}{\alpha L_i^\beta} \right)^2 + 2 \text{Cov}(\hat{\alpha}, \hat{\beta}) \cdot \left( \frac{(\alpha^*)^2 (L_i^{\beta^*})^2 (\log_e L_i) \cdot 10,000}{\alpha^3 L_i^{2\beta}} \right) \quad (15)$$

Because fish length  $L_i$  is a term in both equations (14) and (15), the expectation and variance of  $W_r$  are both conditional on fish length. This conditionality will remain even when the observed pattern of fish growth equals the growth pattern described by the  $W_s$  equation (i.e.,  $\alpha^* = \alpha$ ;  $\beta^* = \beta$ ).

The approximate covariance in  $W_r$  between fish from the same population equaled

$$\text{Cov}(W_{r_i}, W_{r_j}) \approx \text{Var}(\hat{\alpha}) \cdot \left( \frac{(\alpha^*)^2 (L_i L_j)^{\beta^*} \cdot 10,000}{\alpha^4 (L_i L_j)^\beta} \right) + \text{Var}(\hat{\beta}) \cdot \left( \frac{(\alpha^*)^2 (L_i L_j)^{\beta^*} (\log_e L_i) (\log_e L_j) \cdot 10,000}{\alpha^2 (L_i L_j)^\beta} \right) + \text{Cov}(\hat{\alpha}, \hat{\beta}) \cdot \left( \frac{(\alpha^*)^2 (L_i L_j)^{\beta^*} 10,000}{\alpha^3 (L_i L_j)^\beta} \right) \cdot ((\log_e L_i) + (\log_e L_j)) \quad (16)$$

As with the expectation and variance, the covariance of  $W_r$  is conditional on fish length.

The covariance of  $W_r$  between fish from the same population can only equal zero when the following condition holds

$$\text{Cov}(\hat{\alpha}, \hat{\beta}) = - \frac{\left( \frac{\text{Var}(\hat{\alpha})}{\alpha^2} + \text{Var}(\hat{\beta})(\log_e L_i)(\log_e L_{i'}) \right)}{\frac{(\log_e L_i + \log_e L_{i'})}{\alpha}}. \quad (17)$$

Because equation (17) includes fish length, the covariance in  $W_r$  between fish from the same population can never equal zero across all fish; consequently, there will always be some dependency with  $W_r$  data.

The covariance in  $W_r$  between fish from two different populations (i.e.  $W_{r_j}$  and  $W_{r_{j'}}$  where the subscripts  $j$  and  $j'$  are used to index the  $j$ - and  $j'$ -th ( $j \neq j'$ ) populations), equaled

$$\begin{aligned} \text{Cov}(W_{r_j}, W_{r_{j'}}) \approx & \text{Var}(\hat{\alpha}) \cdot \left( \frac{(\alpha_j^*)(\alpha_{j'}^*)(L_j)^{\beta_j^*} (L_{j'})^{\beta_{j'}^*} 10,000}{\alpha^4 (L_j L_{j'})^\beta} \right) + \\ & \text{Var}(\hat{\beta}) \cdot \left( \frac{(\alpha_j^*)(\alpha_{j'}^*)(L_j)^{\beta_j^*} (L_{j'})^{\beta_{j'}^*} (\log_e L_j)(\log_e L_{j'}) 10,000}{\alpha^4 (L_j L_{j'})^\beta} \right) + \\ & \text{Cov}(\hat{\alpha}, \hat{\beta}) \cdot \left( \frac{(\alpha_j^*)(\alpha_{j'}^*)(L_j)^{\beta_j^*} (L_{j'})^{\beta_{j'}^*} 10,000}{\alpha^3 (L_j L_{j'})^\beta} \right) \cdot ((\log_e L_j) + (\log_e L_{j'})) \end{aligned} \quad (18)$$

As with the covariance in  $W_r$  for fish from the same population, equation (18) cannot equal zero across all fish from two different populations. Consequently, there will always be some dependency in  $W_r$  data for fish from two different populations.

### *Estimation and Test Comparison*

The length-weight data for the 4 fish samples (Figure 1.2) permitted the estimation of the statistical properties and the comparison of my suggested testing procedure with the more traditional testing methods under several conditions. The length-weight data from the different populations yielded

substantial differences in the parameter estimates of the allometric growth model (Table 1.1). The populations and species also differed in regards to the amount of variability in the length-weight data and the variability in the parameters of the  $W_s$  equation (Table 1.1).

The conditionality of  $W_r$  on fish length resulted in large differences in the expectation and variance estimates across all fish samples. For all samples, the estimates of the expectation and variance increased with fish length (Figure 1.3). The expectation estimates of  $W_r$  generally were much larger than what typically would be considered as likely  $W_r$  values for a fish sample. For example, the expectation estimates were greater than 1,000 for most fish from the muskellunge sample. To determine what was inflating the expectation estimates, I looked at the relative contribution of each term of equation (14) to the final estimates for the fish samples. The third, fourth, and fifth terms of equation (14) contributed less than 1% to the final expectation estimates for all species. The first term of equation (14),

$$\left( \frac{\alpha^* L_i^{\beta^*}}{\alpha L_i^{\beta}} \cdot 100 \right)$$

which is a comparison of a fish sample's observed growth pattern to the growth pattern described by the  $W_s$  equation, yielded values within a range typical for  $W_r$  (i.e. 80 – 120). The second term of equation (14),

$$\frac{\sigma_w^2 \left( \alpha^* L_i^{\beta^*} \log_e 10 \right)^2}{2} \cdot \left( \frac{100}{\alpha L_i^{\beta}} \right),$$

appeared primarily responsible for inflating the expectation estimates. This term yields a positive number and is primarily a function of the variability in the observed length-weight relationship (see equation (A.7) in Appendix 1). This term will be minimized when the variability in the length-weight relationship for the observed fish sample is low. When variability is high, this term will be large and will bias the expectation estimates. For the sample length-weight data I studied, the relative contribution of this term to the expectation estimates increased with fish length and was different for each sample. The relative contribution of this term to the expectation estimates for each sample was 62-99% for muskellunge, 35-94% for Smoots Pond largemouth bass, 15-83% for Big Pond largemouth bass, and 27-72% for black crappie.

Across all fish samples and all fish lengths, the covariance in  $W_r$  was positive, indicating that the  $W_r$  of one fish could partially be predicted by the  $W_r$  of the other fish in the sample. The covariance was the largest between smaller fish and the lowest between larger fish and between small and large fish. The correlations between fish of different lengths never exceeded 0.01, which indicated that the strength of the dependency was low. The correlations in  $W_r$  between fish from the two largemouth bass samples also never exceeded 0.01.

For the muskellunge  $W_r$  data, the null hypothesis of no difference in  $W_r$  among the length categories was rejected by both ANOVA and the Kruskal-Wallis test (Table 1.2). There was some disparity in the post-hoc testing results. Tukey's multiple comparison procedure indicated that  $W_r$  for pre-stock length fish was significantly greater than  $W_r$  for stock-quality length fish, while the SDCF multiple comparison procedure also indicated that  $W_r$  for preferred-memorable length fish was significantly greater than  $W_r$  for stock-quality length fish (Table 1.2). Conversely, the  $R$  test found no significant overall difference in  $W_r$  among any of the length categories.

The overall hypothesis of no difference in  $W_r$  among the length categories was rejected by all testing methods for each of the largemouth bass samples (Table 1.2). For the Smoots Pond data, the  $R$  test rejected the global hypothesis of no difference in  $W_r$  among the length categories at a much lower level of significance ( $P = 0.079$ ) than the other testing methods ( $P = 0.000$  for both ANOVA and the Kruskal-Wallis test). For the Big Pond sample, the levels of significance for each of the testing methods were approximately equal (Table 1.2). The multiple comparison procedures did yield different results for both largemouth bass samples. Tukey's multiple comparison procedure for the Smoots Pond data indicated that  $W_r$  of stock-quality length fish was significantly greater than  $W_r$  for both quality-preferred and preferred-memorable length fish. The SDCF and  $R_i$  multiple comparison procedures found significant differences in  $W_r$  between stock-quality and quality-preferred length fish. The SDCF and the  $R_i$  tests also gave similar results for the Big Pond sample (Table 1.2). Both multiple comparison procedures found that  $W_r$  for pre-stock length fish was significantly greater than  $W_r$  for stock-quality length fish. Tukey's multiple comparison procedure found no difference in  $W_r$  among any the length categories for the Big Pond sample, even though the overall hypothesis of no difference in  $W_r$  among the length categories was rejected by ANOVA.

Even though I found significant differences in  $W_r$  among the length categories for each of the largemouth bass samples, I combined data across length categories, against the recommendations of Murphy et al. (1991) and Blackwell et al. (2000), to test whether there was an overall difference in mean  $W_r$  between the samples. The Student's- $t$ , Wilcoxon rank sum, and  $R$  test all indicated that  $W_r$  between the largemouth bass samples was significantly different (Table 1.3). The results of the  $R$  test ( $P = 0.007$ ) were more conservative than the results for either the Student's- $t$  ( $P = 0.002$ ) or Wilcoxon rank sum tests ( $P = 0.000$ ). Based on these tests, I would conclude that overall mean  $W_r$  for largemouth bass from Smoots Pond was significantly greater than overall mean  $W_r$  for fish from Big Pond.

For the black crappie sample, all of the testing procedures indicated that there was an overall difference in  $W_r$  among the length categories. Each of the multiple comparison testing procedures indicated that  $W_r$  for stock-quality length fish was significantly greater than  $W_r$  for quality-preferred length fish (Table 1.2). The small number of preferred-memorable length fish ( $n_3 = 1$ ) for the black crappie sample limited my ability to detect a significant difference in  $W_r$  between this and the other length categories.

## DISCUSSION

### *Statistical Properties of $W_r$*

For a random variable to be considered i.i.d., each observation should have equal expectations and variances and the covariances between the observations should equal zero (Hoel et al. 1971). Based on my derivation results, I can conclude that data generated from the  $W_r$  index will violate the i.i.d. assumption to some extent. Expectations, variances, and covariances are conditionally dependent on the length of the fish for which  $W_r$  is being computed. This conditionality will remain even when the pattern of observed fish growth is the same pattern as that described by the  $W_s$  equation. Rather than  $W_r$  data being generated from one common distribution,  $W_r$  data are generated by a unique distribution for each length of fish (Figure 1.4). The exact shapes of these distributions are unknown, but can be estimated using the results of my derivations. Because of the nonlinearity of the  $W_r$  function and because the  $\delta$  method only provides an approximation to the statistical properties, the estimates based on my

derivations will be biased (Zhou 2002). The sample length-weight data I analyzed indicated that this bias can be substantial. Because this bias is primarily influenced by the variability associated with the observed growth pattern of a fish sample, fishery managers can increase the precision of these estimates by collecting a large sample of fish and by ensuring that length and weight measurements are accurate. Because of the bias associated with the  $\delta$  method when studying nonlinear functions, Zhou (2002) recommended that parametric bootstrapping be used for estimating parameters of derived random variables when the underlying distributions of the random variables are known. Parametric bootstrapping would be difficult to apply to  $W_r$  data because of the conditionality of the distributions on fish length and because these distributions are unknown.

The dependence of  $W_r$  data results from the manner in which  $W_s$  is formulated. Predicted values from regression models are correlated (Myers 1990); thus, when  $W_s$  equations are estimated using regression techniques the correlations in predicted values causes dependence among  $W_r$  data. This dependency occurs between fish from the same population as well as fish from different populations. This correlation in  $W_r$  data could be eliminated by using a technique that did not rely upon regression to estimate  $W_s$ , although every method proposed to date for estimating  $W_s$  equations has used regression (Wege and Anderson 1978; Willis 1989; Murphy et al. 1990). My assumption that the weights of fish from the same population were independent did affect the strength of my correlation estimates. Although this is a standard assumption when modeling the length-weight relationship for a sample of fish (Quinn and Deriso 1999), this assumption may not be appropriate. Without that assumption, an additional term

$$\text{Cov}(W_i, W_{i'}) \left( \frac{10,000}{\alpha^2 (L_i L_{i'})^\beta} \right)$$

would have been added to equation (16). Depending on how fish weights might interrelate, this additional term could have either strengthened or weakened the correlation estimates.

My derivation of the expectation of  $W_r$  was different from the result obtained by Gutreuter in Springer et al. (1990). In Gutreuter's derivation, the parameters of the  $W_s$  equation were treated as known constants and so the only random variable in the  $W_r$  function was the observed weight of a fish. Thus in Gutreuter's derivation,  $W_r$  was a linear function of one random variable and its expectation could be found by the rule that the expectation of the product of a constant and a random variable is equal to

the product of the constant and the expectation of the random variable (Hoel et al. 1971). However, the  $W_s$  equation for a particular species must be estimated using a method such as the RLP technique. Consequently, the parameters of the  $W_s$  equation are not constants but random variables. As a result, in my derivation the  $W_r$  index was a nonlinear function of several random variables; thus, a technique such as the  $\delta$  method was needed to find its approximate statistical properties. This difference in what was considered a random variable ultimately led to the difference in my results.

### *Statistical Testing of $W_r$ Data*

With the  $R$  test, the null hypotheses being tested is no difference in group mean  $W_r$ . This testing procedure does assume that  $W_r$  data are distributed normally, although like ANOVA the  $R$  test should be robust to minor violations of this assumption (Neter et al. 1996). Although the  $R$  test uses MLE to estimate group mean  $W_r$ , it does use the results of my derivations to estimate the variance-covariance structure for sample  $W_r$  observations. Because of the potential bias associated with these estimates, fishery managers may want to avoid using this testing procedure when sample sizes are small.

The results of the  $R$  test for the fish samples I studied were more conservative than the results from either the parametric or nonparametric tests. For the muskellunge sample, the conservatism of the  $R$  test resulted in a conclusion of no significant differences in  $W_r$  among fish of different lengths while ANOVA and the Kruskal-Wallis test found a highly significant difference. With a statistical test that assumes i.i.d. data, the Type-I error rate generally increases when the test is applied to positively correlated and heteroskedastic data (Neter et al. 1996; Legendre 1993). Because of the increased likelihood in making a Type-I error, researchers have recommended that non-i.i.d. data be tested with a procedure that doesn't make an i.i.d. assumption (Carroll and Pearson 2000). Other methods for testing non-i.i.d. are to use traditional tests after transforming the data or to use weighted least-squares ANOVA (Neter et al. 1996). I don't recommend transforming  $W_r$  data for the following reasons: (1) the transformation may not work, (2) the test results for the transformed data may not hold for the untransformed data, and (3) monotonic transformations will do little to resolve the lack of independence in  $W_r$  data (Seaman and Jaeger 1990; Neter et al. 1996). Further, weighted least-squares ANOVA and regular ANOVA are specific forms of the testing procedure I devised. Both are likelihood ratio tests that make explicit assumptions concerning the variance-covariance structure of the data (McCullagh and



Nelder 1989). When the variance-covariance structure for the  $R$  test satisfies these assumptions, the  $R$  test reduces to these other tests. The advantage of using the  $R$  test over weighted least-squares ANOVA is that the  $R$  test can account for correlated observations while weighted least-squares cannot.

In addition to statistical tests of location, relative weight data often are analyzed with other statistical procedures, including correlation and regression methods. Correlation and regression have been used to relate  $W_r$  to factors such as proximate composition, fat content, fecundity, and growth rates (Anderson and Neumann 1993). Regression also could be used as an alternative method for testing whether  $W_r$  differs with fish length. The problem with analyzing  $W_r$  data within this context is that most correlation and regression procedures assume i.i.d. data (Neter et al. 1996). When correlation and regression methods are applied to non-i.i.d. data, the results from these procedures will be biased. Such a bias may help explain the difficulty in identifying relationships between  $W_r$  and variables such as fish growth, fish community indices, and system morphology (Blackwell et al. 2000). The results of my derivations could be incorporated into a regression analysis, which may help to establish relationships between  $W_r$  and other variables.

The use of the  $W_r$  index for evaluating condition previously has been criticized for its apparent lack of statistical merit (Cone 1989). Some researchers have advocated the use of least squares regression or analysis of covariance (ANCOVA) of  $\log_{10}$  transformed length-weight data as methods for assessing condition among groups (Kesteven 1947; Le Cren 1951; Cone 1989, and in Springer et al. 1990). The least-squares regression approach has been criticized because it cannot be used to assess length-specific differences in condition (Miranda and Jackson in Springer et al. 1990). Further, the interaction between the parameters of the length-weight relationship makes it difficult to assess condition based on solely on relative sizes of the parameters (Bolger and Connolly 1989). Analysis of covariance of  $\log_{10}$  transformed length-weight data may provide a useful method for assessing condition between two different populations. However, ANCOVA does make certain assumptions concerning data structure that can limit its applicability. First, ANCOVA assumes constancy of slopes of the different sample regression lines. If the slopes of the  $\log_{10}$  transformed length-weight regressions are different, ANCOVA may fail to detect any significant difference among the samples (Neter et al. 1996). Analysis of covariance also

assumes that regression lines have equal variances and so results will be biased if the variability in the  $\log_{10}$  transformed length-weight data is different.

### MANAGEMENT IMPLICATIONS

By explicitly considering the manner in which  $W_r$  is calculated, I was able to formulate a statistical model for the  $W_r$  index, which I could then use to derive the statistical properties of the index. In previous studies looking at the properties of this index, this consideration has been skipped. Most researchers have simply assumed that  $W_r$  data are generated from a single distribution and have used normal-based parameter estimation techniques to assess whether the sample distribution of  $W_r$  data is normally distributed. Most formulas familiar to fishery managers for estimating distribution parameters (e.g., mean, variance, kurtosis, skewness) are accurate only when applied to normal distributions. For example, calculating the arithmetic mean for data from a chi-square distribution will not give an accurate measure of the distribution's location parameter. Fishery managers sometimes base data analysis on the assumption that the data being analyzed are normal i.i.d. without critically evaluating whether these assumptions can be met. This practice can lead to biased estimation, questionable testing results, and ultimately poor management decisions. Before data analysis, fishery managers should explicitly consider how the data was generated in order to determine what assumptions can be met.

Despite recommendations to the contrary, (Packard and Boardman 1988; Cone 1989; Jakob et al. 1996), the use of  $W_r$  for evaluating fish condition has increased with time (Blackwell et al. 2000). Data indices often are appealing because they are easy to calculate and may provide relative measures to factors that may be much more difficult to quantify (Hurlbert 1978; Anderson 2001). The  $W_r$  index possibly may provide a method for approximating factors such as fish health, body composition, growth potential, reproductive potential, and prey availability (Murphy et al. 1991, Anderson and Neumann 1996; Blackwell et al. 2000). The main criticism of indices is that because they are potentially influenced by many variables, the data that results may not be reliable for inferential purposes (Anderson 2001).

I believe that the  $W_r$  index is useful for providing a relative measure of fish condition. However, I do not believe it is appropriate to test  $W_r$  data using traditional parametric or nonparametric statistical techniques. If statistical testing of  $W_r$  data is to be conducted, I recommend that fishery managers use

the  $R$  test. The  $R$  test does not assume i.i.d. data. Even if  $W_r$  data were i.i.d., which because of the conditionality on fish length can never occur exactly, the  $R$  test would provide the same results as ANOVA. Because of the potential bias associated with estimating the statistical properties of  $W_r$  for a fish sample, fishery managers should increase sample size when data will be used to test for differences in condition. When sample sizes are small, statistical testing should be avoided.

The  $R$  test can be easily programmed by those familiar with computer software that can perform matrix manipulations and operations. For those unfamiliar with this method of programming, I have provided SAS (SAS Institute, Inc., Cary, North Carolina) code for conducting this test (Appendix 2). I also have provided bootstrap estimates of the variances and covariance of the  $W_s$  equation parameter estimates for 58 fish species (including purposeful hybrids) whose  $W_s$  equations were developed using the RLP technique (Appendix 3). For those researchers developing new  $W_s$  equations, I encourage the use of bootstrapping to estimate the variances and covariance of the  $W_s$  equation parameter estimates and these estimates should be included within future publications. The SAS code for finding the bootstrap estimates is included in Appendix 4. Minimally, researchers should include parameter estimates of the length-weight relationships for each of the populations used in determining  $W_s$  so that these bootstrap estimates may be found in the future.

Admittedly, a shortcoming of the  $R$  test is that it requires the computation of the length-weight relationship for the samples of interest and so the ease in which  $W_r$  can be calculated and used to test for differences in condition among groups is affected. Because of this, I anticipate that some fishery managers may be resistant to adopting this new testing method. For those who do not find the  $R$  test useful, I discourage the use of traditional statistics for evaluating  $W_r$  data. Even though tests such as ANOVA may be easy to conduct and the tests appear to provide meaningful results,  $W_r$  data violate nearly every theoretical assumption on which these tests are based. Instead, I recommended that statistical analysis of  $W_r$  data be limited to calculation of sample means and interquartile ranges and that fishery managers simply avoid using  $W_r$  data in an inferential testing manner. If an inferential testing procedure is required and the assumptions can be met, ANCOVA may provide the only other option to the  $R$  test for testing differences in condition among groups.

Table 1.1. Parameter estimates used for the calculations of expectation, variance, and covariance for the muskellunge, largemouth bass (LMB\* = Smoots Pond; LMB\*\* = Big Pond), and black crappie  $W_t$  data.

Parameter	Muskellunge	LMB*	LMB**	Black crappie
$\alpha^*$	9.316E-07	6.866E-06	5.269E-06	1.454E-05
$\beta^*$	3.299	3.109	3.136	2.974
$\sigma_w^2$	2.018E-03	1.983E-03	1.833E-03	4.758E-03
$\alpha$	8.590E-07	2.965E-06	2.965E-06	2.410E-06
$\beta$	3.325	3.273	3.273	3.345
Var( $\alpha$ )	4.953E-14	7.736E-14	7.736E-14	3.781E-13
Var( $\beta$ )	1.570E-03	2.500E-04	2.500E-04	2.240E-03
Cov( $\alpha, \beta$ )	-8.782E-09	-4.369E-09	-4.369E-09	-2.891E-08

Table 1.2. Overall and multiple comparison test results for testing no difference in  $W_r$  among the length categories for the muskellunge, largemouth bass (LMB\* = Smoots Pond; LMB\*\* = Big Pond), and black crappie samples. All tests were conducted at  $P_\alpha = 0.10$ . For the multiple comparison procedures, length categories that were found to be significantly different and how they differed are indicated (PS = pre-stock, S = stock-quality, Q = quality-preferred, P = preferred-memorable; NS = no significant difference in any of the length categories were found; “–” = no multiple comparison procedure conducted).

	Muskellunge	LMB*	LMB**	Black crappie
ANOVA				
<i>F</i>	3.56	10.58	2.45	12.89
df	4,96	3,60	3,46	2,179
<i>P</i>	0.009	0.000	0.076	0.000
Tukey's	PS>S	S>Q, S>P	NS	S>Q
Kruskal-Wallis				
<i>H</i>	12.39	24.78	7.79	38.93
df	4	3	3	2
<i>P</i>	0.015	0.000	0.050	0.000
SDCF	PS>S, P>S	S>Q	PS>S	S>Q
<i>R</i> test				
<i>R</i>	0.30	2.37	2.38	8.83
df	4,96	3,60	3,46	2,179
<i>P</i>	0.879	0.079	0.082	0.000
$R_i$	–	S>Q	PS>S	S>Q

Table 1.3. Test results for testing the hypothesis of no difference in  $W_r$  between the largemouth bass samples.

Test	Results
Student's- <i>t</i>	
<i>T</i>	3.18
df	106
<i>P</i>	0.002
Wilcoxon rank sum	
<i>W</i>	4324
<i>P</i>	0.000
<i>R</i> test	
<i>R</i>	7.40
df	1,112
<i>P</i>	0.0075

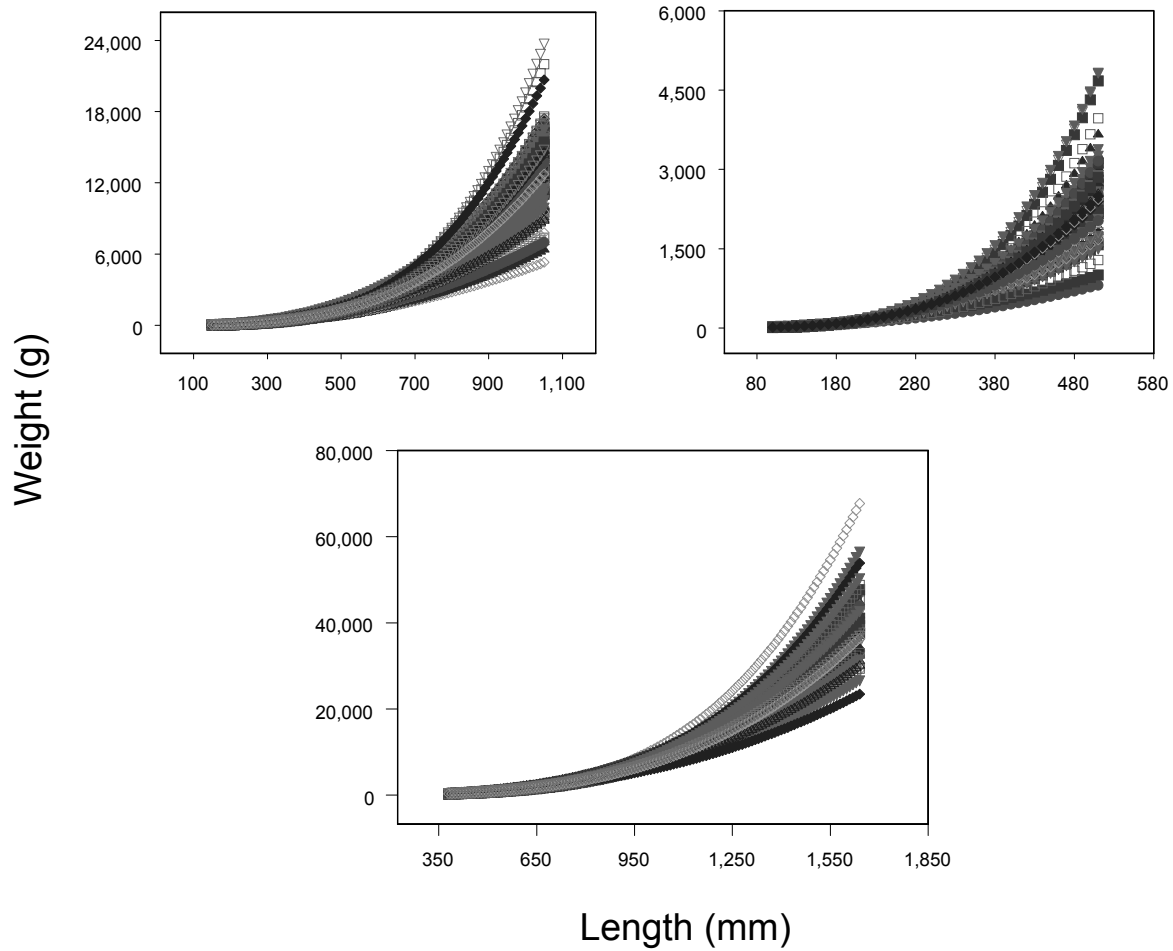


Figure 1.1. Predicted weight versus length relationships for muskellunge (top left; Neumann and Willis 1994), walleye *Sander vitreus* (top right; Murphy et al. 1990), and black crappie (bottom; Neumann and Murphy 1991) for the populations used to determine  $W_s$  for each species.

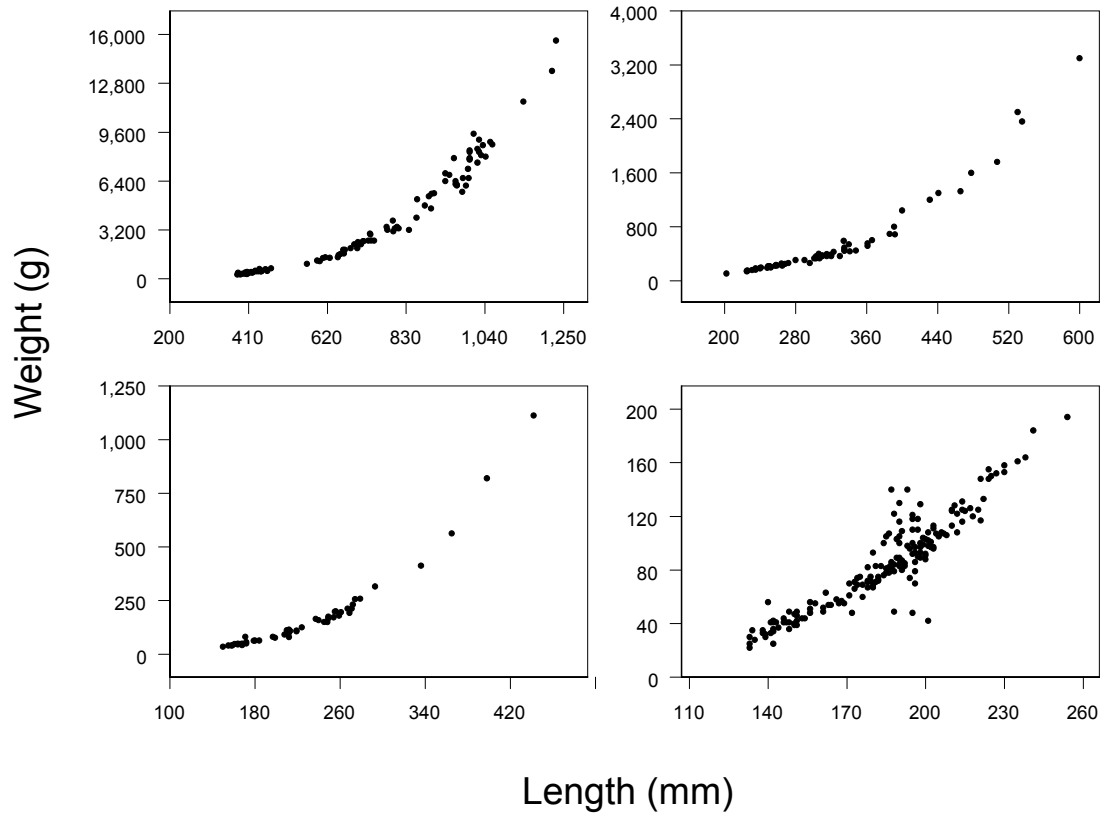


Figure 1.2. Scatterplot of length versus weight for the muskellunge (top left), largemouth bass (Smoots Pond – top right; Big Pond – bottom left), and black crappie (bottom right) electrofishing samples.



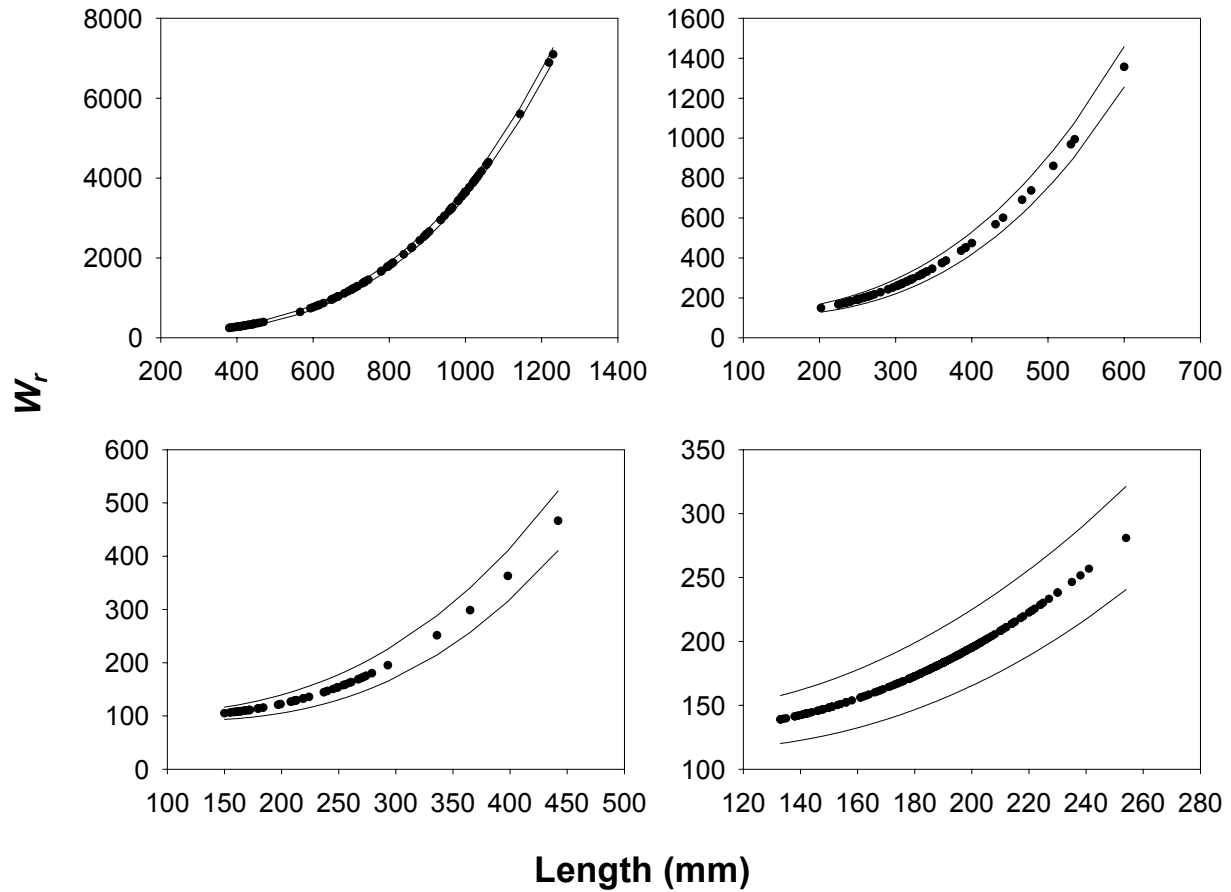


Figure 1.3. Plots of  $W_r$  expectations (black dots)  $\pm 2$  SE (connected lines;  $SE = \sqrt{\text{Var}}$ ) for the muskellunge (top left), largemouth bass (Smoots Pond - top right; Big Pond - bottom left), and black crappie (bottom right) length-weight data.

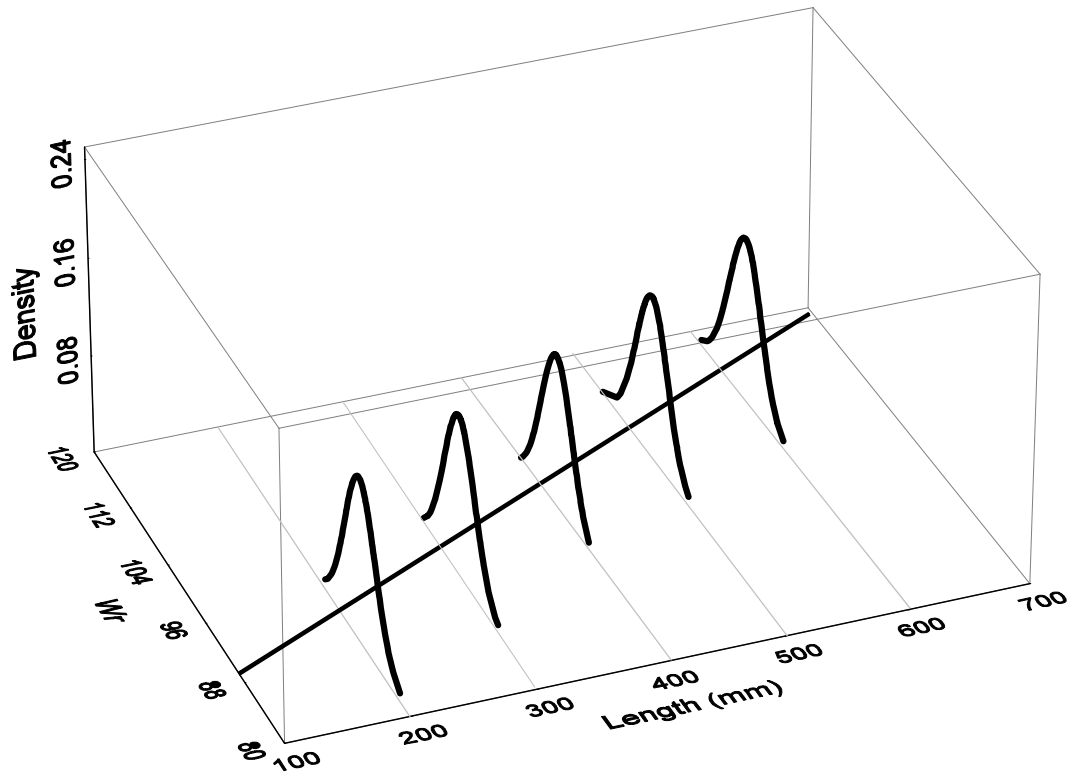


Figure 1.4. An illustration of the conditionality of  $W_r$  on fish length. Rather than being generated from a common distribution, the  $W_r$  data are generated by a unique distribution for each fish length under study. The straight line indicates a trend in mean  $W_r$  that might be found for a sample of fish and how  $W_r$  might be distributed around such a mean. Although the distributions are depicted as equally shaped and normal, this is only for illustrative purposes and is not meant to imply that this is the true nature of  $W_r$  distributions.

## CHAPTER 2: THE NEW RIVER, VIRGINIA, MUSKELLUNGE FISHERY: POPULATION DYNAMICS, HARVEST REGULATION MODELING, AND ANGLER ATTITUDES

### ABSTRACT

Although muskellunge *Esox masquinongy* fisheries in northern U.S. states and Canada provinces are increasingly being managed with restrictive harvest regulations (e.g., 1,370-mm minimum length limits), southern U.S. muskellunge fisheries continue to be managed with comparatively liberal regulations (e.g., 762-mm minimum length limits). I studied the population dynamics of the New River, Virginia, muskellunge fishery and used predictive modeling to determine whether restrictive harvest regulations also might prove beneficial for a southern latitude fishery. Additionally, an access/roving creel survey on the New River was conducted to learn more about angler attitudes regarding the muskellunge fishery. New River muskellunge grew quickly, with fish reaching harvestable lengths (762 mm) in 2 to 3 years. Muskellunge fishing pressure, harvest rates, and voluntary release rates were low compared to reports for more northern areas. Most anglers, regardless of how often they fished for muskellunge, defined “trophy” muskellunge to be approximately 1,050 to 1,100 mm in length. Although angler support for restrictive harvest regulations was low, abundance of memorable-length ( $\geq 1,070$  mm) muskellunge was predicted to increase under all evaluated length limits. Muskellunge yield would remain static at 914- and 1,016-mm length limits because of the fast growth of fish, but yield would decline dramatically with a 1,143-mm size limit because male muskellunge rarely exceeded 1,100 mm. Because of fast growth and low release rates, implementation of higher length limits (e.g., 965 to 1067 mm) may indeed prove beneficial for augmenting “trophy” muskellunge production on the New River. Angler support for higher minimum length limits may be increased by educating anglers regarding the fast growth rates of muskellunge and the anticipated size structure changes that will result from regulation modifications. Detection of size structure changes resulting from restrictive harvest regulations may be difficult because of variable recruitment and potential increases in fishing pressure, thus long-term monitoring, perhaps partially based on angler sampling, may be needed to ensure that new regulations are indeed benefiting the fishery.

## INTRODUCTION

Although anglers typically associate muskellunge *Esox masquinongy* with waterbodies in northern U.S. states and Canadian provinces, muskellunge fisheries also exist in several southern U.S. regions (e.g., Tennessee, North Carolina, Virginia, West Virginia). While muskellunge fisheries in northern areas increasingly are being managed with restrictive harvest regulations tailored to system-specific attributes (e.g., fish abundance, harvest rates, growth rates; Simonson and Hewett 1999), southern U.S. muskellunge fisheries are managed with comparatively liberal harvest regulations that are implemented statewide. For example, Virginia, North Carolina, and Tennessee muskellunge fisheries are all managed with statewide 762-mm minimum length [this and all lengths reported herein are total length (TL) measurements] limits and 2-fish/day creel limits (NCWRC 2003; TWRA 2003, VDGIF 2003). West Virginia muskellunge fisheries also are managed with a statewide 762-mm minimum length limit and a 2-fish/day creel limit, although a few special regulation areas (e.g., waterbodies with 914-mm minimum length limits) have been designated in that state (WVDNR 2003). Conversely, muskellunge fisheries in places such as Wisconsin and Ontario have length limits as high as 1,270 to 1,371 mm, and as many as 20% of the fisheries are managed with regulations that differ from statewide or province-wide limits (Simonson and Hewett 1999; OMNR 2003). Considering that most muskellunge fisheries, regardless of locale, are managed as “trophy” fisheries (Hanson et al. 1986), this geographical difference in management approaches raises a question regarding the effectiveness of statewide, liberal harvest regulations in southern regions.

The liberal harvest regulations used to manage southern latitude muskellunge fisheries possibly might be needed under some circumstances. If intraspecific competition for food resources limited muskellunge growth, then liberal harvest regulations might serve to reduce fish densities, thereby improving fish growth (Simonson and Hewett 1999). Liberal harvest regulations also might be needed if environmental conditions physiologically restricted muskellunge from reaching large sizes. Many southern U.S. states lie beyond muskellunge’s naturalized range, so environmental conditions in these systems might not be conducive to muskellunge growth. If southern latitude muskellunge are physiologically incapable of reaching large sizes, high length limits might mean that much of the population will not attain harvestable lengths, which would result in wasted recreational opportunities for

anglers. Liberal harvest regulations also might be justified if a high degree of voluntary catch-and-release angling limited muskellunge harvest or if fishing pressure on muskellunge was low. Low minimum length limits would thus allow anglers that perhaps unintentionally catch a muskellunge the opportunity to harvest a fish that they personally identify as a “trophy.”

Despite the possible need for liberal harvest regulations, southern latitude muskellunge fisheries may continue to be managed with such regulations because fishery biologists have lacked suitable information to determine whether the fisheries would benefit from more restrictive harvest regulations. Low length and high creel limits were once a fairly common management approach for muskellunge fisheries, but regulations generally have become more restrictive as interest in muskellunge sportfishing has increased and the impact of overharvest has become more evident (Crossman 1986; Graff 1986). Since very little research addressing muskellunge fisheries has been conducted in southern regions [notable exceptions include Parsons (1959), Miles (1978), Brewer (1980); Axon (1981), and Monaghan and Borawa (1988)], biologists have lacked data to accurately estimate demographic features (e.g., growth rates, mortality rates) of muskellunge stocks. Without reliable information pertaining to southern latitude muskellunge fisheries, predicting the impact and justifying alternative harvest regulations would be difficult.

The New River, located in southwest Virginia, presents an excellent opportunity for studying whether a southern U.S. muskellunge fishery also might benefit from implementation of more restrictive harvest regulations. Very little is known about muskellunge in this system as fish are not frequently collected by Virginia Department of Game and Inland Fisheries (VDGIF) personnel during regular fish sampling. The fishery is managed for the production of trophy fish and presumably is sustained through annual stocking of fingerling ( $\approx 100$  mm) fish. In recent years, some anglers have become concerned that Virginia’s statewide 762-mm minimum length and 2 fish/day creel limits do not afford sufficient protection to fish and that overharvest stemming from incidental catch of muskellunge may be limiting “trophy” fish production. The objectives of this research were to study the population dynamics of the New River muskellunge fishery, predict the effect that alternative harvest regulations might have on the production of trophy fish, and measure angler attitude regarding the fishery.

## STUDY SITE

The New River originates in northwest North Carolina and flows northward through southwest Virginia and into West Virginia (Figure 2.1). The New River merges with the Gauley River in West Virginia to form the Kanawha River, which is a tributary to the Ohio River. Naturalized expansion of muskellunge into the New River from the Ohio and Kanawha Rivers, to which muskellunge are native, possibly was prevented by Kanawha Falls, a waterfall located 3 river kilometers (rkm) below the confluence of the New and Gauley Rivers (Jenkins and Burkhead 1993). Stocking of muskellunge into the New River by VDGIF began in 1963.

The Virginia portion of the New River is 245 rkm in length and is impounded by five dams: Buck, Byllesby, Claytor, Fields, and Fries Dams (Figure 2.1). Muskellunge currently are stocked in two sections of the river, from the North Carolina-Virginia border to Fries Dam (upper section) and from Claytor Dam to the Virginia-West Virginia border (lower section). Approximately 1,000 fingerling muskellunge are stocked in the upper section and 4,000 fingerlings are stocked in the lower section each year. Stocking of muskellunge in the middle section of the New River (Fries Dam to Claytor Lake) was discontinued in 1994 because of the belief that muskellunge might be detrimentally impacting the walleye *Sander vitreus* fishery in this section of the river.

## METHODS

### *Data Collection*

Muskellunge were sampled by boat electrofishing during daylight hours from late fall/early winter to late spring/early summer in 2000, 2001, 2002, and 2003. Sampling was conducted only in the lower and middle sections of the New River, as insufficient water depth at access sites in the upper river section limited operability of the electrofishing equipment. Sampling in the middle section of the river was conducted so that fish occurrence possibly stemming from natural reproduction could be determined. The electrofishing unit consisted of a 4.8-m boat with two drop wire boom-mounted anodes and a Type VI-A electrofisher (Smith Root, Inc., Vancouver, Washington). Electrofishing was conducted using

pulsed-DC output at 4-A amperage and a frequency of 60 Hz. Electrofishing principally was conducted along riverbanks in water depths > 1 m. Muskellunge was the only species targeted when sampling.

Upon capture, muskellunge length was measured to the nearest mm and fish were weighed, depending on size, to the nearest 0.001, 0.01, or 0.1 kg. Sex was determined based on the width of the anal opening and its surrounding tissue relative to that of the urogenital papilla (LeBeau and Pageau 1989). If sex could not be conclusively determined in this manner, sex was recorded as unknown. A pelvic fin ray from each fish was clipped with wire cutters as close to the body as possible and stored dry in coin envelopes for future aging (Johnson 1971).

Several anglers and a Virginia taxidermist provided length, weight, sex, and fin rays from muskellunge that had been caught by angling. One angler provided length and weight data from more than 200 muskellunge that he had caught from the New River since 1998 through a diary that he maintained. The taxidermist provided otoliths from muskellunge that anglers brought to him for mounting as well, but attempts at aging fish from these structures were not successful.

Fin rays from fish captured by angling and electrofishing were transversely sliced into thin sections, mounted on glass microscope slides with an epoxy, and ground/polished using 600- and 1,500-grit sandpaper. Fin ray sections were viewed with a SAC-410NA video color camera (Samsung Electronics America, Ridgefield Park, New Jersey) and a SZ60 zoom stereo microscope (Olympus America Inc., Melville, New York). Digital images of fin ray sections were created and archived with Image-Pro Plus imaging software (Media Cybernetics, Silver Springs, Maryland). Fin ray sections and images were prepared only for fish longer than 500 mm, as young esocids generally can be aged by modal analysis of length frequency histograms (Casselman 1996).

Three readers independently aged each fin ray section. If at least two readers agreed as to the age of a particular fish, then that age was assigned to that individual. If age estimates of the three readers were different, then the readers collectively examined the fin ray section and tried to reach a consensus regarding age. If a consensus could not be reached, then that fish was excluded from age-related analyses.

Cleithra from 21 muskellunge ranging in length from 593 to 1,230 mm were removed and sent to researchers with the Cleithrum Project (Casselman and Crossman 1986) for aging. Cleithrum age

estimates were then compared to fin ray age estimates for the same fish. Although this comparison of age estimates does not validate pelvic fin rays as an aging structure for muskellunge (DeVries and Frie 1996; Campana 2001), it was felt that the comparison would provide some measure of accuracy of fin ray age estimates, since the cleithrum is regarded as the most accurate structure for aging esocids (Casselman 1979).

Many of the muskellunge captured by electrofishing were tagged in an effort to obtain precise data concerning fish growth. In 2000, muskellunge were tagged with either uniquely numbered t-bar anchor tags (Hallprint Pty Ltd, South Australia) or passive integrated transponder (PIT) tags (Biomark Inc., Meridian, Idaho). In 2001, 2002, and 2003, muskellunge were tagged exclusively with PIT tags. Anchor tags were inserted just below the dorsal fin, while PIT tags were injected into the body cavity proximately posterior to the pelvic girdle. When captured, muskellunge were visually checked for anchor tags or were scanned for PIT tags using a Mini-Portable Reader (Biomark Inc., Meridian, Idaho).

Forty-seven adult (> 600 mm) fish captured at Claytor Dam and Whitethorne from 2000 to 2002 were equipped with internal trailing-whip antenna radiotelemetry transmitters (Advanced Telemetry Systems, Isanti, Minnesota) so that more complete information concerning sources of fish mortality could be collected. Weekly attempts to locate these fish were conducted from March 2000 to June 2003. Tracking typically was conducted only in the areas where muskellunge were originally tagged and released. However, at least once yearly, the entire lower section of the New River was surveyed in an intensive tracking effort meant to detect whether fish had moved outside of the areas regularly surveyed. In 2000, the intensive survey was conducted from an airplane that flew directly over the river. Subsequent surveys consisted of the following components: (1) Claytor Dam to Whitethorne - surveyed from a boat, (2) Whitethorne to Eggleston – surveyed from nearby roads, (3) Eggleston to either Bluff City or Ripplemead – surveyed from a boat, (4) Bluff City to Glen Lyn – surveyed from nearby roads (Figure 2.1). In March 2003, approximately 60% (24 out of 40 rkm) of the New River between Bluestone Dam and the Virginia-West Virginia border was surveyed from a boat to determine whether any telemetered fish had moved to West Virginia sections of the New River.

Radiotelemetry transmitters listed the contact information for district VDGIF personnel and a notice that a reward would be given to those who returned the tag. The type of reward, a muskellunge



fishing lure, was not specified on the transmitter as it was hoped that anglers who harvested a tagged fish would at least contact VDGIF personnel to inquire about the reward, which would provide some indication that a fish had been harvested, regardless of whether the transmitter actually was returned.

Angler attitude regarding the New River muskellunge fishery was measured through a creel survey conducted from 16 March 2002 to 8 November 2002 by VDGIF personnel. The survey was stratified temporally by season (Spring: 16 March to 7 June; Summer: 8 June to 23 August; Fall: 24 August to 8 November) and day type (weekday: Monday to Thursday; weekend: Friday to Sunday, holidays). The survey also was stratified spatially into 5 regions: Region A: Virginia-North Carolina border to Byllesby Reservoir, Region B: Byllesby Reservoir to Allisonia, Region C: Claytor Dam to Whitethorne, Region D: Parrot to Ripplemead, Region E: Bluff City to Glen Lynn (Figure 2.1). Angler intercept method differed between the regions. Region A consisted of an access/roving combination, whereby one creel clerk would stay at an individual access site, while another creel clerk conducted a roadside roving survey. Regions B and C were access point surveys. Region D was an on-water roving survey. Region E was a bus route survey. Survey questions pertaining to the muskellunge fishery that were asked included how many days per year anglers fished exclusively for muskellunge, how many muskellunge had anglers caught and harvested in the past three years, what length of muskellunge did anglers regard as trophies, what minimum length did anglers regard as harvestable, whether anglers believed that harvest regulations should be changed, and whether anglers belonged to specialized fishing clubs. Clerks also asked about targeted species and catch/harvest for the current fishing trip.

### *Data Analyses*

Size structure of the New River muskellunge population was assessed through length-frequency histograms and size structure indices. Length-frequency histograms were constructed for individual years and method of capture, as well as for combined data. Size structure indices [i.e., proportional stock density (PSD) and relative stock density (RSD)] were used to summarize each of the length-frequency histograms. The length classes used in calculating size structure indices were stock (510 to 759 mm),

quality (760 to 969 mm), preferred (970 to 1,069 mm), memorable (1,070 to 1,269 mm), and trophy ( $\geq$  1,270 mm; Gabelhouse 1984).

Muskellunge length-weight data were  $\log_{10}$  transformed and regressed using least-squares simple linear regression [Proc GLM function in SAS (SAS Institute, Inc., Cary, North Carolina)]. Differences in slopes of the length-weight regressions between years and capture method (no interaction) were tested using analysis of covariance (ANCOVA). Difference in slopes of the length-weight regressions between sexes also was tested using ANCOVA. Condition of the New River muskellunge population was determined by computing relative weight ( $W_r$ ) of fish greater than 380 mm using the standard weight equation from Neumann and Willis (1994). Differences in  $W_r$  between six length classes [the five aforementioned length classes plus a pre-stock length class (380 to 569 mm)] were tested using the  $R$  test (Brenden et al. 2003).

Agreement of fin ray age estimates among the three readers was assessed using pairwise age bias plots and mean coefficients of variation (Campana et al. 1995). Because of small sample sizes, an age bias plot and mean coefficient of variation were not used to compare cleithrum and fin ray age estimates. Instead, a scatterplot of fin ray versus cleithrum estimates was created and the kappa coefficient (Cohen 1960) was used to provide a chance-corrected index of agreement between the aging methods. The kappa coefficient ranges from a maximum of one when there is perfect agreement between methods to a minimum of zero (Cohen 1960).

Growth of the New River muskellunge population was modeled with the von Bertalanffy growth model

$$L(t) = L_{\infty} \cdot \left[ 1 - \exp^{-\kappa \cdot (t - t_0)} \right],$$

where  $L(t)$  is fish length at age  $t$ ,  $L_{\infty}$  is asymptotic fish length,  $\kappa$  is the Brody growth parameter, and  $t_0$  is the theoretical age at which fish length is zero. Because of inconsistencies in the shape of the sectioned fin rays, fish length was not back-calculated (Krueger and Hubert 1997). Instead, only lengths at current ages were used when estimating fish growth. Sex specific growth equations were estimated within the same model by use of a sex-specific indicator variable, and by assuming a common variance but different parameter sets for the sexes. Differences in parameter estimates of the von Bertalanffy growth equations between males and females were tested using a likelihood ratio test (Quinn and Deriso 1999).

Because fish sex could not be conclusively determined for any fish younger than age 2, sex of age-1 fish was assigned randomly so that this age class could be incorporated in the growth model. The parameters of the growth model were fit using nonlinear regression and the Levenberg-Marquardt iterative estimation procedure (PROC NLIN function in SAS).

Fish mortality was estimated using both catch curve analysis and the telemetry method of Hightower et al. (2001). For the catch curve analysis, all age data, regardless of sampling year, were pooled. Based on the appearance of the fish age versus  $\log_e$  catch plot (see *Results* below), two catch curve regressions were fit to the data. The first catch curve regression was fit to the  $\log_e$  catches of age-1 to age-4 fish, and the second catch curve regression was fit to the  $\log_e$  catches of age-4 and older fish. Based on estimated fish growth and the size limit currently in effect, it was believed that the first catch curve would provide primarily an estimate of natural mortality, while the second catch curve would incorporate both fishing and natural mortality.

The telemetry method of Hightower et al. (2001) estimates mortality by modeling the expected number of relocated fish that were tagged and released during previous time periods. Specifically, the expected number of fish “released” at time  $i$  and relocated at time  $i+1$  is modeled as

$$Loc_{i+1} = R_i \cdot \exp^{(-F_i - M_i)} \cdot p_{i+1}$$

where  $Loc_{i+1}$  is the number of fish located at time  $i+1$ ,  $R_i$  is the number of fish “released” at time  $i$ ,  $F_i$  and  $M_i$  are the instantaneous rates of fishing and natural mortality at time  $i$ , and  $p_{i+1}$  is the probability of locating an individual at time  $i+1$ . Two different types of “releases” are distinguished with this method, an actual release and a virtual release. The actual release of a fish occurs when the fish is first tagged and released into the system. Virtual releases occur each time period that fish are subsequently relocated alive. Thus, if a fish is located alive at time  $i$ , it is considered to be virtually released at time  $i$ .

Even though telemetered muskellunge were located weekly, a monthly time-step was used to quantify mortality. A fish was considered located for a particular month if it was located at least once during that month, unless it was determined that the fish had been harvested or died from natural causes during that month. Fish that were repeatedly found in the same location were assumed to have died from natural causes (although hooking mortality cannot be ruled out), and it was assumed that the fish had died immediately before it was first located at its final location. Only those fish that were confirmed to be

alive at least four months after transmitter implantation were included in the analysis, so that mortality estimates would not be biased by mortality stemming from surgical implantation of transmitters.

Because the duration of the study lasted longer than the expected battery life of some of the transmitters, the temporal scale of the mortality analysis was reduced by scaling all fish location histories to a common 19-month time span that began in November and lasted through the following February. Thus, fish that were equipped with transmitters during the same month of different years were considered to have been released at the same time. Fate of fish after the 19-month time frame was ignored, regardless of whether fish were harvested, died from natural causes, or survived. Nineteen months was selected as the time span because that was the minimum expected battery life of all transmitters.

The computer program RELEASE (Burnham et al. 1987), which was implemented through MARK (White and Burnham 1999), was used to convert the relocation histories of all fish into a summary table of relocations for each tracking period. Instantaneous fishing and natural mortality rates were estimated with SURVIV (White 1983), which estimates model parameters by numerical optimization [additional detail provided in White and Garrott (1990)]. Mortality rates were estimated using several models in which mortality rates either remained constant, varied quarterly, or varied monthly (Hightower et al. 2001). Akaike's information criterion corrected for small sample sizes ( $AIC_c$ ) and Akaike weights were constructed for each candidate model. Model-average estimators (Anderson et al. 2000) of fishing and natural mortality rates were computed using the mortality estimates and Akaike weights of each model (Hightower et al. 2001).

Because angling parties were the sampling unit for the creel survey questions concerning angler attitudes, results were summarized based on the number of interviewed angling parties (as opposed to the total number of anglers across all parties). Creel survey results were summarized according to how often anglers fished for muskellunge (see *Results* below). Response differences among angler subgroups were tested with a multi-response permutation procedure (MRPP; Mielke and Berry 2001), which is a distribution-free method for testing differences among groups. The MRPP compares intra-group average distances in responses to distances calculated after permutation of the observed data (Cade and Richards 2001). Overall significant differences among angler subgroups were followed with Bonferroni-corrected pairwise MRPP comparisons between subgroups. The MRPP tests were conducted

using BLOSSOM (USGS 2004b) and *P*-values for the tests were obtained using a Pearson Type-III approximation to the permutation distribution (Cade and Richards 2001). All statistical tests were conducted with an experimentwise Type-I error rate of 0.05.

The effect of more restrictive length limits on the New River muskellunge fishery was predicted using a dynamic pool model (see Ricker 1975) as implemented through FAST (Slipke and Maceina 2000). Regulations that were evaluated were 914-, 1,016-, and 1,143-mm (36-, 40-, and 45-inches) minimum length limits. Because of differences in growth between the sexes (see *Results* below), the effects of alternative harvest regulations were modeled separately for males and females, but results were combined across sexes during final evaluation. An initial population size of 2,000 fish per sex was assumed. Harvest regulations were modeled with conditional mortality (natural and fishing) rates ranging from 5 to 30%. The effects of alternative harvest regulations were evaluated based on the percent change in abundance of memorable-length ( $\geq 1,070$  mm) muskellunge in the population and the percent change in total number of fish harvested. Yield-per-recruit changes also were used to evaluate the effects of alternative size limits. Recruitment of muskellunge to the population was assumed to occur at age 1.

## RESULTS

### *Muskellunge Population Dynamics*

Between 1998 and 2003, 523 muskellunge were collected from the New River, 236 fish by electrofishing and 285 fish by anglers. Two fish were found dead in the river. A total of 445 muskellunge were seen, but not necessarily captured, when electrofishing. The median electrofishing CPUE for all sites sampled was 1.36 fish per electrofishing hour. The median number of fish seen (but not necessarily captured) was 2.57 fish per electrofishing hour. Of the 146 captured muskellunge for which sex was identified, the ratio of males to females was equivalent (female: 49%; male: 51%).

Of the fish captured by electrofishing, 17 fish were collected in the middle (unstocked) section and 219 fish were collected in the lower (stocked) section. Muskellunge catch in the middle section was concentrated at Fosters Falls and Austinville (Table 2.1). In the lower section, catch of muskellunge was

heavily concentrated at Whitethorne, nearly 70% of all electrofished muskellunge were captured at this site (Table 2.1). In terms of catch rates, Claytor Dam, Pembroke, Peppers Ferry, Rich Creek, and Whitethorne had similar CPUEs, and CPUE at these five sites was greater than the catch rates at Bluff City, Dedmon Center, and Eggleston. The catch rates at Bluff City, Dedmon Center, and Eggleston were similar to the catch rates at the sites sampled in the middle section of the river.

Total length of captured muskellunge ranged from 358 to 1,270 mm. Comparison of sampling methodologies suggested that angling was biased towards larger (> 800 mm) fish, while electrofishing was biased towards smaller (< 800 mm) fish (Figure 2.2). Such difference in sampling effectiveness affected yearly size structure estimates. In 1998 and 1999, muskellunge were collected exclusively by angling, thus size structure estimates were skewed towards larger fish relative to the 2000 through 2003 samples in which fish were collected either by a combination of electrofishing and angling or solely by electrofishing (Figure 2.2). Muskellunge PSD, RSD-P, and RSD-M for all years combined were 87, 38, and 12, respectively.

Recapture of tagged fish during this study was low. Of 103 muskellunge tagged with either PIT or anchor tags, seven fish were recaptured once and two fish were recaptured two or more times. Eleven muskellunge equipped with radiotelemetry transmitters were seen during subsequent electrofishing efforts, although these fish were not always netted so as not to further stress the fish. During later sampling efforts, captured muskellunge did not show indications of a previous pelvic fin ray clipping. Consequently, it was believed that fish captured during later sampling were indeed newly caught fish, as opposed to the alternative possibilities that tags were either lost or were undetectable.

$\log_{10}$  transformed length-weight relationships did not differ by method (ANCOVA:  $F = 2.36$ ,  $df = 1,511$ ,  $P = 0.125$ ) or year (ANCOVA:  $F = 0.90$ ,  $df = 1,503$ ,  $P = 0.482$ ) of capture. However, there was a significant difference in the slopes of the length-weight relationships between the sexes (ANCOVA:  $F = 4.73$ ,  $df = 1,142$ ,  $P = 0.0312$ ). The  $\log_{10}$  transformed length-weight relationships for females and males were

$$\log_{10}W_f = -6.496 + 3.459 \cdot \log_{10}L_f$$

and

$$\log_{10}W_m = -5.991 + 3.280 \cdot \log_{10}L_m,$$

where  $W_f$  and  $W_m$  are female and male fish weights (measured in g), and  $L_f$  and  $L_m$  are female and male fish lengths (measured in mm), respectively. The higher slope estimate for females indicates that females became more rotund than males with increasing length (Anderson and Neumann 1996). Overall, there were no significant differences in  $W_f$  among the muskellunge length classes ( $R$  test:  $R = 1.045$ ,  $df = 5$ ,  $507$ ,  $P = 0.393$ ). Mean muskellunge  $W_f$  across all length classes equaled 92.

Pelvic fin rays were obtained from 194 muskellunge. Anglers provided 55 fin rays, while the remaining fin rays were obtained from fish captured during electrofishing or from the fish found that were found dead in the river. Sex of fish from which fin rays were collected was identified for 119 fish. Based on the modal separation of early age classes in the length-frequency histograms (Figure 2.2), 84 muskellunge were assumed to be either age-0 or age-1 fish (depending on date of capture). Given sampling seasonality, all of these fish were assumed to be age 1 for analyses.

The three readers were able to assign ages to all fin ray sections that were examined, except for a fin ray from an 897-mm female. Age estimates for this particular fish ranged from 7 to 11 years, which were ages that seemed unlikely compared to the age estimates for fish of similar size. Since an agreed-upon age could not be reached between the readers, this fish was excluded from all age-related analyses.

At least two of the three readers' age estimates agreed for 87% of the fin ray sections that were examined. Readers 1 and 2 gave consistent estimates for age-4 and younger fish, but Reader 2 typically gave lower estimates than Reader 1 for age-5 and older fish (Figure 2.3). Consistency between Readers 1 and 3 was highly nonlinear. Relative to age estimates for Reader 1, Reader 3 overestimated fish age for young fish but underestimated fish age for old fish (Figure 2.3). Similarly, Reader 3 overestimated fish age for young fish and underestimated fish age for old fish relative to the estimates from Reader 2 (Figure 2.3). The mean coefficient of variation (CV) in age estimates for all three readers was 17.8%. From a pairwise standpoint, the mean CV in age estimates was 5.6% for Readers 1 and 2, 17.5% for Readers 1 and 3, and 17.8% for Readers 2 and 3.

Fin ray age estimates agreed with cleithrum age estimates for 76% ( $n = 16$ ) of the muskellunge that were aged with both methods. Age estimate agreement within one year was 100%. Fin rays overestimated age for two fish and underestimated age for three fish relative to the cleithrum-age

estimates (Figure 2.4). The kappa coefficient ( $\pm$  95% confidence interval) for the cleithrum and fin ray age estimates was  $0.70 \pm 0.23$ .

Muskellunge growth rates differed between the sexes (likelihood-ratio test:  $F = 5.99$ ,  $df = 3,183$ ,  $P$ -value = 0.006). Female muskellunge grew faster and attained longer ultimate lengths than males (Figure 2.5). Based on plots of predicted versus actual lengths, it was believed that  $L_{\infty}$  for both sexes was poorly predicted with the original coefficient estimates for the growth model. Asymptotic lengths were estimated at 1,200 and 1,070 mm for females and males, respectively, but all data sources indicated that both sexes routinely attained longer lengths. As a result, a decision was made to re-estimate the growth model with  $\kappa$  and  $t_0$  as the only parameters to be estimated. Asymptotic fish lengths were selected based on available data. The final model that was chosen was that which visually fit the length-at-age data and which did not appreciably lower the model pseudo  $r^2$ . Model pseudo  $r^2$  was calculated as

$$\text{Pseudo } r^2 = 1 - \frac{\text{Sum of Squares (Residual)}}{\text{Sum of Squares (Total}_{\text{Corrected}})}.$$

The pseudo  $r^2$  for a nonlinear model is conceptually similar to the  $r^2$  for a linear model in that it measures the amount of variance in the observed data that is explained by the model (Myers 1990). The final growth model that was selected predicted fish growth with the equations

$$L_f(t) = 1,300 \cdot \left[ 1 - \exp^{-0.3169 \cdot (t+0.2743)} \right]$$

and

$$L_m(t) = 1,100 \cdot \left[ 1 - \exp^{-0.4263 \cdot (t+0.1536)} \right],$$

where  $L_f(t)$  and  $L_m(t)$  are predicted lengths at age for females and males, respectively. Predicted lengths from this final growth model appeared to better approximate fish growth at all ages (Figure 2.5) and caused only a slight decrease in pseudo- $r^2$ . The pseudo  $r^2$ s for the original and final growth models were 0.958 and to 0.946, respectively.

Predicted length changes from the final von Bertalanffy growth model were compared to observed length changes of the muskellunge that were marked and later recaptured (Table 2.2).

Predicted length changes were calculated with the equation

$$\Delta L_i = (L_{\infty} - L_{1i}) \cdot \left( 1 - \exp^{-\kappa \cdot \Delta t_i} \right),$$



where  $\Delta L_i$  is predicted length change,  $\Delta t_i$  is elapsed amount of time between marking and recapture,  $L_{1i}$  is length at initial marking, and  $L_\infty$  and  $\kappa$  are the von Bertalanffy growth model parameters described above (Quinn and Deriso 1999). Deviations of predicted changes from observed length changes ranged from -43 to 99 mm (Table 2.2). Mean absolute error between predicted and observed length changes was approximately 30 mm, which suggested that the final von Bertalanffy growth model accurately predicted muskellunge length changes.

Based on the appearance of the catch-curve plot (Figure 2.6), it was believed that muskellunge fully recruited to the sampling gear at age 1. A catch-curve regression fit to the  $\log_e$  catches of all muskellunge age classes gave an instantaneous total mortality ( $Z$ ) estimate of 0.39 (Figure 2.6). The catch-curve regression fit to  $\log_e$  catches of age-1 to age-4 fish gave a  $Z$  estimate of 0.22, while the catch-curve regression fit to the  $\log_e$  catches age-4 and older fish gave a  $Z$  estimate of 0.40 (Figure 2.6). Assuming that total mortality of age-1 to age-4 fish is comprised primarily of natural mortality  $M$  and that this rate remains constant for older fish, the instantaneous fishing mortality  $F$  estimate of muskellunge age-4 and older would be approximately 0.18. Regression diagnostic measures (i.e., HAT diagonal,  $R$ -student value; Myers 1990) indicated that although only one 11-year old fish was captured, this data point did not unduly influence the regression equation and so it was not deemed necessary to delete this data point before calculating the catch-curve regression.

Of the 47 muskellunge equipped with radiotelemetry transmitters, 10 fish were censored from the analysis because of possible surgery-related mortality (natural mortality occurred within 4 months of transmitter implantation), transmitter malfunction, or movement outside areas regularly surveyed. Of the 37 fish retained in the analysis, 3 fish apparently died from natural causes, 6 fish were harvested based upon either tag return or conversation with anglers, and 21 fish survived the time period under consideration. The remaining 7 fish were assumed to have been harvested, as their presence in the New River was never detected during any of the intensive tracking efforts.

Fishing and natural mortality rates estimated from the telemetry data exhibited strong seasonality (Figure 2.7). Fishing mortality peaked from spring to fall, while natural mortality occurred primarily in August. Despite this apparent seasonality, the most parsimonious mortality model based on  $AIC_c$  model selection was the model where fishing and natural mortality were kept at constant rates (Table 2.3). The

second-best model consisted of a quarterly fishing mortality rate and a constant natural mortality rate (Table 2.3). The constant fishing and natural mortality model had a relative likelihood nearly three times that of the quarterly fishing and constant natural mortality model. The model-average estimators of  $F$  and  $M$  (scaled to an annual time frame) were 0.15 and 0.05, respectively.

Both the catch-curve and telemetry method gave similar estimates of instantaneous fishing mortality,  $F = 0.18$  and  $0.15$ , respectively. Averaging the mortality rates from the two methods yielded an instantaneous fishing mortality estimate of  $0.165$ . Natural mortality estimates were not as precise as the fishing mortality estimates ( $M = 0.22$  and  $0.05$  for the catch curve and telemetry methods, respectively). The average of the catch curve and telemetry mortality estimates was  $0.135$ . In terms of annual conditional rates, fishing ( $cf$ ) and natural ( $cm$ ) mortality rates were estimated to equal  $15.2$  and  $12.6\%$ , respectively. The annual exploitation rate of New River muskellunge was estimated at  $14.2\%$ .

### *Angler Attitudes*

A total of 770 angling parties (hereafter referred to as anglers) were interviewed during the New River creel survey. Twelve percent ( $n = 91$ ) of the interviews were repeat interviews, meaning that those interviewed had been previously interviewed at least once before. When conducting a repeat interview, clerks only asked questions related to the current fishing trip (i.e. target species, catch/harvest of muskellunge) and did not repeat questions concerning angler opinions of the muskellunge fishery. Muskellunge was indicated to be the target species for the current fishing trip by approximately  $2.2\%$  of anglers. All interviews in which muskellunge was identified as the target species occurred on the lower section of the New River, and  $65\%$  ( $n = 11$ ) occurred at Whitethorne. Thirty-five percent ( $n = 6$ ) of the anglers specifically targeting muskellunge had caught a muskellunge during that particular fishing trip, with one fish approximately  $1,200$  mm in length having been harvested.

Of the interviews conducted in which muskellunge was not the target species for the current fishing trip, 8 muskellunge had been caught by 7 anglers. One fish was caught in the upper section of the river, while the remaining fish were caught in the lower section. One fish approximately  $920$  mm in length was harvested. All anglers that caught a muskellunge, but were not specifically targeting muskellunge,

indicated that the targeted species during that particular fishing trip was *Micropterus* spp. Overall release rate of muskellunge combined across anglers was 86%.

Interviewed anglers fished for muskellunge an average of 4 days/year, with the number of days specified ranging from 0 to more than 100 (Figure 2.8). For the purpose of differentiating angler attitudes, angler subgroups were defined in the following manner: those who never fished for muskellunge were considered non-muskellunge anglers, those who fished 1 to 5 days/year were considered occasional muskellunge anglers, those who fished 6 to 25 days/year were considered moderately-dedicated muskellunge anglers, and those who fished > 25 days/year were considered dedicated muskellunge anglers. More than 80% ( $n = 555$ ) of interviewed anglers were classified as non-muskellunge anglers (Table 2.4). Of those anglers that fished at least once a year for muskellunge, 50% ( $n = 61$ ) were occasional, 30% ( $n = 37$ ) were moderately-dedicated, and 20% ( $n = 25$ ) were dedicated muskellunge anglers. Only one interviewed angler belonged to a muskellunge fishing club. That angler was a member of a West Virginia Muskies Inc. chapter and fished frequently enough to be considered a dedicated muskellunge angler.

No significant differences in what lengths of muskellunge were considered “trophies” (Table 2.4) were found among the angler subgroups (MRPP:  $\delta = 0.261$ ,  $P$ -value = 0.322). Most anglers defined “trophy” muskellunge to be fish approximately 1,050 to 1,100 mm in length (Figure 2.9). Approximately 74% of anglers ( $n = 302$ ) that had an opinion ( $n = 408$ ) believed that a “trophy” length was at least 1,016 mm, while 11% ( $n = 22$ ) believed that a “trophy” length was at least 1,270 mm.

Angler subgroups differed as to what minimum length of muskellunge (Table 2.4) was regarded as harvestable (Figure 2.9; MRPP:  $\delta = 15.58$ ,  $P$ -value < 0.0001). Non-muskellunge anglers identified lengths that were significantly smaller than lengths identified by occasional (MRPP:  $\delta = 4.676$ ,  $P$ -value = 0.005), moderately-dedicated (MRPP:  $\delta = 4.343$ ,  $P$ -value = 0.006), and dedicated (MRPP:  $\delta = 22.882$ ,  $P$ -value < 0.0001) muskellunge anglers. Dedicated muskellunge anglers identified minimum harvestable lengths that were larger than the lengths identified by occasional (MRPP:  $\delta = 6.314$ ,  $P$ -value = 0.001) and moderately-dedicated (MRPP:  $\delta = 6.019$ ,  $P$ -value = 0.001) muskellunge anglers. There was no significant difference in the minimum harvestable lengths identified by occasional and moderately-dedicated muskellunge anglers (MRPP:  $\delta = 0.775$ ,  $P$ -value = 0.879).

At least a few anglers from all subgroups when asked about minimum harvestable lengths replied that all muskellunge caught would be voluntarily released (Table 2.4). Although the global test as to whether angler subgroups differed in the percentages of anglers that specified voluntary release of muskellunge would be practiced was found to be significant (MRPP:  $\delta = 2.54$ ;  $P$ -value = 0.026), none of the pairwise MRPP comparisons between angler subgroups were significant ( $P$ -value > 0.0083). Overall, 40% ( $n = 240$ ) of those anglers that had an opinion regarding minimum harvestable lengths of muskellunge ( $n = 604$ ) specified that voluntary release would always be practiced.

Angler subgroups differed in the percentage of anglers that had caught a muskellunge in the past 3 years (Table 2.4; MRPP:  $\delta = 55.07$ ;  $P$ -value < 0.0001). Percentage of anglers that had caught a muskellunge in the past 3 years was lower for non-muskellunge anglers than for occasional (MRPP:  $\delta = 32.43$ ;  $P$ -value < 0.0001), moderately-dedicated (MRPP:  $\delta = 33.55$ ;  $P$ -value < 0.0001), and dedicated (MRPP:  $\delta = 62.60$ ;  $P$ -value < 0.0001) muskellunge anglers. There was no difference between occasional and moderately-dedicated muskellunge anglers in the percentage of anglers that had caught a muskellunge in the past 3 years (MRPP:  $\delta = 0.08$ ;  $P$ -value = 0.351). A higher percentage of dedicated muskellunge anglers had caught a muskellunge than occasional (MRPP:  $\delta = 7.94$ ;  $P$ -value = 0.0004) and moderately-dedicated (MRPP:  $\delta = 4.31$ ;  $P$ -value = 0.007) muskellunge anglers. Of the anglers that had caught a muskellunge in the past 3 years, the percentage that also harvested a muskellunge also differed between subgroups (MRPP:  $\delta = 2.17$ ;  $P$ -value = 0.039). The only significant difference between subgroups was between non- and moderately-dedicated muskellunge anglers (MRPP:  $\delta = 4.45$ ;  $P$ -value = 0.0065). Forty-seven percent ( $n = 11$ ) of moderately-dedicated anglers that had caught a muskellunge in the past three years also had harvested a muskellunge, compared to 19% ( $n = 17$ ) of non-muskellunge anglers that had caught a muskellunge. None of the other percentages between angler subgroups significantly differed ( $P$ -value > 0.0083).

Anglers indicated that a total of 58 fish had been harvested in the past 3 years out of an estimated 1,263 muskellunge that had been caught (overall release rate = 95%). The ratio of the number of muskellunge harvested versus the number of muskellunge caught was similar between non- (3.1%), occasional (6.0%), and dedicated (1.5%) muskellunge anglers, but the ratio of caught versus harvested

for moderately-dedicated muskellunge anglers (22.7%) was higher than the other angler subgroups. The average length of muskellunge harvested by anglers in the past 3 years was 962 mm (Table 2.4).

The percentage of anglers that believed muskellunge harvest regulations should be changed was significantly different among angler subgroups (MRPP:  $\delta = 20.21$ ;  $P$ -value  $< 0.0001$ ). A lower percentage of non-muskellunge anglers believed that regulations needed to be changed than occasional (MRPP:  $\delta = 9.71$ ;  $P$ -value = 0.00012), moderately-dedicated (MRPP:  $\delta = 5.22$ ;  $P$ -value = 0.004), or dedicated muskellunge (MRPP:  $\delta = 30.17$ ;  $P$ -value  $< 0.0001$ ) anglers (Table 2.5). None of the other angler subgroups differed in the percentage of anglers that believed regulations should be changed ( $P$ -value  $> 0.0083$ ; Table 2.5). Of the anglers that thought harvest regulations for muskellunge should be changed ( $n = 99$ ), 86% ( $n = 85$ ) thought the creel limit should be changed, while 56% ( $n = 55$ ) thought that the size limit should be changed. Of those anglers that thought the creel limit should be changed, the percentage that wanted a lower creel limit differed among angler subgroups (MRPP:  $\delta = 5.67$ ;  $P$ -value = 0.0005). A lower percentage of non-muskellunge anglers believed that a lower creel limit should be implemented compared to the percentage of occasional (MRPP:  $\delta = 5.43$ ;  $P$ -value = 0.003) and dedicated (MRPP:  $\delta = 5.90$ ;  $P$ -value = 0.002) muskellunge anglers. Non-muskellunge and moderately-dedicated muskellunge anglers did not differ in the percentage of anglers that believed a lower creel should be implemented (MRPP:  $\delta = 3.10$ ;  $P$ -value = 0.019). Likewise, occasional, moderately-dedicated, and dedicated muskellunge anglers did not differ in the percentage of anglers that believed a lower creel limit should be implemented ( $P$ -value  $> 0.0083$ ).

Of the anglers interviewed that believed the size limit for muskellunge should be changed, the percentage of anglers that thought a higher minimum length limit should be implemented differed among angler subgroups (MRPP:  $\delta = 4.56$ ;  $P$ -value = 0.002). A lower percentage of non-muskellunge anglers believed that a higher minimum length limit should be implemented than occasional muskellunge anglers (MRPP:  $\delta = 7.40$ ;  $P$ -value = 0.0006). The percentage of anglers that believed a higher minimum length limit should be limited was not significantly different between any of the other angler subgroups ( $P$ -value  $> 0.0083$ ). Of the anglers that believed a higher minimum length limit should be implemented, the mean length specified (regardless of angler subgroup) was 988 mm and ranged from 863 to 1,219 mm. The overall weighted-average proposed size limit, which was found by adding the mean size limit identified by

anglers that wanted a lower limit with the mean size limit identified by anglers that wanted a higher size limit (multiplied by angler percentages), ranged from 527 to 973 mm (Table 2.5).

### *Alternative Length Limit Evaluations*

Alternative length limit modeling indicated that at current mortality estimates ( $cm = 12.6\%$ ,  $cf = 15.2\%$ ), increasing the minimum length limit from 762 to 914 mm would increase the abundance of memorable-length ( $\geq 1,070$  mm) muskellunge in the population by approximately 25% (Figure 2.10). At other mortality rates, though, the expected abundance increase could be between 5 and 50%. Total number of harvested fish would be expected to decline by approximately 20%, although as much as a 40% decrease could be expected with lower natural and higher fishing mortality estimates (Figure 2.11). Yield of muskellunge would actually increase, albeit only slightly, under a 914-mm minimum length at current mortality estimates (Figure 2.12). This increase in yield would be expected to occur, despite the decline in the total number of harvested fish, because of muskellunge's fast growth rates. Delaying harvest allowed muskellunge to add sufficient amounts of biomass, which would offset the decrease in total number of fish harvested. An increase in yield with a 914-mm minimum length limit would be even more significant at low natural and high fishing mortality rates (Figure 2.12).

With a 1,016-mm minimum length limit, abundance of memorable-length ( $\geq 1,070$  mm) muskellunge in the population would be expected to increase by 50% at current mortality levels (Figure 2.10). Expected abundance increases could be as high as 130% with low natural and high fishing mortality rates, but also as low as 10% with low fishing mortality rates. At current mortality estimates, harvest of muskellunge would decline by 40% under a 1,106-mm minimum length limit (Figure 2.11). At a post-stocking survival rate of 5%. Yield would be expected to decline by approximately  $0.25 \text{ kg}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$  per recruit at current mortality estimates, but also could be expected to increase by as much as  $1.25 \text{ kg}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$  per recruit with higher fishing mortality rates (Figure 2.12).

As expected, changing the minimum-length limit to 1,143 mm resulted in the largest increase in abundance of memorable-length ( $\geq 1,070$  mm) muskellunge in the population. At current mortality estimates, abundance of memorable-length muskellunge would nearly double (Figure 2.10), although total number of harvested fish also would be expected to decline by as much as 80% (Figure 2.11).

Unlike the other size limits that were considered, yield with a 1,143-mm minimum length limit was found to decline regardless of the mortality rates considered (Figure 2.12). This primarily would result from male muskellunge's inability to obtain lengths in excess of 1,100 mm. Thus, for all practical purposes, a 1,143-mm length limit would turn the New River into a female-only muskellunge fishery.

## DISCUSSION

### *New River Muskellunge Population Dynamics*

The New River muskellunge fishery consisted of fast-growing individuals that become harvestable at young ages under Virginia's current 762-mm minimum length limit. Nearly all New River muskellunge exceeded 762 mm by 3 years of age, and fish could exceed of 1,000 mm by age 5. This rate of growth is among the fastest that has been reported for any muskellunge population. Ontario muskellunge typically do not attain 762 mm in length until ages 5 or 6; in some populations, fish may not reach this length until 9 years of age (Casselman et al. 1999). Although fast-growing muskellunge in Wisconsin may reach 762 mm by age 4, in other populations, fish may not reach this length until 10 years of age (Johnson 1971). In a study of 15 northern Wisconsin, it took muskellunge an average of 11.5 years to reach 1,016 mm (Margenau and AveLallemant 2000). Muskellunge in Pennsylvania and New York may not reach 762 mm until 4 years of age (Harrison and Hadley 1979). Growth of New River muskellunge also was rapid when compared to growth rates from other southern populations. In North Carolina's French Broad River, muskellunge did not attain 762 mm until ages 4 or 5 (Monaghan and Borawa 1988). Likewise in Tennessee, West Virginia, and Kentucky, riverine muskellunge did not reach 762 mm until 5 to 6 years of age (Parsons 1953; Miles 1978; Axon and Kornman 1986).

The fast growth of fish from the New River supported the hypothesis that riverine muskellunge grow faster earlier in life than lacustrine muskellunge (Harrison and Hadley 1979). This hypothesized growth difference has been attributed to differences in prey availability between environments (Harrison and Hadley 1979). In rivers, cyprinids are believed to provide an abundant and appropriately sized prey base for young muskellunge (Harrison and Hadley 1979). Conversely, prey items such as gizzard shad *Dorosoma cepedianum* (Wahl and Stein 1988, 1993) are believed to be more readily available in

lacustrine environments and permit faster growth than riverine muskellunge later in life (Harrison and Hadley 1979). Within the New River, cyprinids, such as the telescope shiner *Notropis telescopus* and white shiner *Luxilus albeolus*, are common (Jenkins and Burkhead 1993) and are preyed upon heavily by muskellunge under 600 mm (Brenden et al. in press), which may help explain the fast growth rates that were observed for the muskellunge population. At older ages, New River muskellunge switch to feeding predominantly on catostomids (Brenden et al. in press), which also are common in the New River (Jenkins and Burkhead 1993) and which may permit continued growing to lengths in excess of 1,200 mm.

Thermal conditions in the New River also may be well suited for muskellunge feeding and growth. Growth and feeding of muskellunge remain high at temperatures ranging from 20 to 30°C, and will not stop until water temperature approaches 5°C (Bevelhimer et al. 1985). Temperature of the New River remains within this 20 to 30°C range throughout the entire summer, and water temperature only drops below 5°C for two months (early December to early February) out of the year (T. O. Brenden, unpublished data). This 10-month feeding and growing season for muskellunge in the New River may in some cases be much longer than muskellunge's growing season in northern-latitude waterbodies, which may further help to explain why growth of New River muskellunge is much faster relative to other muskellunge populations.

Much of the results of this study are predicated on pelvic fin rays providing accurate age estimates for muskellunge. Whenever fish are aged, two types of errors may affect estimates, a process error associated with the structure being examined and an interpretive error resulting from the reader subjectivity in distinguishing periodic features on the aging structure (Campana 2001). To account for process error, it is recommended that an age validation study be conducted for whichever aging structure is used to ensure that frequency of growth formation increment is correct (Campana 2001). Johnson (1971) conducted a validation study for aging muskellunge with pelvic fin rays by marking, recapturing, and aging 1,734 fish with this structure. Fin ray sections were found to provide relatively accurate age estimates for muskellunge up to 10 years of age, but aging errors increased in frequency for fish older than 10 years. Specifically, pelvic fin rays were less than 50% accurate for fish older than 10 years of age, compared to greater than 70% accuracy for fish younger than 10 years of age (Johnson 1971). Because muskellunge in northern latitudes can live to be older than 30 years of age (Casselman et al.



1999), it generally has been accepted that fin rays are not suitable aging structures for muskellunge and fish typically have been aged with cleithra (Casselman 1979; Casselman and Crossman 1986). However, if southern latitude muskellunge only live to a maximum of 11 to 12 years, then the results of Johnson's (1971) validation study may mean that fin rays might provide a reasonably accurate and, most importantly, non-lethal alternative to aging muskellunge with cleithra.

Although an age validation study was not conducted in this study, 21 fish were aged using both cleithra and pelvic fin rays, and the results from this comparison indicated that age estimates from these structures were similar. This type of comparison is not considered validation as exact ages of fish remain unknown (DeVries and Frie 1996). Further, it is to be expected that aging multiple structures from the same fish would provide similar age estimates, as conditions that cause a false annulus to form on one structure might also cause a false annulus to form on other structures (Campana 2001). Nevertheless, if one assumes that the cleithrum age estimates provided by the Cleithrum Project researchers are accurate, then the high rate of agreement between cleithrum and pelvic fin ray age estimates provides some circumstantial evidence as to the accuracy of age estimates within this study. The agreement between aging structures also points to the potential utility of aging southern-latitude muskellunge populations with fin rays. A large scale validation study similar to that of Johnson (1971), but conducted specifically for southern-latitude muskellunge would help clarify the usefulness of fin rays as an aging structure for southern U.S. muskellunge fisheries.

The measure of precision (mean CV = 17.8%) between the readers that aged the pelvic fin rays indicated that interpretive error may be problematic when aging muskellunge with fin rays. Interpretive error arises from reader subjectivity in distinguishing growth increments (Campana 2001). Reader subjectivity in identifying annuli from false-annuli is one source of interpretive error that may arise when aging fish (DeVries and Frie 1996). Distinguishing between the core or nucleus of the aging structure and the first annulus is an additional subjective element that can cause interpretive errors (Campana 2001). Differentiating between the outer edge of the fin ray nucleus and the first annulus is believed to be one of the major sources of error for aging muskellunge with fin rays (J. Casselman, Ontario Ministry of Natural Resources, personal communication). Indeed, much of the imprecision between Readers 1 and 2 was due to disagreements as to whether the first observed increment was the outer edge of the nucleus or

was in fact the first annulus. In comparison, most of the disagreements with Reader 3 resulted from Reader 3 counting false-annuli (as identified by the other readers) as annuli. This discrepancy between readers may have been linked to prior aging experience. Both Readers 1 and 2 had previously aged other fish species using otoliths and/or scales, so both readers had at least some experience in distinguishing annuli from false-annuli. Conversely, Reader 3 had no previous experience in aging fish. Both Readers 1 and 2 agreed that distinguishing the nucleus of the fin rays was more difficult than identifying the nucleus of aging structures such as fish scales. If muskellunge are to be aged using pelvic fin rays, it may be helpful for readers to decide in advance what criteria will be used to distinguish between the nucleus and first annulus and between annuli and false-annuli. Reaching such decisions in advance may help to increase the precision of age estimates, although it may not necessarily affect aging accuracy.

Because of muskellunge's popularity as a sportfish and its past history of overexploitation (Crossman 1986), exploitation rates have been estimated for a number of muskellunge fisheries. Compared to other muskellunge fisheries, the 14.2% exploitation rate observed in this study was low. Although exploitation rates ranging from 5.4 to 15% have been reported for muskellunge fisheries in New York (Bimber and Nicholson 1981) and Wisconsin (Hanson 1986), exploitation rates in excess of 25% have been reported for fisheries in West Virginia, Kentucky, and Wisconsin (Miles 1978; Brewer 1980; Axon 1981; Brege 1986; Hanson 1986; Hoff and Serns 1986; Cornelius and Margenau 1999). Hanson (1986) believed that exploitation rates greater than 25% were too high to manage a quality muskellunge fishery. Based on these findings, it seems unlikely that overharvest of New River muskellunge fishery was problematic. Therefore, suggested regulation changes are intended primarily for enhancement of muskellunge size structure, and not for alleviating overharvest.

The difference in muskellunge size selectivity between angling and electrofishing that was observed in this study has been previously observed with *Esox* spp. (Mann 1996). The sizes of lures used by muskellunge anglers typically are geared more towards larger fish, and so anglers may handle few fish smaller than 800 mm. In turn, electrofishing may be less effective at sampling larger muskellunge due to the ability of larger muskellunge to avoid electrical fields and because the habitats that larger fish occupy may not be conducive to electrofishing (Mann 1996). This difference in sampling

effectiveness implies that the most complete information regarding muskellunge size structure might be derived from a sampling plan that combines angling with electrofishing. Such a combination of sampling techniques particularly might be beneficial in riverine environments, where river discharge limits the use of other sampling techniques (e.g., trapnetting). If angling is selected as a technique for sampling muskellunge, fishery biologists might be encouraged to enlist the assistance of experience muskellunge anglers (Oehmcke et al. 1986). One experienced angler in this study handled more muskellunge than all the fish handled by electrofishing personnel, which illustrates the potential benefit of enlisting the assistance of even a few anglers especially when resources available for sampling muskellunge (e.g., time, money, personnel) are otherwise lacking. Anglers could be asked to maintain diaries that provided information such as catch rates, length/weight of angled fish, sex, and number of other anglers seen fishing for muskellunge in the immediate area (Younk and Cook 1992). Additionally, biologists could ask anglers to harvest muskellunge of particular lengths so that more in-depth information concerning such things as fish age could be obtained. Many muskellunge anglers, even those that routinely release caught fish, might be willing to harvest some fish if it was explained how the information might aid management of the fishery.

As previously mentioned, stocking of muskellunge in the middle section (Fries Dam to Claytor Lake) of the New River was discontinued in 1994. Of the 17 fish captured by electrofishing in this section of the river, 14 fish were too young to have been hatchery-released fish from these earlier stocking efforts. These 14 fish either had to have immigrated from other sections of the river or else have been offspring from natural reproduction. Upstream immigration from the lower New River is not possible as Claytor Dam is not equipped for fish passage. Downstream immigration would have required passage either over the spillway or through the turbines of 3 dams: Buck, Byllesby, and Fries. While passage of these dams cannot be considered impossible, it seems unlikely that it would result in the fish densities collected at Austinville and Fosters Falls. Natural reproduction seems a more plausible explanation. Reproduction of muskellunge in several Virginia rivers, including the New River, has long been suspected, but has been difficult to detect because of annual stocking of hatchery fish (Jenkins and Burkhead 1993). Muskellunge spawning occurs in 1- to 2-m-deep water and in areas consisting of organic detritus, sand, or silt (Dombeck et al. 1984; Strand 1986; LaPan et al. 1996; Farrel et al. 1996;

Farrel and Werner 1999). Spawning usually peaks at water temperatures of 10 to 13°C (Minor and Crossman 1978; Farrel et al. 1996). With such fairly general spawning requirements, it seems that much of the New River, including areas of the lower section, would be suitable for muskellunge spawning to occur. Although actual spawning of muskellunge was never observed, muskellunge in near-ready spawning condition (milt and eggs released when slight pressure was applied to the abdomen) were collected in the months of April and May, which supports the occurrence of at least a limited amount of natural reproduction.

### *Angler Attitudes*

Angler attitudes regarding the New River muskellunge fishery provided an interesting contrast to surveys from northern-latitude muskellunge fisheries. A lower percentage of anglers targeted muskellunge and anglers fished less often for muskellunge in the New River than what has been found in places such as Kentucky and Wisconsin. Between 11.8 and 67.3% of anglers fishing on 8 northern Wisconsin lakes were found to be specifically targeting muskellunge (Hanson 1986), which is substantially greater than the 2.2% of anglers that were targeting muskellunge on the New River. Percent of anglers targeting muskellunge was also higher on Cave Run Lake, Kentucky. From 1976 to 1979, 7.5 to 14.0% of all angling trips targeted muskellunge (Axon 1981). New River anglers fished for muskellunge an average of 4 days/year, which is more than 2/3 less than the what Wisconsin anglers fished for muskellunge ( $\bar{x}$  = 13 days/year; Margenau and Petchenik 2004).

Lengths of “trophy” muskellunge identified by New River anglers were smaller than the lengths identified by Wisconsin anglers. Eighty-nine percent of general anglers surveyed in Wisconsin believed that a “trophy” muskellunge needed to be greater than 1,016 mm, and 44% of anglers believed that fish needed to be greater than 1,270 mm (Margenau and Petchenik 2004). In comparison, 74% of New River anglers believed that “trophy” muskellunge needed to be greater than 1,016 mm, and 11% of anglers believed that muskellunge needed to be greater than 1,270 mm. Lengths of “trophy” muskellunge identified by muskellunge anglers also differed between Wisconsin and the New River. Ninety-eight percent of anglers in Wisconsin that were members of a muskellunge fishing club believed that

muskellunge needed to be greater than 1,016 mm to be a “trophy”, and 62% believed that a fish needed to be at least 1,270 mm (Margenau and Petchenik 2004). In comparison, 92% of anglers in this study that fished the most often for muskellunge believed that a “trophy” muskellunge needed to be at least 1,016 mm, and 13% believed that a “trophy” muskellunge needed to be at least 1,270 mm. Although there was a difference in how the groups were defined, the differences between the studies nevertheless are quite striking.

Although New River anglers that fished less often for muskellunge identified smaller minimum harvestable lengths and were more likely to suggest that higher creel or lower size limits should be enacted than anglers that fished more often for muskellunge, there is little evidence to indicate that harvest by non-muskellunge anglers is negatively influencing the New River muskellunge stock. While incidental catch of muskellunge on the New River is not a rare occurrence, non-muskellunge anglers are just as likely as muskellunge anglers to release fish. Experienced muskellunge anglers certainly handle far more muskellunge per-capita basis than other anglers in the New River, but experienced anglers also will harvest a few of these fish each year. Based on these results, it would seem that if the New River muskellunge fishery was overharvested, it would result from the collective behavior of all anglers.

Although voluntary release of muskellunge is routinely practiced in some areas (Fayram 2003; Margenau and Petchenik 2004), New River anglers appear to have a greater inclination to harvest muskellunge. Ninety percent of general anglers and 98% of muskellunge anglers generally release muskellunge caught by angling in Wisconsin (Margenau and Petchnik 2004). The overall release rate for muskellunge in some areas of Wisconsin is as high as 99.9% (Fayram 2003). In comparison, only 35% of New River anglers indicated that they would release all muskellunge caught, and the estimated release rate for muskellunge was 92%. While the difference in release rates between the New River and Wisconsin may not appear substantial, the release rate calculated for New River muskellunge may be a conservative estimate. The data used to calculate the release rate was based on angler recollection from a three-year time span. While anglers may reasonably be expected to accurately recollect the number of muskellunge harvested in this time span given its rarity of occurrence, such long recall periods may cause anglers to overestimate the actual number of fish that were caught (Carline 1972; Fisher et al. 1991). An alternative source of data for estimating release rates for Virginia muskellunge is Virginia Angler's

Recognition Program (VARP), which is a program administered by VDGIF that gives formal recognition to anglers that catch “trophy” size. Anglers that register a “trophy” fish receive certificates from the program and can receive distinctions such as Master Angler or Expert Angler. When anglers register a VARP fish, they must indicate whether the fish was released or harvested. Between 1997 and 2003, 190 “trophy” ( $\geq 1,016$  mm or  $\geq 6.8$  kg) muskellunge were registered with VARP. Of these 190 fish, 46% ( $n = 87$ ) were released (VDGIF, unpublished data). The release rate for every Virginia muskellunge registered with VARP ( $n = 408$ ) was 42%. While the harvest/release data from VARP may not be representative of all anglers, it nevertheless indicates that New River anglers, as well as many anglers in Virginia, may have a much greater tendency to harvest muskellunge than anglers in northern latitude regions such as Wisconsin.

One factor that might lead to high harvest rates for New River muskellunge, as well as southern southern-latitude muskellunge fisheries, is the lack of specialized muskellunge angling clubs (e.g., Muskies, Inc.) in southern regions. Such clubs often promote voluntary release angling both within the club and to the general angling public (Gasbarino 1986; Oehmcke et al. 1986). This peer pressure to release muskellunge may be a significant factor shaping angler behavior in locales where the clubs operate. In areas without active clubs, there may be less of an incentive for anglers to release fish.

### *Alternative Harvest Regulations*

Under all alternative length limits evaluated, abundance of memorable-length ( $\geq 1,070$  mm) muskellunge in the population increased. At estimated mortality rates, abundance was predicted to increase by 25, 50, and 100% at length limits of 914, 1,016, and 1,143 mm. Although overall number of harvested fish would decline with these length limits, yield per recruit in some cases would increase (914-mm minimum length limit) or only slightly decrease (1,016-mm minimum length limit). A 1,143-mm minimum length limit would result in the largest decrease in yield. While it may be true that for a muskellunge fishery yield is less of a concern than the abundance of “trophy” fish (Simonson and Hewett 1999), yield nevertheless provides a useful measure for integrating growth and mortality rates and can be used to identify at what point fish mortality exceeds fish growth. With length limits much greater than

1,000 mm, New River muskellunge would be dying far quicker than fish would be growing, and very high length limits would result in a “female only” fishery due to the inability of many muskellunge to reach lengths in excess of 1,100 mm. In northern-latitudes, “female only” muskellunge fisheries are not of a concern to biologists (Simonson and Hewett 1999) and length limits in excess of 1,270 mm are being implemented in an effort to produce the next world-record muskellunge. However in an introduced, southern latitude fishery where anglers perhaps view muskellunge fishing as a novelty, yield of the fishery may be of a greater concern to biologists.

While it might seem unequivocal that higher length limits will lead to increases in the abundance of larger fish, this is not always true. Cornelius and Margenau (1999) found that abundance of large muskellunge in Bone Lake, Wisconsin initially remained stable after the lake's size limit was increased from 762 to 864 mm. Similarly, Margenau and AveLallemant (2003) did not find abundance of large muskellunge to have increased with implementation of a 1,106-mm minimum length on seven northern Wisconsin lakes. Factors that can prevent changes in muskellunge size structure from occurring with regulation changes include increased fishing pressure and harvest rates corresponding with regulation changes, angler self-imposed limits that were more stringent than the original harvest regulation, and variable fish recruitment (Cornelius and Margenau 1999; Margenau and AveLallemant 2003). Increased fishing pressure and harvest rates with changes to the length limit seems a very real possibility for the New River muskellunge fishery. The New River is already considered one of Virginia's premier muskellunge fisheries and an increase in the muskellunge length limit may bring more anglers to the system. As for variable recruitment, post-stocking survival of muskellunge was found to play a major role in the magnitude of changes that could be expected from implementation of more restrictive harvest regulations. Post-stocking survival can be influenced by a myriad of factors such as size at stocking, predator communities, and environmental stressors (Wahl 1999). Accordingly, post-stocking survival can be highly variable among years even within individual lakes. Since muskellunge are stocked in the New River as fingerlings ( $\approx 100$  mm), survival can reasonably be expected to be less than 5 to 10%, in some years survival may be even less than 1% (Hanson et al. 1986b; Wahl 1999; Farrell and Werner 1999). Natural reproduction of muskellunge also may affect the exact magnitude of change in abundance of large fish with alternative harvest regulations. Although this study provides anecdotal evidence for the

occurrence of natural reproduction, a more detailed study will be necessary to determine to what extent natural reproduction of muskellunge contributes to the fishery.

This study did not address other types of harvest regulations that could be enacted on the New River, such as lower creel limits or closed seasons, because it was believed that such changes either would have little effect or else would have little chance of being implemented. Even though a higher percentage of anglers favored changing the creel limit over the length limit, the proportion of anglers that actually creel 2 fish/day is believed to be low, so reducing the creel limit to 1 fish/day would have little effect on muskellunge harvest rates. Seasonal limits were not considered as a closed season would probably need to be enacted during the summer months to be of much benefit to the fishery, since it is from mid-May to late-August that most muskellunge harvest occurred on the New River. Closing the muskellunge fishery during the summer months was not seen as a viable management option.

### **MANAGEMENT IMPLICATIONS/CONCLUSIONS**

As previously stated, liberal harvest regulations for muskellunge fisheries might be needed if one of several conditions – intraspecific competition for food resources resulting in slow growth, physiological inability to reach large sizes, low angler use or high voluntary release rates – was met. Neither slow growth nor physiological inability to reach large sizes appeared to be problematic for the New River muskellunge fishery. Although overall angler use of the New River muskellunge fishery was low (compared to angler participation rates in other areas), voluntary release of muskellunge appeared low as well. Since none of the conditions that might justify liberal harvest regulations were met, implementation of more restrictive harvest regulations may indeed improve production of “trophy” muskellunge in the New River.

Given the fast growth of muskellunge to lengths in excess of 1,000 mm and the fact that most New River anglers identify “trophy” muskellunge to be fish greater than 1,050 mm in length, an increase in the minimum length limit to within a range of 965 to 1,067 mm (38 to 42 inches) may be of greatest value to the fishery. Although abundance of large muskellunge would be maximized by increasing the length limit to 1,143 mm or higher, such a drastic change in the size limit seems unnecessary given angler opinions concerning “trophy” lengths of muskellunge. The fact that a small minority of even the



most dedicated muskellunge anglers rarely identified “trophy” muskellunge to be greater than 1,270 mm means that few anglers may be supportive of length limits that exceed 1,100 mm. Even winning support for a 965 to 1,067 mm size limit might prove difficult given the low percentage of anglers that believe the minimum length limit needs to be changed. Support for a length limit change possibly could be increased by publicizing the fast growth rates of muskellunge and explaining how higher limits will result in a greater abundance of “trophy” fish.

Negative consequences that could result from a 965- to 1,067-mm minimum length limit include reduced growth rates of muskellunge as a result of higher intraspecific or interspecific competition for food resources and increased predatory impacts on other New River fish species. To assure that muskellunge growth is not impacted, growth rates of fish, particularly during early life stages, should be monitored subsequent to harvest regulation changes. If it becomes evident that muskellunge growth rates have been reduced, the harvest regulation may need to be reverted to the original limits. In terms of increased consumption of other New River fish species, I estimate that, based upon previous research (Brenden et al. in press), muskellunge consumption per initial abundance of 100 age-1 muskellunge would increase from 1.77 to 2.35  $\text{kg}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$  with a minimum length limit of 1,067 mm. Species such as northern hogsuckers *Hypentelium nigricans* and smallmouth bass would be the most heavily impacted by the higher muskellunge densities, given that these species are the predominant items consumed by adult muskellunge. Specifically, consumption of northern hogsuckers and other catostomids would increase from 0.63 to 0.95  $\text{kg}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$  (63% increase), while consumption of smallmouth bass would increase from 0.18 to 0.26  $\text{kg}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$  (44% increase) per initial abundance of 100 age-1 muskellunge. Continued monitoring of muskellunge growth rates and concurrent assessment of northern hogsucker and smallmouth bass densities will be required to ensure that this elevated consumption will not impact stocks of either species.

This research was initiated to determine whether a southern-latitude muskellunge fishery might benefit from more restrictive harvest regulations. While the results from this study do indicate that the New River would benefit from a higher length limit, it remains to be seen whether these results are typical among other southern latitude muskellunge fisheries. Growth of muskellunge in other populations may not be nearly as fast, nor may fish be able to attain lengths as large as those from the New River

population. The one factor that possibly might remain similar among fisheries is a higher likelihood for anglers to harvest muskellunge, since many southern U.S. regions lack specialized muskellunge angling clubs. Before length limits are changed in other fisheries, biologists should assure that conditions within the fishery warrant the change. If biologists lack suitable data or resources for assessing these conditions, collaboration with experienced muskellunge anglers may provide a convenient means to collect required information.

Table 2.1. Total numbers of muskellunge captured and seen while electrofishing at the twelve sites sampled on the middle and lower sections of the New River from 2000 to 2003. The median number of muskellunge captured per electrofishing hour and the median number of muskellunge seen per electrofishing hour for the 12 sites also are displayed.

Section	Location	Median	Total	Median	Total
		CPUE	Captured	SPUE	Seen
Middle	Austinville	0.00	8	0.82	13
	Foster's Falls	0.00	6	1.55	13
	Ivanhoe	0.00	1	0.00	1
	Rte. 100	0.55	2	1.64	4
Lower	Bluff City	0.00	6	1.94	10
	Claytor Dam	1.29	23	3.15	43
	Dedmon Center	0.00	1	1.64	3
	Eggleston	0.00	1	0.00	1
	Pembroke	1.83	15	4.09	28
	Pepper's Ferry	1.77	5	2.80	6
	Rich Creek	1.42	3	2.83	4
	Whitethorne	1.80	165	3.07	317

Table 2.2. Observed TL changes of marked and recaptured muskellunge by tag type and sex versus length changes that were predicted using sex-specific von Bertalanffy growth equations. Growth equations were calculated using age estimates from pelvic fin ray sections.

Tag Type	Sex	Age at Tagging (yrs)	Length at Tagging (mm)	Elapsed Time (days)	Observed Length Change (mm)	Predicted Length Change (mm)	Absolute Error (mm)
Floy	female	10	1219	327	37	20	17
Floy	female	4	1010	101	44	24	20
Floy	female	4	958	356	48	91	43
Floy	female	6	995	354	55	81	26
Floy	female	4	1054	376	36	69	33
PIT	female	1	352	279	303	204	99
PIT	female	1	364	426	299	289	10
PIT	male	1	376	342	293	238	55
PIT	male	2	650	679	220	246	26
PIT	male	3	825	51	5	16	11
PIT	male	2	669	405	158	162	4
Radio	male	5	985	365	0	40	40
Radio	male	2	682	785	258	251	7
Mean Absolute Error							30

Table 2.3. Candidate models for estimating instantaneous fishing ( $F$ ) and natural ( $M$ ) mortality rates for the New River muskellunge telemetry data. The models differed as to whether the mortality rates remained constant or were allowed to vary quarterly or monthly. Candidate models are sorted according to the Akaike Information Criterion  $AIC_c$  for each model. Also shown is the  $\Delta AIC_c$ , which is the difference in each models  $AIC_c$  from the minimum model  $AIC_c$ , the relative likelihood of each model, the Akaike weight, which is the relative likelihood of each model, and the mortality estimates associated with each model. The model-average estimates of fishing and natural mortality are found by the summation of each model's mortality estimates multiplied by the Akaike weights of that model. The scaled estimates of mortality are the model-average estimates scaled to a yearly basis, as opposed to a 19-month time frame.

<u>Temporal Variation of</u>		Number of					<u>Mortality</u>	
<u>Mortality Rates</u>			Parms.	$AIC_c$	$\Delta AIC_c$	Akaike	<u>Estimates</u>	
$F$	$M$							Weights
Constant	Constant	3	54.90	0.00	0.588	0.19	0.08	
Quarter	Constant	7	57.03	2.12	0.203	0.42	0.08	
Constant	Quarterly	7	57.52	2.62	0.159	0.00	0.07	
Quarter	Quarterly	11	59.83	4.93	0.050	0.42	0.07	
Monthly	Constant	20	73.36	18.45	0.000	0.41	0.08	
Monthly	Quarterly	24	76.68	21.78	0.000	0.41	0.07	
Constant	Monthly	20	79.68	24.78	0.000	0.00	0.07	
Quarter	Monthly	24	82.56	27.66	0.000	0.42	0.07	
Monthly	Monthly	37	101.20	46.29	0.000	0.41	0.07	
Model-Average Mortality Estimates (12 month time frame)						0.15	0.05	

Table 2.4. Response of angler subgroups to questions asked during a creel survey conducted on the New River in 2002 regarding the muskellunge fishery. Anglers that stated they had no opinions regarding the muskellunge fishery were excluded from the analysis.

	Trophy Length (mm)	Minimum Harvestable Length (mm)	Anglers That Caught a Muskellunge (%)	Anglers That Harvested a Muskellunge (%) <sup>a</sup>	Number of Fish Harvested/Number of Fish Caught (%)	Average Length Harvested
Non- Muskellunge	1,036	858	15.7	19.5	3.1	946 mm
Occasional	1,051	936	52.5	21.8	6.0	1,023 mm
Moderately- Dedicated	1,071	922	62.2	47.8	22.7	916 mm
Dedicated	1,074	1,109	92.0	34.8	1.5	995 mm

<sup>a</sup> Percentages are calculated out of those anglers caught a muskellunge.

Table 2.5. Response of angler subgroups as to whether harvest regulations for New River muskellunge should be changed. Anglers with no opinions regarding regulation changes were combined with anglers that did not believe regulations needed to be changed. The suggested size limited proposed by the angler subgroups is a weighted average of the mean size limit suggested by anglers that wanted a higher limit and the mean size limit suggested by anglers that wanted a lower limit.

	Support Regulation Change (%)	Change Creel Limit (%) <sup>a</sup>	Lower Creel Limit (%) <sup>b</sup>	Change Size Limit (%) <sup>a</sup>	Higher Size Limit (%) <sup>c</sup>	Suggested Size Limit (mm)
Non- Muskellunge	10	83	31	33	32	527
Occasional	28	76	77	76	92	973
Moderately- Dedicated	27	80	75	50	40	550
Dedicated	56	79	82	71	80	897

<sup>a</sup> Percentages are calculated out of those anglers that think regulations should be changed.

<sup>b</sup> Percentages are calculated out of those anglers that think the creel limit should be changed.

<sup>c</sup> Percentages are calculated out of those anglers that think the size limit should be changed.

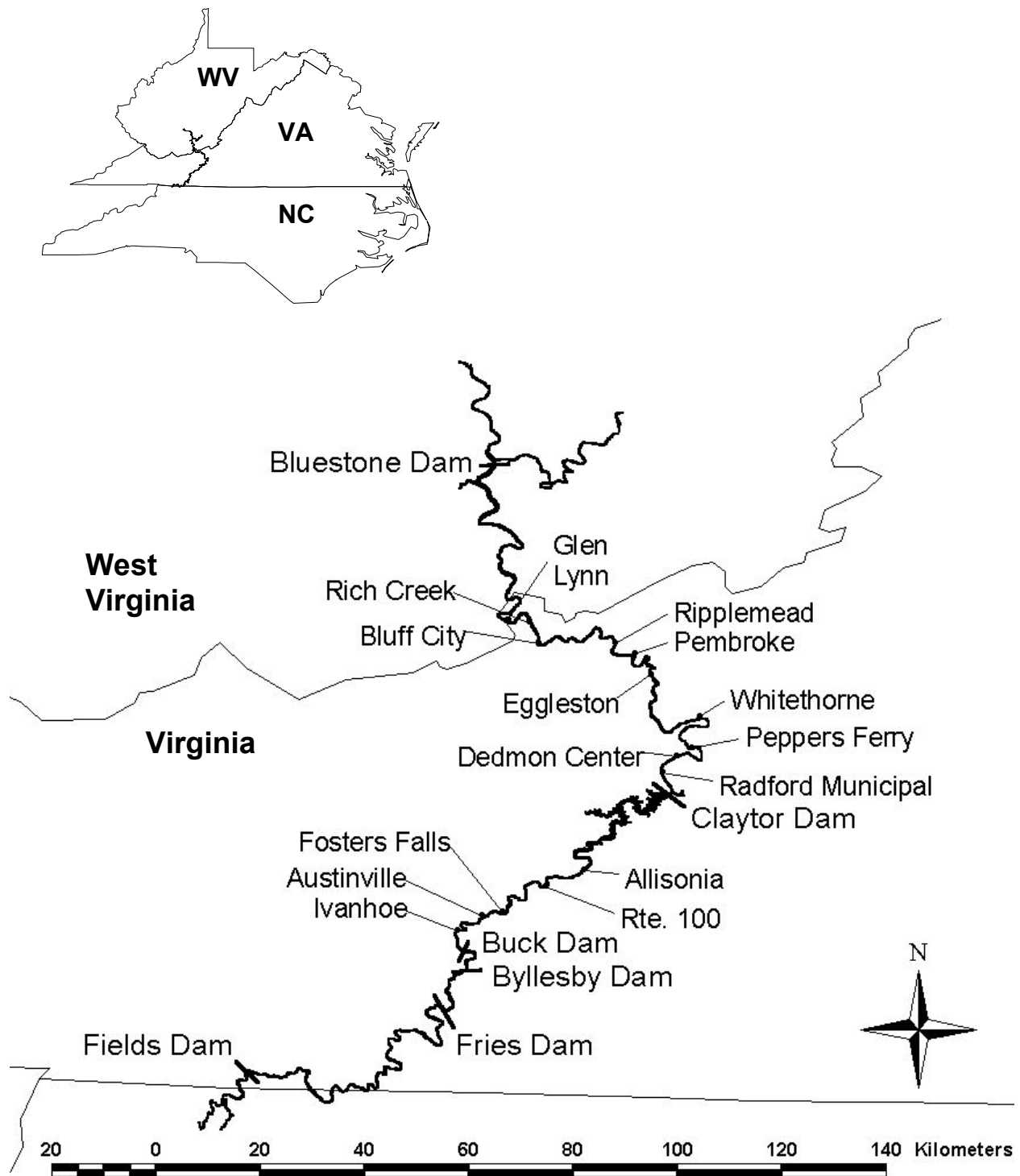


Figure 2.1. Map of the New River in southwestern Virginia and specific locations of sites (e.g., dams, sampling areas) mentioned in the text.



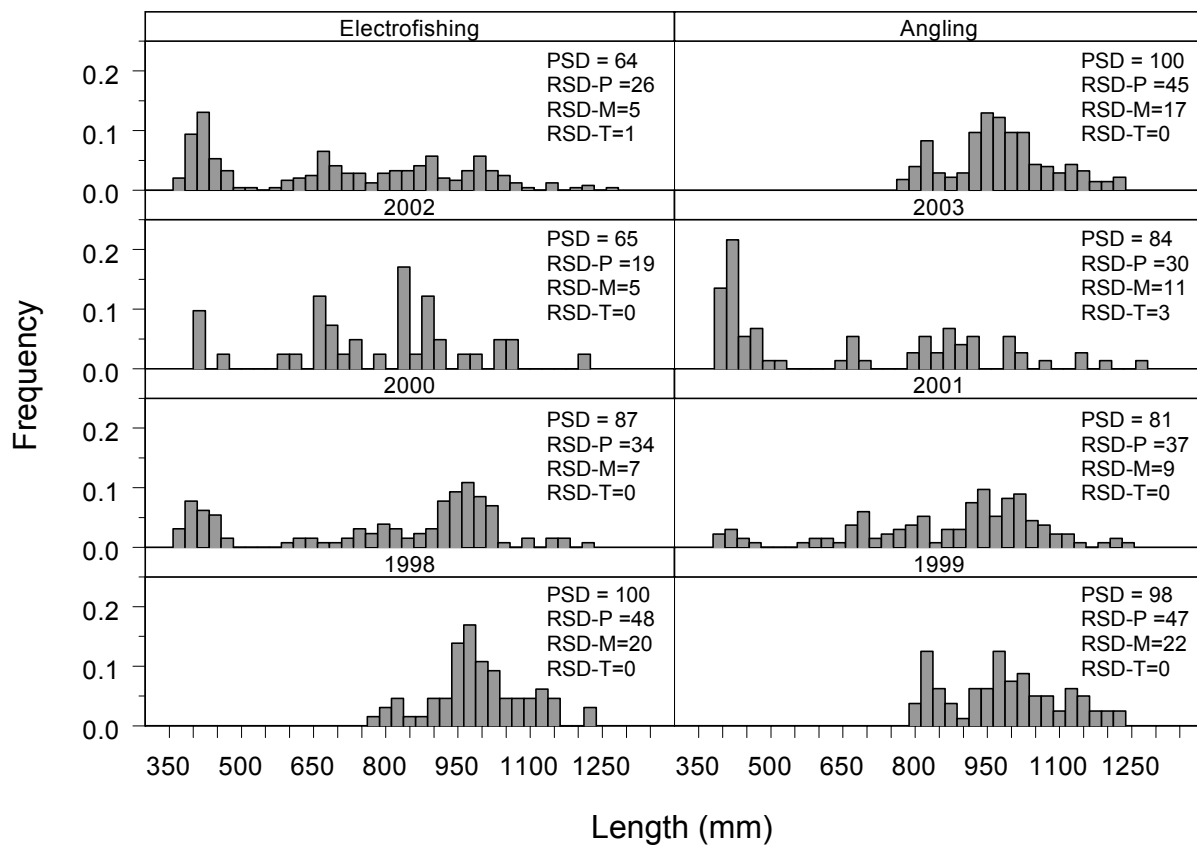


Figure 2.2. Length-frequency histograms and size structure indices (PSD = proportional stock density; proportion of fish  $\geq 510$  mm that also are  $\geq 760$  mm, RSD = relative stock density; proportion of fish  $\geq 510$  mm that also are  $\geq 970$  mm (RSD-P),  $\geq 1,070$  mm (RSD-M), and  $\geq 1,270$  mm (RSD-T)) for muskellunge captured among different years and method of capture.

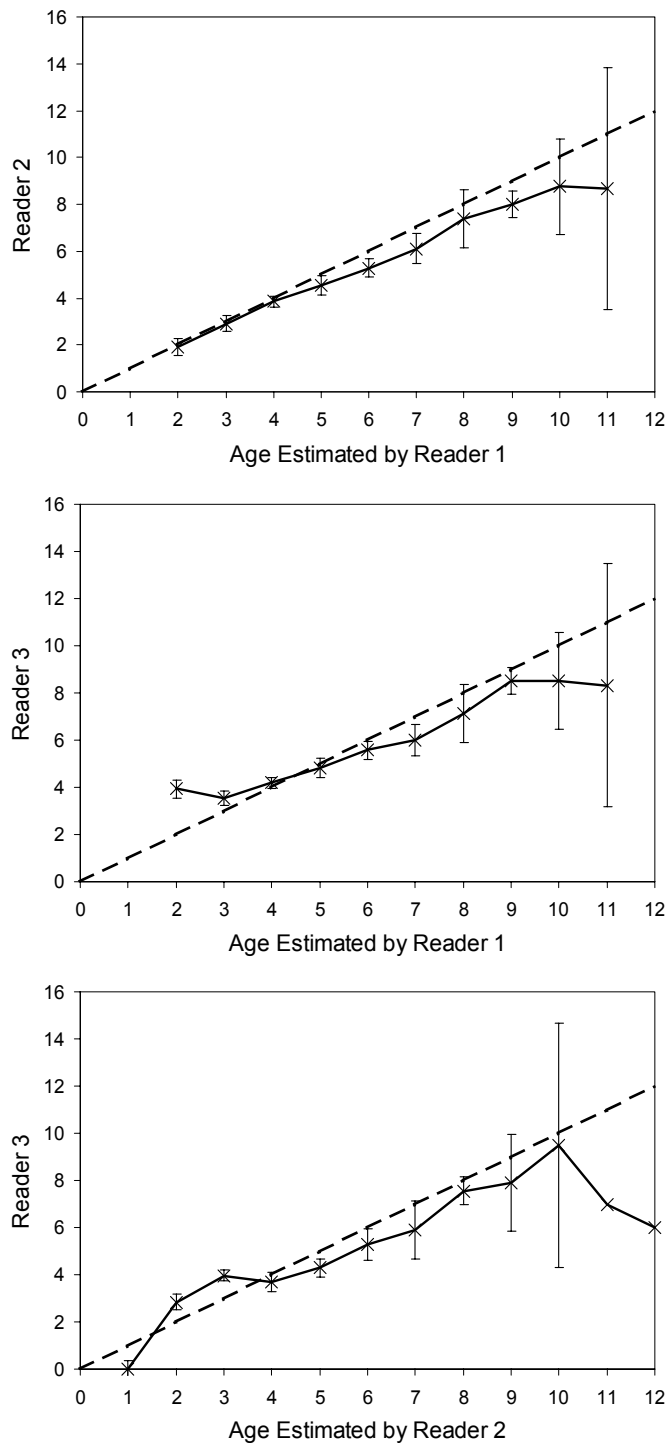


Figure 2.3. Pairwise age-bias plots calculated for the three readers. Each plot indicates the mean age and associated 95% confidence interval for the ages assigned by one reader relative to the ages assigned by another reader. The 1:1 equivalence (dashed line) is also indicated on each graph.

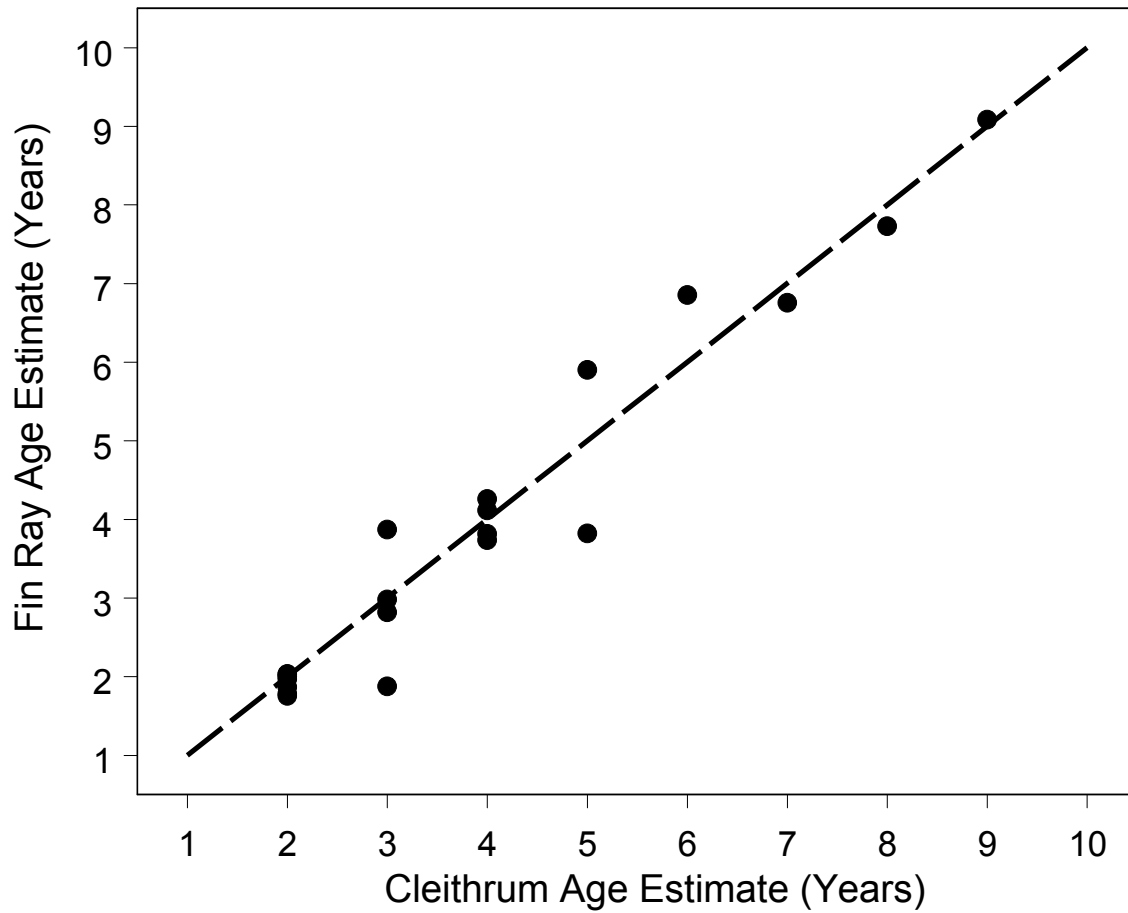


Figure 2.4. Scatterplot comparison of cleithrum age estimates to sectioned pelvic fin ray estimates for 21 muskellunge ranging in length from 593 to 1,230 mm. A slight Y-direction jitter has been applied to the data points to prevent overlap. The dashed line represents a perfect agreement between the estimates.

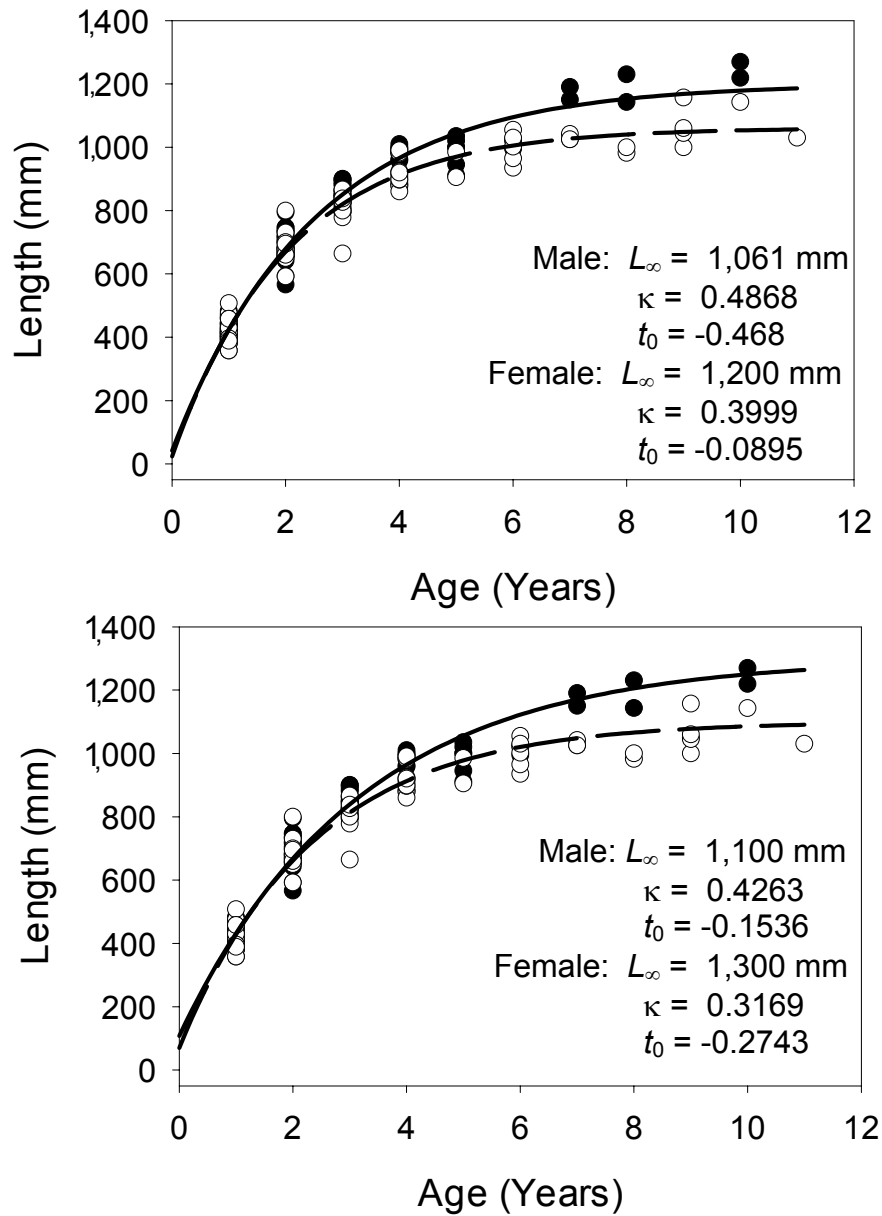


Figure 2.5. Predicted versus actual length-at-age data for two von Bertalanffy growth models fit to the age data. The top panel shows predicted versus actual length-at-age data for a von Bertalanffy growth model where all six parameters were estimated (solid dots and line = females; open dots and dashed line = males). The lower panel shows predicted versus actual length-at-age data for the von Bertalanffy growth model where  $L_{\infty}$  for the sexes was selected based on available data. Coefficients for each growth equation are shown on the graphs.

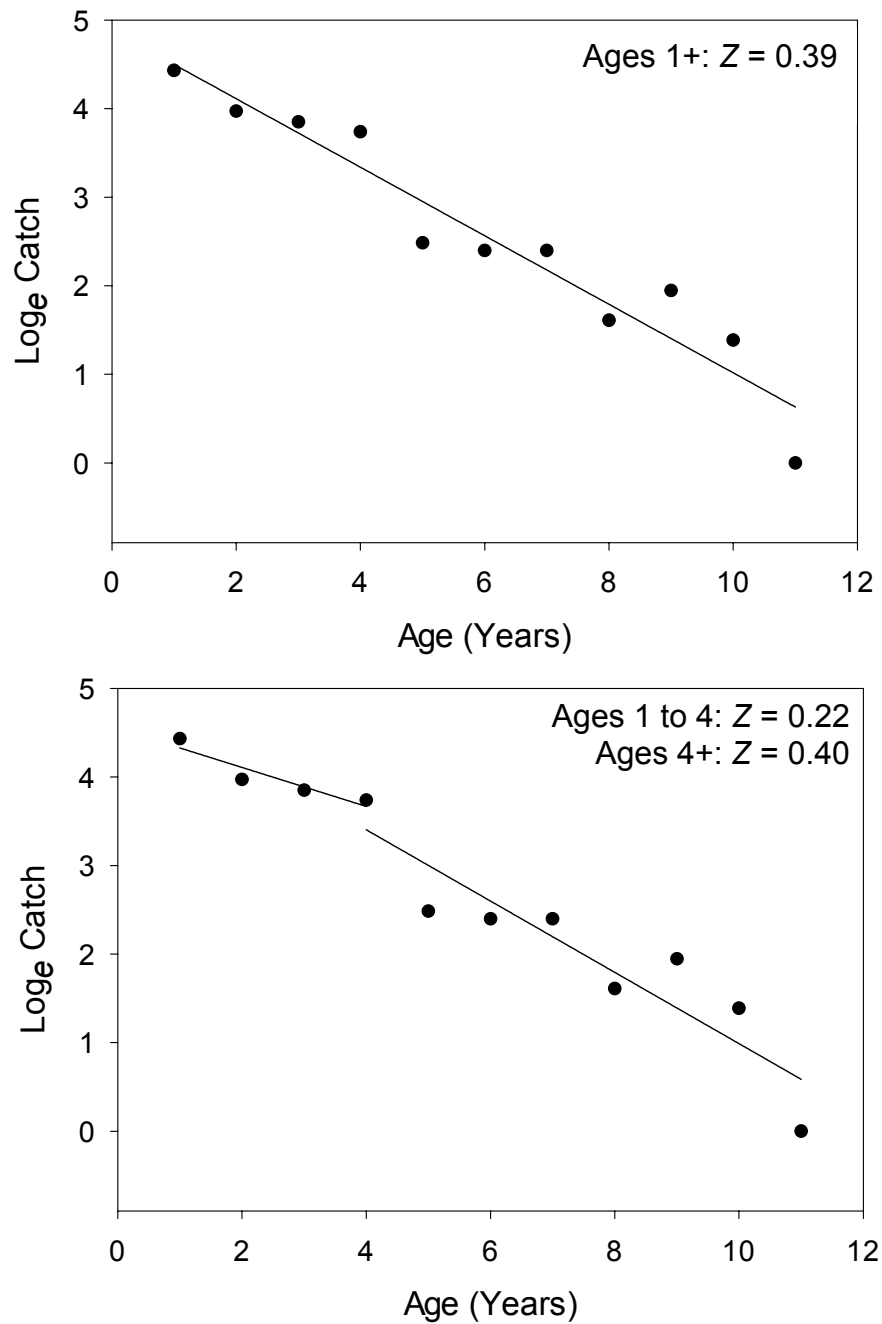


Figure 2.6. Catch curves fit to the  $\log_e$  catch at age data. Based on the plots, it was believed that muskellunge fully recruited to the sampling gear at age 1. The top panel shows the catch curve and resulting estimate of  $Z$  fitted to all of the age data. The lower panel shows catch curves and the associated estimates of  $Z$  fitted individually to fish ages 1 to 4 and to fish ages 4 and higher.

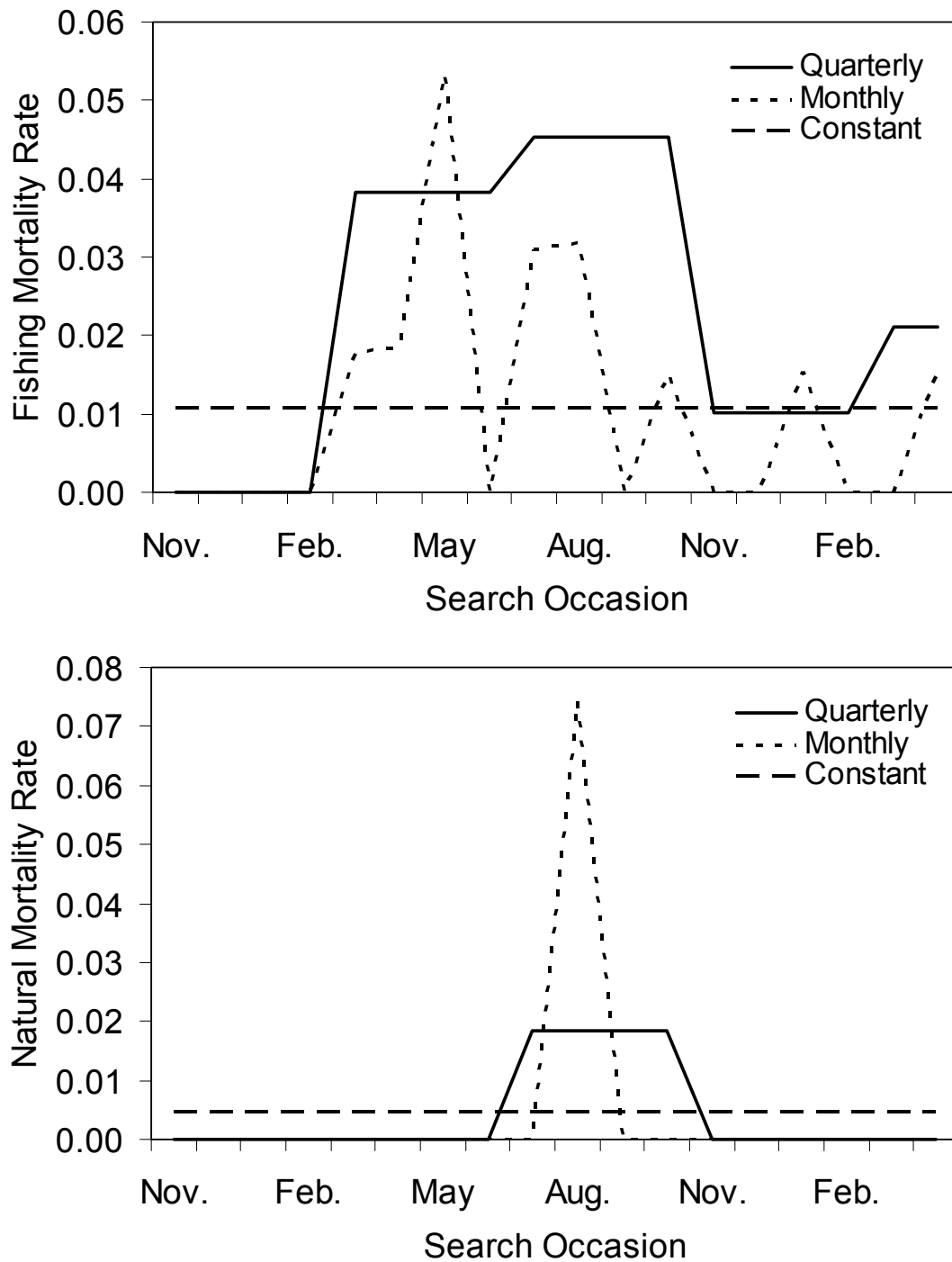


Figure 2.7. Estimated monthly instantaneous fishing mortality rates (top panel) and instantaneous natural mortality (lower panel) for the New River. Each graph shows the estimated mortalities for models where the rates were allowed to vary monthly (dotted lines), quarterly (solid line), or to be constant (dashed line).

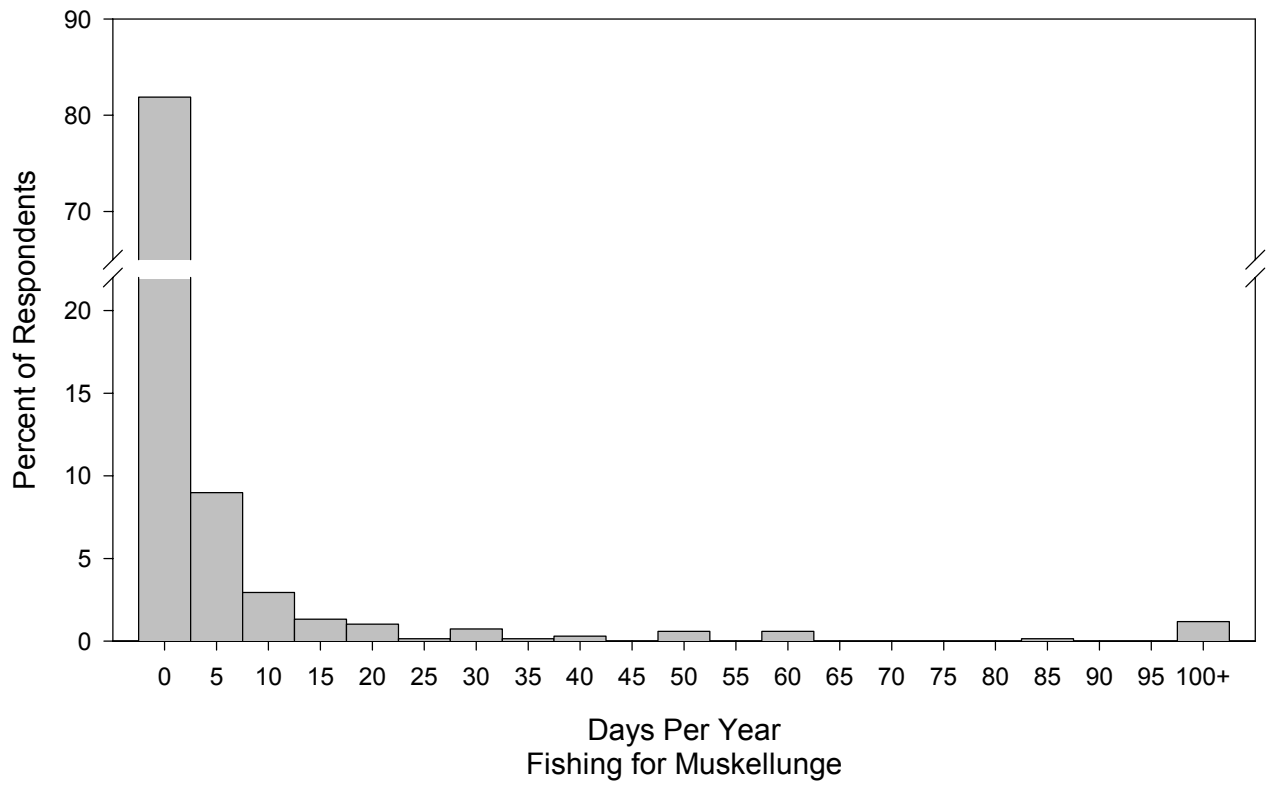


Figure 2.8. Number of days per year that New River anglers indicated they fished for muskellunge.

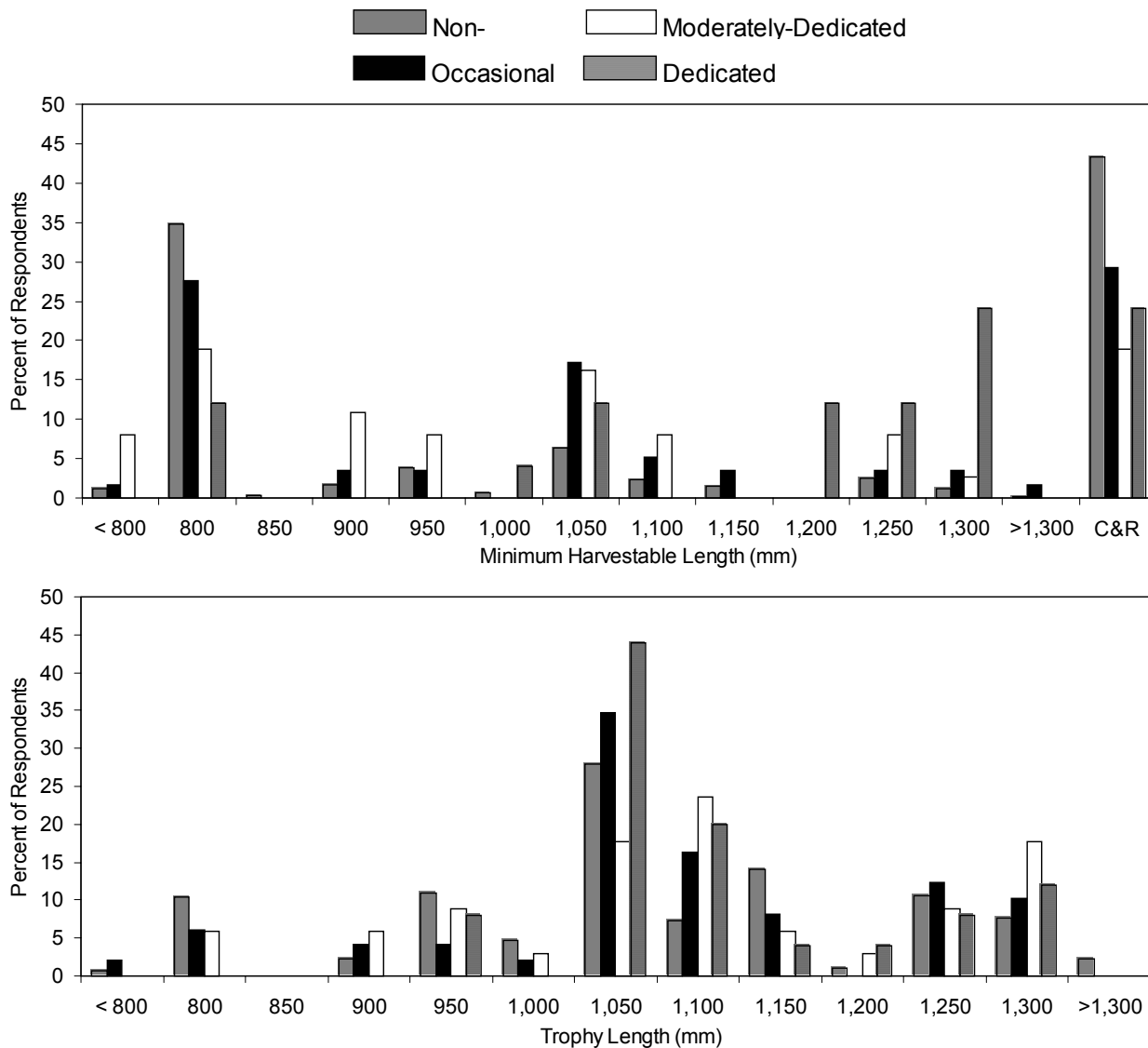


Figure 2.9. Length of muskellunge considered a “trophy” (bottom) and minimum harvestable lengths (top) identified by non-, occasional, moderately-dedicated, and dedicated muskellunge anglers. The percent of anglers that specified all muskellunge would be released are under the category marked C&R (catch and release).



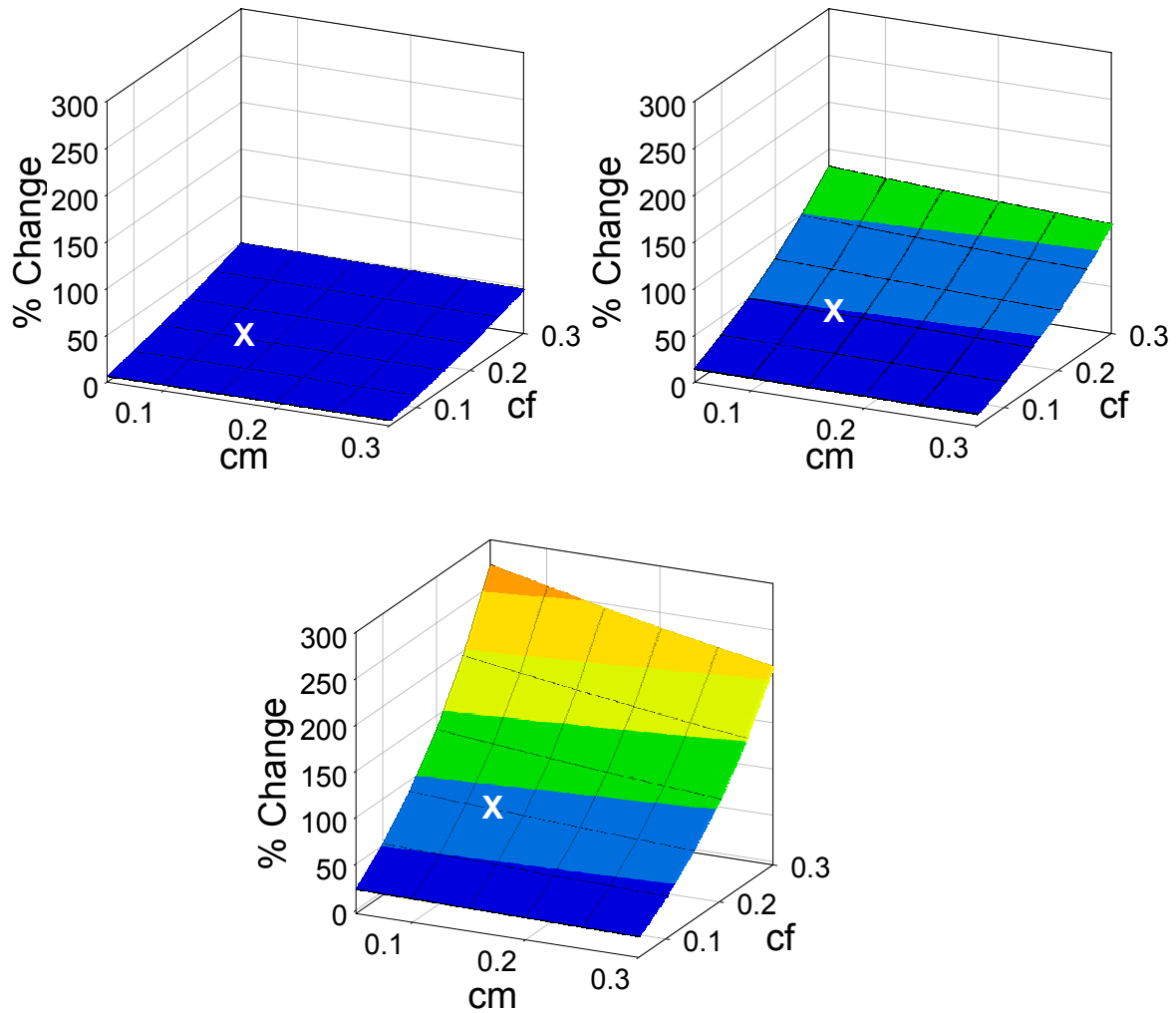


Figure 2.10. Percent expected changes in the number of memorable length ( $\geq 1,070$  mm) muskellunge in the New River muskellunge fishery with the implementation of a 914-mm (top-left), 1,016-mm (top-right), and 1,143-mm (bottom) minimum length limit. Current annual mortality rate estimates (cm = conditional natural mortality; cf = conditional fishing mortality) are denoted on the graphs with an "X".

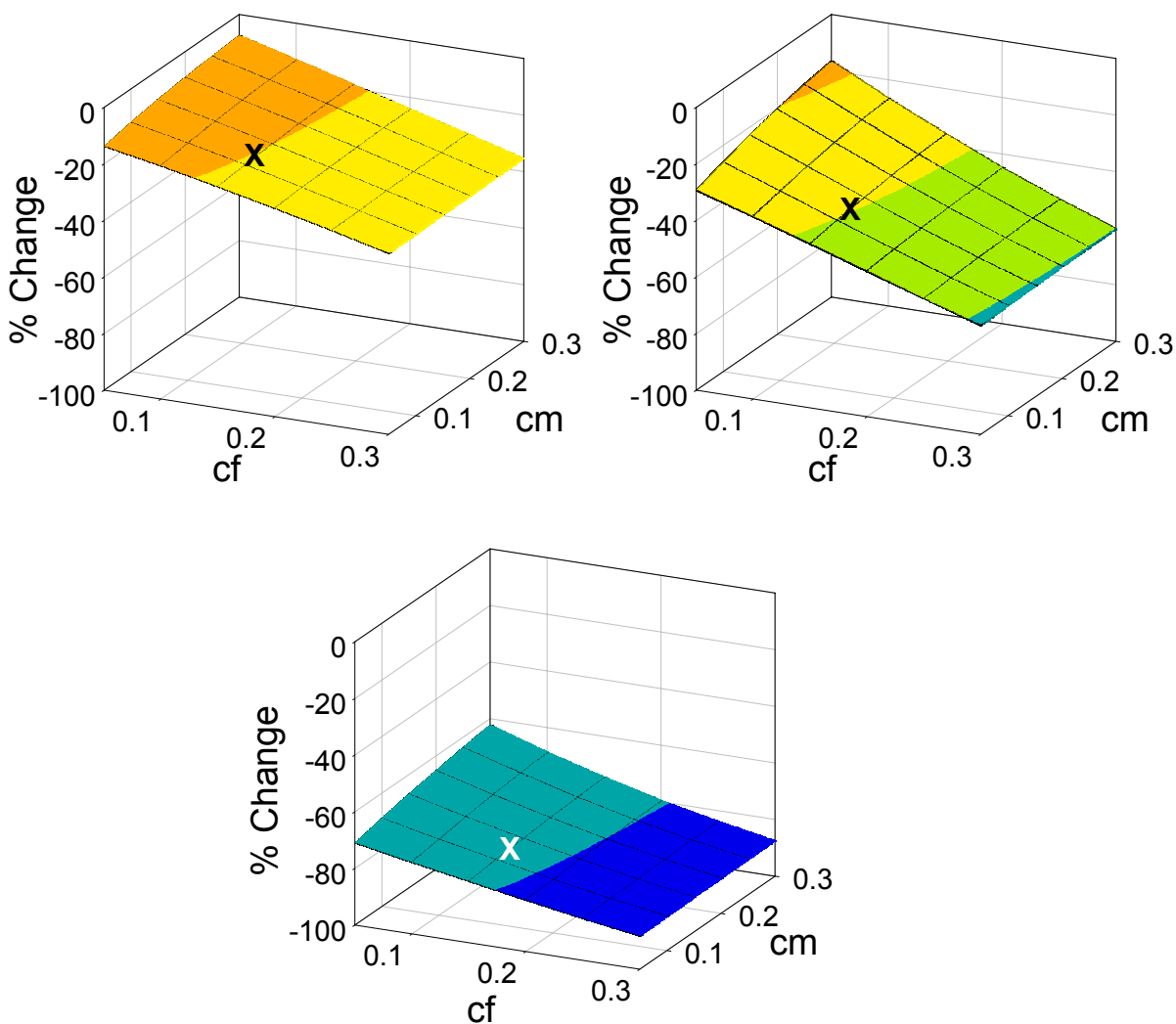


Figure 2.11. Percent expected changes in the number of harvested fish from the New River muskellunge fishery with the implementation of a 914-mm (top-left), 1,016-mm (top-right), and 1,143-mm (bottom) minimum length limit. Current annual mortality rate estimates (cm = conditional natural mortality; cf = conditional fishing mortality) are denoted on the graphs with an "X".

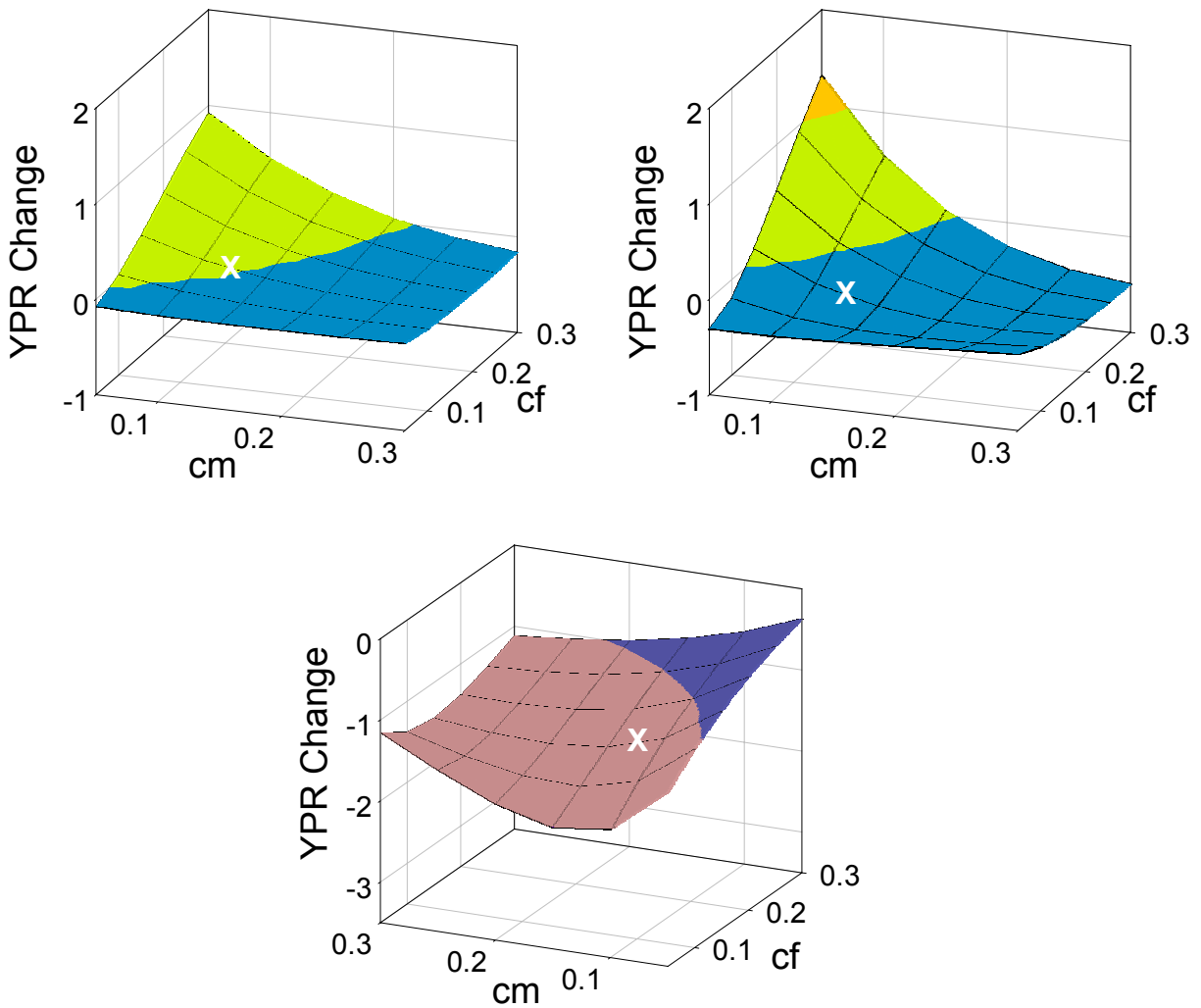


Figure 2.12. Expected yield per recruit (YPR) changes of the New River muskellunge fishery with the implementation of a 914-mm (top-left), 1,016-mm (top-right), and 1,143-mm (bottom) minimum length limit. Current annual mortality rate estimates (cm = conditional natural mortality; cf = conditional fishing mortality) are denoted on the graphs with an "X".

### CHAPTER 3: ESTIMATING TOTAL ERROR IN LOCATING RADIOTELEMETRY TRANSMITTERS BY HOMING IN A RIVERINE ENVIRONMENT

#### ABSTRACT

When estimating fish position via radiotelemetry, final deviations of recorded fish locations from actual locations (total error) are influenced by two separate types of error, locating error and mapping error. Although locating error is increasingly addressed in radiotelemetry studies, quantification of total error is much less common. I describe an anchor design useful for positioning test transmitters in a riverine environment where high discharge is capable of repositioning test transmitters. Further, I quantify and contrast total error when test transmitters are located by homing and their position recorded using two types of global positioning system (GPS) receivers. Directional error was not uniform; instead, it was biased in a northerly direction. I attribute this northerly bias to inaccuracy when mapping the original placement of transmitters. Median distance error was approximately 4 m. No significant difference in distance error between test transmitters or GPS receiver type was observed, and distance error was independent of time. I conclude that the anchored transmitters remained stationary throughout the study.

#### INTRODUCTION

When estimating locations of fish via radiotelemetry, two types of error can influence final position estimates: locating and mapping error (Withey et al. 2001). Assuming that a fish is stationary at a particular time and location ( $P$ ), where  $P$  can be defined spatially in 1- to 3-dimensions, locating error is the deviation of the fish's estimated position ( $P_L$ ) in the field from its actual position ( $P$ ). Mapping error is the deviation of a fish's recorded position ( $P_M$ ) from the field estimate ( $P_L$ ). Thus the total error, or the deviation of a fish's recorded location ( $P_M$ ) from its actual location ( $P$ ), actually consists of two separate error components (Figure 3.1).

Locating and mapping error are each influenced by several factors. Locating error is influenced by factors such as equipment choice, radio signal reflection, depth, operator error or bias, and electromagnetic interference (Simpkins and Hubert 1998; Withey et al. 2001; Freund and Hartman 2002).

Mapping error primarily is a function of the method by which fish locations are recorded. For example, when fish position is recorded in the field by directly marking a map, mapping error will depend on factors such as map accuracy, mark size, and the ability of the recorder to accurately place field locations on the map (Withey et al. 2001).

Since the advent of the global positioning system (GPS), electronic determination and recording of field locations has become fairly routine. Further, the discontinuation of selective availability, an intentional degradation of GPS accuracy by the U.S. Department of Defense (Leva et al. 1996), has meant that most GPS receivers can reliably record locations to within 25 m (Cosentino and Diggle 1996). Nevertheless, final accuracy of recorded GPS positions is still influenced by a number of factors, including the number of satellites within view of the GPS receiver, satellite geometry, clock error, signal reflection (i.e., multipath), receiver noise, and atmospheric delays of satellite signals (Leva et al. 1996).

When addressing error in fish telemetry studies, focus typically has been placed on quantifying locating error. Researchers will measure or estimate deviation of estimated location from actual location based on either visual observation of telemetered fish or by conducting pre-study field trials (Bégout Anras 1999; Bjoro 2000; Simpkins et al. 2000; Paukert and Willis 2002). Researchers typically ignore the effect of mapping error and instead assume that estimates of fish locations in the field can be accurately recorded. Consequently, the magnitude of total error in most radiotelemetry studies involving fish is either underestimated or unknown.

To quantify total error, Withey et al. (2001) recommended placing test transmitters throughout the study area, recording their precise position using the most accurate means available, and then attempting to locate and map test transmitters positions with the same methodology used to locate telemetered fish. Total error can then be assessed by comparing recorded positions of test transmitters to actual positions. In a riverine environment where discharge has the potential to displace test transmitters, developing an anchoring system that will ensure test transmitters remain stationary is an important consideration. If test transmitters are entrained during the period of error evaluation, total error estimates may unknowingly be inflated. The objectives of this study were to evaluate a test transmitter anchor design that could be used in a riverine environment, and to quantify total error associated with locating radiotelemetry transmitters through homing and recording their position using two GPS receiver types.

## METHODS

The test transmitter anchor was constructed of concrete and polyvinyl chloride (PVC) pipe (Figure 3.2). A form for the anchor was constructed from a plastic tub commonly used for mixing concrete. The tub was approximately  $0.6 \times 0.4 \times 0.1$  m in length, width, and depth. A circular opening approximately 7 cm in diameter was cut into the bottom of the tub near the center through which a PVC pipe was threaded. Two smaller openings, approximately 1 cm in diameter, were cut into opposite sides of the form. The concrete was poured into the form and once it began to harden, masonry anchors were inserted into the anchor through the small openings and several metal bars were inserted into the surface of the anchor.

Once the concrete was dry, a radiotelemetry transmitter was placed inside the PVC tube. The tube was sealed at both ends with silicone and a PVC cap. The transmitter antenna was threaded through a hole drilled into the top cap to prevent attenuation of the radiotelemetry signal. Eyebolts were screwed into the masonry anchors, which provided points of attachment to the anchor. Once completed, an anchor weighed approximately 40 kg. In total, 4 anchors were constructed.

The anchors were deployed in a section of the New River, VA near the Whitethorne boat landing (UTM Zone 17N: 538,561 E; 4,116,984 N). Anchors were placed in at least 2 m of water, which was of sufficient depth that the anchors could never be seen from the water surface. Two anchors were placed in mid-channel areas and two were placed near the river bank.

Once an anchor site was selected, a length of rope was threaded through both eyebolts and the anchor was lowered into the water. Once in the water the anchor was allowed to freefall to the river bottom so that the momentum of the anchor would help drive the metal bars protruding from the bottom of the anchor into the substrate. A diver ensured that the anchor was level and seated upright on the river bottom. The position of each anchored transmitter was recorded using a GPS Pathfinder<sup>®</sup> Pro XRS receiver (Trimble Navigation Limited, Sunnyvale, CA), which was interfaced with a Ranger Series 200T (Tripod Data Systems, Corvallis, OR) field data collector running TerraSync<sup>™</sup> software (Trimble Navigation Limited, Sunnyvale, CA). Real-time differential correction of GPS positions was provided through a commercial satellite provider (OmniSTAR USA, Inc, Houston, TX)). When recording the positions of the test transmitters, the maximum position dilution of precision (PDOP) was 4.2. The GPS

Pathfinder<sup>®</sup> Pro XRS receiver using this form of differential correction at this PDOP can be expected to provide position estimates accurate to within 1 m (Trimble Navigation Limited 2001).

Anchored transmitters were relocated weekly by the same person who had not been present when the anchors were deployed. Transmitters were located by homing, whereby antennae directionality and signal strength was used to navigate towards the test transmitters (Samuel and Fuller 1994). The antenna used was a bi-directional loop antenna. However, as the operator approached the test transmitter and signal strength reduced receiver sensitivity, the loop antenna was disconnected and only a coaxial cable was used as an omnidirectional antenna (Niemela et al. 1993; Samuel and Fuller 1994). At the location where the radiotelemetry signal amplitude was at its peak and the operator believed the test transmitter was located, the operator's position was recorded using either a Garmin 48 GPS (GPS 48) receiver or a Garmin 76 GPS (GPS 76) receiver (Garmin International Inc., Olathe, KS). The major difference between these GPS receivers is that the GPS 76 receives real-time differential correction of GPS positions through the Wide Area Augmentation System (WAAS), which is a differential correction service maintained by the U.S. Federal Aviation Administration (USFAA 2005). Boat position over the estimated location of the test transmitters was maintained while several waypoints for that location could be recorded.

Mapped locations and estimated locations of anchored transmitters were defined two dimensionally; thus, total error could be assessed in terms of both direction and distance. Error in direction was the azimuth angular deviation of the estimated location from the mapped locations, while error in distance was the Euclidean distance between the estimated and mapped locations. Angular errors were summarized and tested using circular statistical methods. The sample mean and 95% confidence intervals of the angular errors for each of the anchored transmitters and GPS receivers were estimated using methods described by Upton and Fingleton (1989). I tested for differences in the mean angular errors between the test transmitters (grouped by GPS receiver type) using the Mardia-Watson-Wheeler uniform scores test (Upton and Fingleton 1989).

Because of skewness in the data, distance error was summarized by calculating sample medians and interquartile ranges. Differences in distance error between GPS units and anchored transmitters were tested using a nonparametric two-factor randomization test (number of randomizations = 1,000;

Manly 1997). I tested for independence in the distance error combined across GPS receiver types for each of the test transmitters using the nonparametric runs test. The level of significance for the statistical tests was set at  $\alpha = 0.05$ .

## RESULTS

Test transmitters were deployed on 12 December 2001 and relocated until 19 December 2002, with a total of 46 location estimates being collected for each transmitter. Of the 184 location estimates, 52 estimates were made using the GPS 48 receiver and the remaining 132 estimates were made using the GPS 76 receiver (Figure 3.3). During this year-long time span, the average and maximum discharge for this section of the New River [measured 22 rkm upstream at the U.S. Geological Survey (USGS) Radford gage (USGS Station 0317100)] was approximately 56 and 920 m<sup>3</sup>/s, respectively (USGS 2004c).

Angular deviations between the weekly tracking estimates and the original mapped positions of the test transmitters were not uniform, rather deviations were concentrated in a northerly direction (Figure 3.4). The mean ( $\pm$  95% confidence interval) angular deviations for each of test transmitters (grouped by GPS type) was: 359  $\pm$  27° (48.311 – GPS 48), 354  $\pm$  26° (48.311 – GPS 76), 13  $\pm$  37° (48.331 – GPS 48), 358  $\pm$  38° (48.331 – GPS 76), 7  $\pm$  51° (48.815 – GPS 48), 44  $\pm$  54° (48.815 – GPS 76), 33  $\pm$  26° (48.835 – GPS 48), and 23  $\pm$  25° (48.835 – GPS 76). No significant difference in the angular deviations was evident (Mardia-Watson-Wheeler uniform scores test:  $W = 21.57$ ,  $df = 14$ ,  $P = 0.09$ ).

Distance error was similar across test transmitters and GPS receiver type (Figure 3.5). Median distance error was approximately 4 m; 95% of all locations were within 8 m. I found no difference in linear error between either transmitters or GPS type (two-factor randomization test: transmitter,  $P = 0.68$ ; GPS type,  $P = 0.64$ ; transmitter  $\times$  GPS type interaction,  $P = 0.67$ ). No trend in distance error over time was observed (Figure 3.6). Results of the runs test indicated that distance error was independent of time (Transmitter 48.311:  $K = 3.61$ ,  $P = 0.68$ ; Transmitter 48.331:  $K = 4.08$ ,  $P = 0.89$ ; Transmitter 48.815:  $K = 3.59$ ,  $P = 0.51$ ; Transmitter 48.835:  $K = 4.24$ ,  $P = 0.98$ ).

Because of the directional bias that was observed, the status of the test-transmitter anchors was checked by a diver in the fall of 2003. Using the GPS 76 receiver, a boat was navigated towards the



original mapped location of the test transmitters. Once the mapped location was found, a scuba diver dove to the river bottom and attempted to find the anchors. The diver carried one end of a coaxial cable, which was connected to the radiotelemetry receiver. As the diver searched the river bottom, a person in the boat listened for strength changes in the radiotelemetry signal. As the diver approached the test transmitters and the radiotelemetry signal peaked in amplitude, the person in the boat informed the diver by repeatedly tugging on the coaxial cable. The two anchors that were placed in mid-channel areas were easily found. The general location of the two anchors that were placed near the river bank was determined, but these anchors were not observed as they had apparently become buried in alluvial deposits. The diver attempted to find the anchors by digging away the deposited sediment but was not successful in exposing the anchors. Based on the amplitude of the radiotelemetry signal, it was believed that the diver was within 1 meter of the location of the anchored transmitters.

After the diver located the anchors, their positions were recorded for comparison with their original mapped locations. A length of rope was attached either directly to the anchor (for those anchors that were exposed) or to a nearby object (for those anchors that were covered). At the water surface, the diver pulled the rope taut so that he was positioned directly over the anchor and then he recorded his position with a GPS receiver (GPS 76). On average, I measured a 4- m discrepancy between where the anchor was believed to have been placed and this final measurement was measured. The azimuth angular discrepancy averaged approximately 5°. No damage to the anchors that were exposed was evident.

## DISCUSSION

Based upon my error measurements and the visual inspection of the anchors that were found, I believe that the anchored test transmitters were not displaced by river discharge during this study. If test transmitters had been displaced, directional error would have been biased in the direction of river flow and either a jump or steady increase in distance error would have been observed. Although a northerly directional error was evident, I don't attribute this to test transmitter entrainment. Rather, I attribute the bias to imprecise measurement of original test transmitter placement. The angular discrepancy between the initial and final mapped position estimates was indeed in a northerly direction. When the weekly

location estimates were plotted relative to the final mapped position, the final mapped positions were within the centers of the weekly location estimates. The disparity between the original and final mapped positions probably resulted from wind or river discharge repositioning the boat from which the anchors were deployed. If the boat was moored properly, the boat could have shifted position slightly so that when the position of the boat was recorded with the GPS Pathfinder® Pro XRS receiver it was not located directly over the anchors. This disparity illustrates the importance of accurately measuring original transmitter placement, as well as the difficulty associated with measuring transmitter placement in a riverine environment.

I believe that this anchor design is well-suited for ensuring test transmitters remain stationary in either lentic or lotic systems. I find it highly unlikely that the anchors will be entrained at discharges less than 1,000 m<sup>3</sup>/s. I encourage those who might replicate this design to place the anchors in areas with soft substrate (e.g., sand, mud), as the metal bars protruding from the anchor bottom will more easily penetrate soft substrate and probably will be more secure than if the anchor was placed on bedrock. The PVC pipe in which the test transmitter is placed possibly could be broken if hit by floating debris. If the PVC pipe was broken, the test transmitter possibly could be relocated. A design modification to prevent such an occurrence would be to partially encase the transmitter in the concrete. As long as the antenna remained exposed, the radiotelemetry signal would not be attenuated. If researchers anticipate a need to relocate the anchor, I would encourage tying a small buoy to the anchor, which would make the anchors easier to find at a later date.

The statistically insignificant differences in error between the GPS types suggests that when using GPS to record locations of telemetered fish, a GPS receiver that differentially corrects waypoints may not be necessary or that users should be cautious in selecting a particular differential correction service. Depending on study location, several real-time differential correction services are potentially available to GPS users (e.g., WAAS, U.S. Coast Guard beacon system, commercial satellite providers). In addition, positions can be differentially corrected by post-processing. Costs differ between each of these methods in terms of both equipment and use of service (Lewis 1996). Similarly, there is a difference in position accuracy between the correction methods (Oderwald and Boucher 1997). The advantage of WAAS is that the service is free, and GPS receivers that can receive WAAS corrections are

relatively inexpensive (US\$200 in 2002). However, considering that no difference in distance error between the uncorrected and WAAS differentially corrected GPS was observed, whether this form of differential correction is useful for a radiotelemetry study is questionable. Other methods of differential correction may be more expensive than WAAS (e.g., the Trimble GPS Pathfinder<sup>®</sup> Pro XRS receiver along with the data collector, necessary software, and subscription to the differential correction service cost nearly US\$10,000 in 2002), but also may provide more precise measurements of location. Whether or not increased position accuracy is needed ultimately depends on study objectives (Adrados et al. 2002).

Researchers should acknowledge that whenever fish positions are estimated, some error will inevitably occur, whether the error is associated with locating fish, mapping positions, or both. As a result, when analyzing location data it may be more suitable to treat individual locations as regions rather than points. Simpkins et al. (2000) referred to this location region as an area of probable occurrence (APO). Treating locations as APOs will complicate analysis, particularly when an APO encompasses more than one habitat type, which may occur routinely when studying an edge favoring species. Several options are available for analyzing habitat use when a location is treated as an APO. One method is to randomly assign a location somewhere within the APO (Samuel and Kenow 1992) and proceed with a traditional analysis. Such a random assignment could be repeated to determine how error affects final results. Alternatively, one could calculate the probability of a fish's location occurring within different habitat types based on individual APOs (Findholt et al. 2002).

Total error is an important consideration in radiotelemetry studies. When the objective of a radiotelemetry study is to analyze fish locations in relation to habitat availability, total error dictates the scale at which reliable inferences can be derived. Even if locating error is negligible, mapping error of even a few meters may mean that a study cannot address resource use at a microhabitat scale; instead, researchers may have to settle for studying mesohabitat characteristics. Because time and effort potentially could be wasted collecting habitat information that is of too low a resolution to address the question at hand, a total-error quantification assessment should be conducted prior to the initiation of any radiotelemetry study.

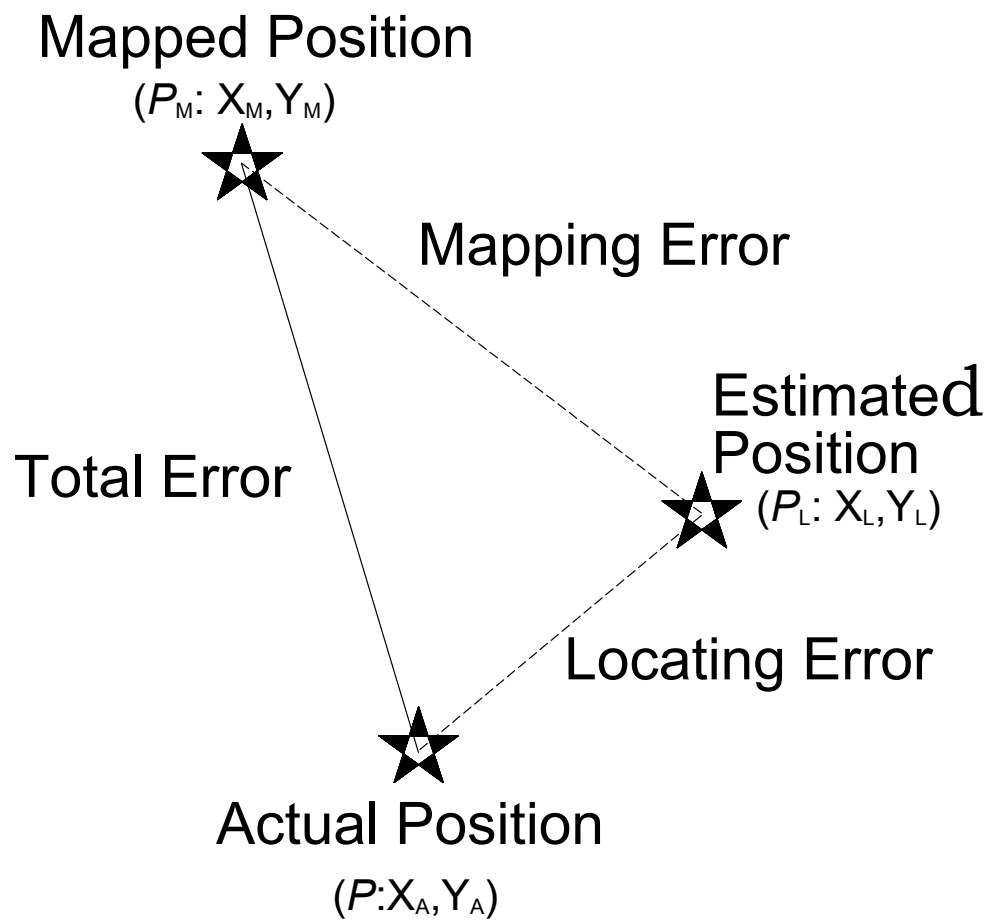


Figure 3.1. Illustration of the relative influence of locating and mapping error on total error where telemetered fish position is recorded as a two-dimensional (X,Y) attribute.



Figure 3.2. Top and side profile of a completed transmitter anchor.

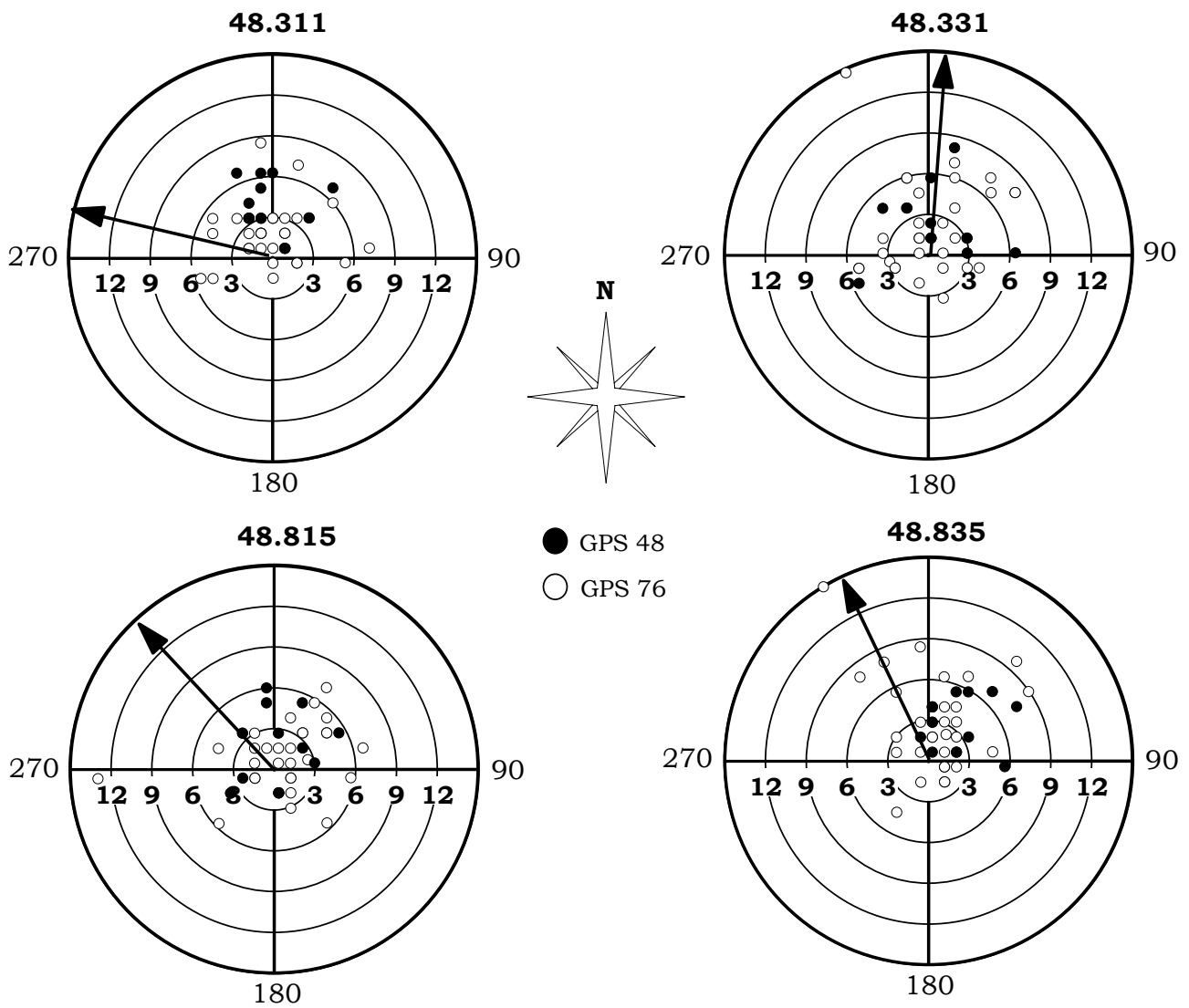


Figure 3.3. Polar plots of recorded test transmitter positions in relation to original mapped positions. Distance units for each polar plot are in m. The arrows on the polar plots indicate the direction of river flow at that particular site.

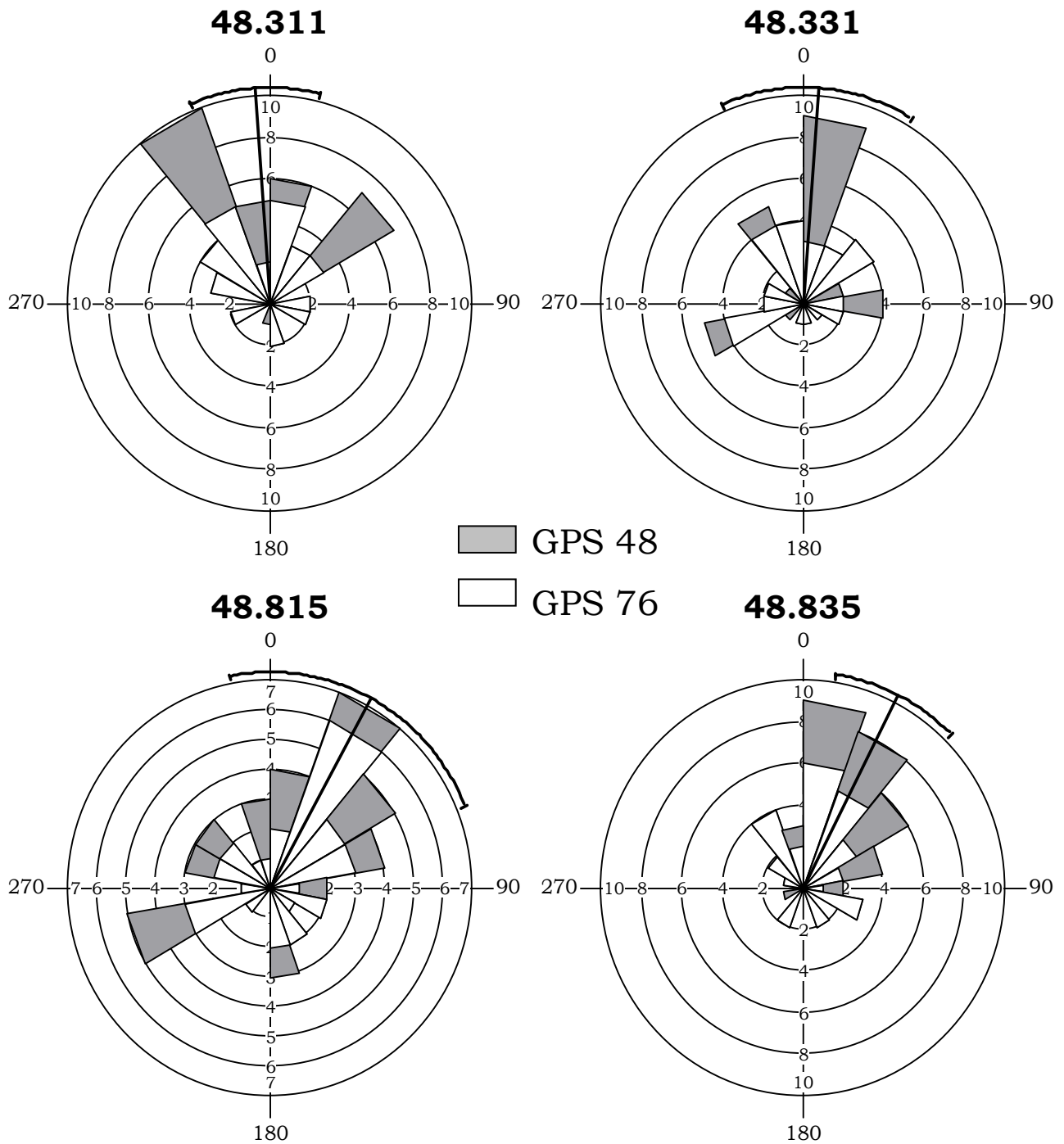


Figure 3.4. Rose diagram for the azimuth angular deviations in the weekly location estimates of the test transmitter anchors relative to the original mapped locations. On each diagram, the mean angular deviation is indicated by the black line running from the center of each diagram. The arc extending from this line at the edge of the diagram represents the upper and lower 95% confidence interval.

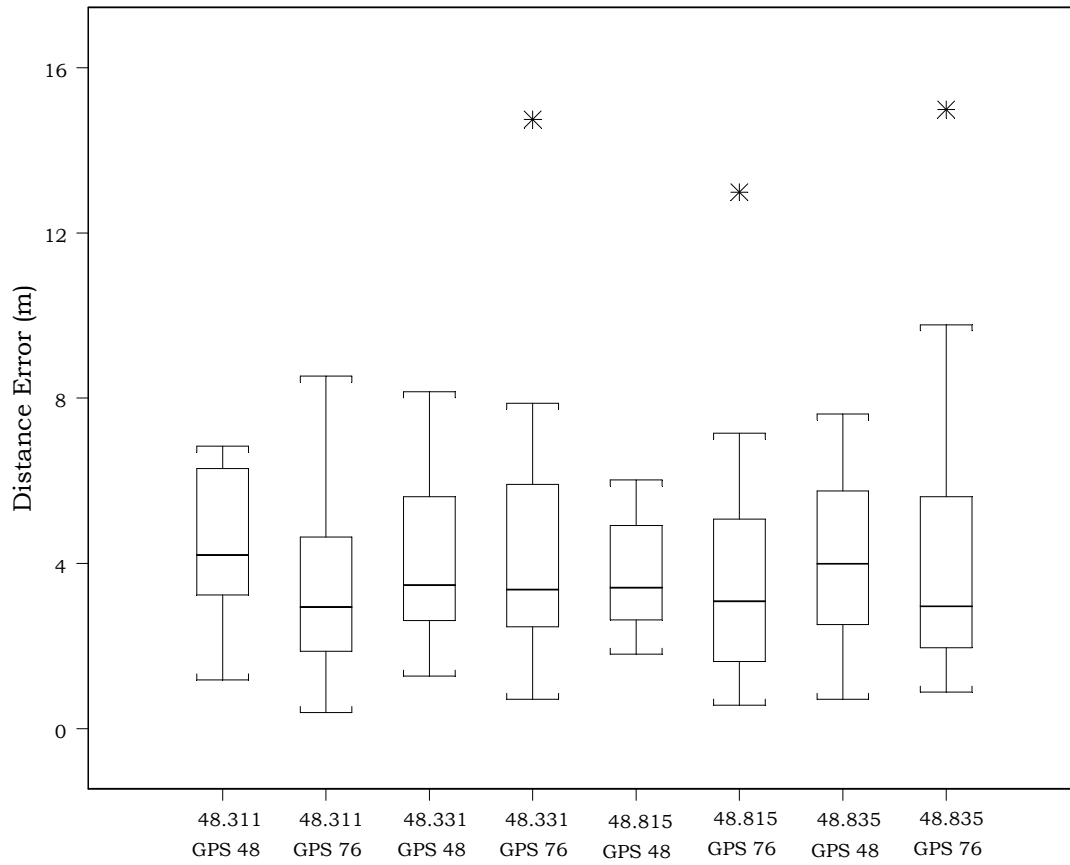


Figure 3.5. Boxplots of distance error for each test transmitter and GPS receiver type. The asterisks indicate outliers, which are data points lying 1.5 times the inter-quartile range beyond the upper or lower quartiles.



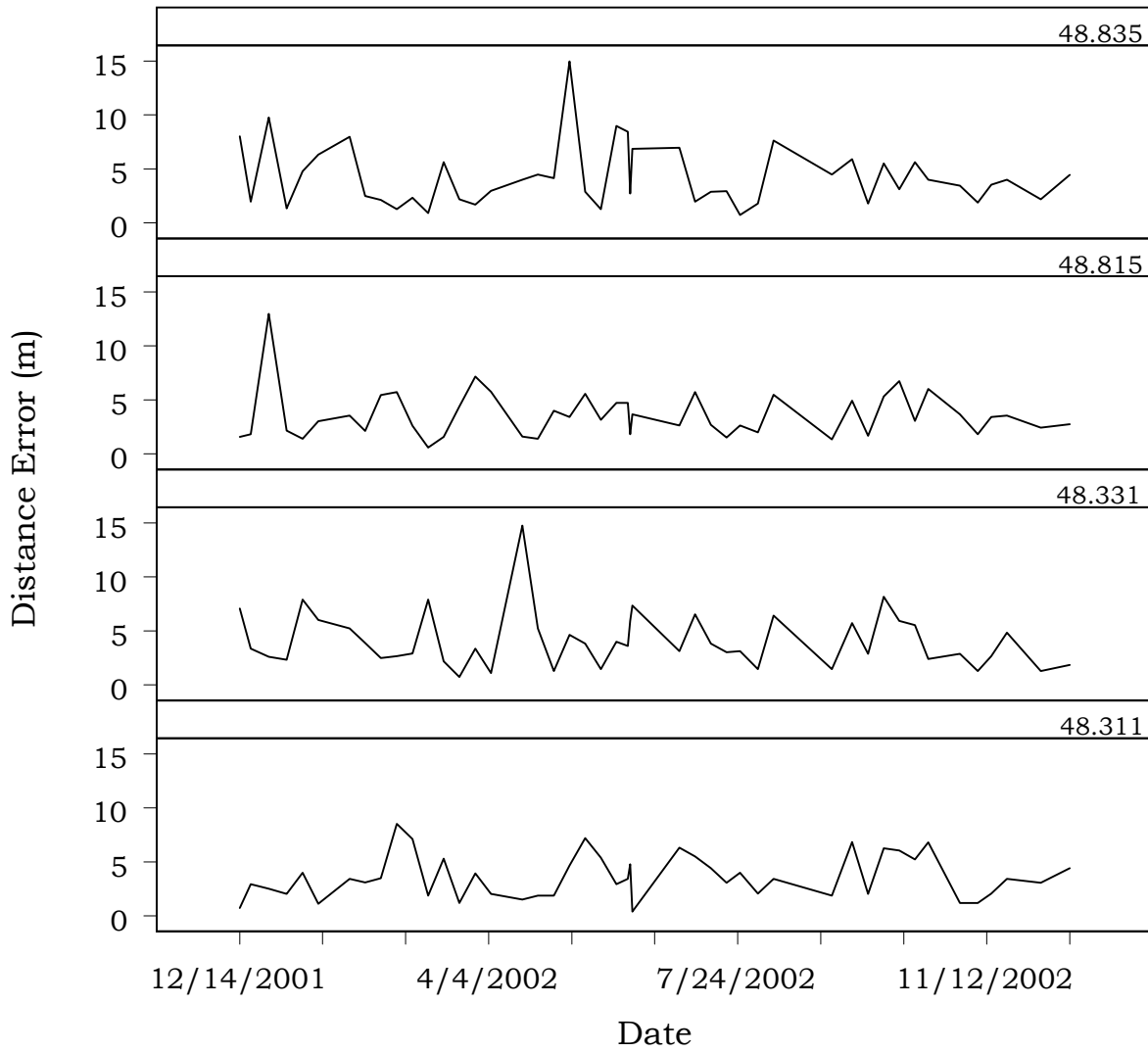


Figure 3.6. Time-series plot of distance error combined across GPS receiver type for each test transmitter.

**CHAPTER 4: MULTI-SCALE HABITAT SELECTION BY MUSKELLUNGE IN A SOUTHEASTERN U.S.  
WARMWATER RIVER**

**ABSTRACT**

Information concerning muskellunge *Esox masquinongy* habitat use in warmwater rivers in the southeastern United States primarily has been derived from descriptions of habitat at muskellunge sampling sites. The usefulness of such descriptions from scientific and management standpoints is limited, however, because of biases associated with sampling methodology. To help fill this information gap, radiotelemetry was used to monitor habitat use of 42 muskellunge in a 17-river-kilometer reach of the New River, VA. Habitat availability was mapped using global positioning system and hydroacoustic technologies. Habitat selection probability functions at two spatial scales were created using model averaging in combination with logistic regression models and generalized additive modeling. The effect of discharge on habitat use and selection was assessed to determine how fluctuations in discharge affected fish behavior. Measures of patch shape complexity were the only landscape pattern and composition metrics that were consistently related to probability of habitat use, which possibly results from complex patch shapes providing suitable feeding cover for muskellunge or higher prey densities. Habitat selection at micro-level scales was most strongly related to focal-site water depth; however, there was some evidence suggesting that site occupancy also was affected by juxtaposition of areas to deep-water habitats. Increased river discharge was significantly correlated with fish moving closer to shorelines and into shallow areas; thus, muskellunge may seek refuge from higher water velocities in such areas. Comparison of habitat selection probability functions constructed for fish locations made during low (< 45.3 m<sup>3</sup>/s) and high (> 45.3 m<sup>3</sup>/s) discharges also indicated that muskellunge abandoned deeper habitats during periods of high discharge. When evaluating warmwater rivers in terms of habitat suitability for muskellunge, biologists should look for sites with juxtaposition of shallow- and deep-water habitat patches.

## INTRODUCTION

The muskellunge *Esox masquinongy* is a primarily piscivorous fish species whose native range is restricted to the St. Lawrence, Mississippi, Ohio, and Tennessee River drainages of North America (Crossman 1978). Due to its popularity as a sportfish, though, muskellunge have been propagated and stocked throughout North America (Crossman 1986). In the southern United States, muskellunge have been introduced into waterbodies in Alabama, Arkansas, Georgia, Kentucky, North Carolina, South Carolina, Tennessee, Virginia, and West Virginia (USGS 2004a). Some of the most productive muskellunge fisheries in southern U.S. regions are riverine stocks, which may be linked to lower summer water temperatures in these environments. In Virginia, the top trophy-producing muskellunge fisheries have been the New and James Rivers. Since 1990, these rivers have produced 51% ( $n = 550$ ) of the trophy ( $\geq 1,016$  mm or  $\geq 6.8$  kg) muskellunge registered as part of Virginia's Angler Recognition Program, with the remaining percentage divided between 17 other lakes, reservoirs, and rivers [Virginia Department of Game and Inland Fisheries (VDGIF), unpublished data].

Despite the potential importance of rivers to muskellunge fisheries in southern U.S. regions, very little information concerning muskellunge biology and ecology is available for these systems. The only information concerning muskellunge habitat use in southern warmwater rivers comes from descriptions at sites where fish have been collected during sampling (Parsons 1959; Miles 1978; Brewer 1980; Axon and Kornman 1986; Monaghan and Borawa 1988). The ability to link such descriptions to actual habitat selection, though, is premised on sampling being equally effective across all habitat types, an assumption that rarely is met. Boat electrofishing, which is a frequently-used method for sampling muskellunge in rivers (Miles 1978; Axon and Kornman 1986; Monaghan and Borawa 1988), is generally effective over a limited range of water depths (Reynolds 1996). Electrofishing also is often conducted only along shorelines, thus it cannot be known to what extent muskellunge use mid-channel habitats. Although research into muskellunge habitat use and selection using techniques such as radiotelemetry has been conducted in lacustrine environments in northern latitudes, the question regarding transferability of results limits applicability of these findings to southern warmwater rivers (Leftwich et al. 1997).

Research into muskellunge habitat use and selection in southern warmwater rivers would be beneficial from both basic and applied scientific standpoints. From an applied perspective, results would assist in the development of a standardized sampling protocol for muskellunge in warmwater rivers, which currently is lacking and which prevents broad spatial and temporal comparison of sampling results (Bonar and Hubert 2002). Additionally, results would aid in the identification of areas where muskellunge introductions would have the greatest likelihood of success (Evans and Olver 1995; Mladenoff et al. 1999). Given that muskellunge stocking is often controversial because of possible predatory impacts on other fish species (Siler and Beyerle 1986; Moyle 2002), stocking muskellunge only in those areas that have the best chances of supporting a fishery may help to prevent stakeholder conflicts. The purpose of this research was to study muskellunge habitat selection at multiple spatial scales in a warmwater river in Virginia. Specific objectives addressed in this research included an evaluation of hydroacoustic technology for mapping habitat availability for the purpose of studying habitat selection in fish, a comparison of habitat selection among different ontogenetic stages of muskellunge, a comparison of muskellunge habitat selection between seasons (summer and winter), and a comparison of habitat selection between different discharge events.

### **STUDY AREA**

The New River originates in northwest North Carolina and flows northward through southwest Virginia and into West Virginia (Figure 4.1). The river basin lies within two Virginia physiographic provinces, the Southern Blue Ridge Mountain and Ridge and Valley Provinces. The New River merges with the Gauley River near Anstead, West Virginia to form the Kanawha River, which is a tributary to the Ohio River.

Compared to other drainages in Virginia and the eastern United States as a whole, the New River drainage has a low number of native aquatic fish species (Jenkins and Burkhead 1993). Only 46 freshwater fish species are believed to be native to the drainage; 42 other species have been introduced (Jenkins and Burkhead 1989). Although muskellunge is native to both the Ohio and Kanawha Rivers (Crossman 1978; Miles 1978), natural invasion into the New River possibly was prevented by Kanawha Falls, a waterfall located 3 river kilometers (rkm) below the confluence of the New and Gauley Rivers.

Kanawha Falls is believed to have largely isolated the New River from other rivers within the Ohio River drainage and to have led to a high endemism rate for fishes in the New River drainage (Jenkins and Burkhead 1993). Stocking of muskellunge in the New River by VDGIF began in 1963.

Muskellunge habitat selection was studied within a 17-rkm section of the New River (Figure 4.1). The study area began approximately 80-rkm upstream from the Virginia/West Virginia border and extended downstream to a shallow section of the river located near Parrot, Virginia. The approximate midpoint of the study area was the Whitethorne boat landing (UTM Zone 17N: 538,561 E; 4,116,984 N). This section of the river was selected for this research because it offered a variety of habitat types and because it was one of the longest stretches of the New River that could be accessed by boat even during low river discharge. The study reach encompassed a total area of 300 ha and had an average wetted river width of 175 m. Discharge in this section of the New River is primarily regulated by Claytor Hydroelectric Dam, which is located 30-rkm upstream from the Whitethorne boat landing. Mean annual discharge for this section of the New River is 109 m<sup>3</sup>/s (USGS 2004c).

## METHODS

### *Transmitter Implantation and Tracking Methodology*

Forty-two muskellunge [total length (TL) range: 655 – 1,256 mm] were collected by boat electrofishing ( $n = 36$ ) and angling ( $n = 6$ ) from early winter to late spring in 2000 ( $n = 15$ ), 2001 ( $n = 13$ ), and 2002 ( $n = 14$ ) and surgically outfitted with internal radiotelemetry transmitters (Advanced Telemetry Systems, Isanti, Minnesota) operating in the 48 to 50 MHz bandwidth range. Transmitter mass ranged from 28 to 90 g. Transmitters, on average, weighed  $1.03 \pm 0.12\%$  ( $\bar{x} \pm 2 \cdot \text{SE}$ ) of fish body weight. Captured fish were placed ventral side up in a restraint cradle constructed from aluminum and nylon fabric. Transmitters were surgically inserted into the peritoneum through an incision made proximate to the mid-ventral line and posterior to the pelvic girdle. Transmitter antennae were threaded outside of the body cavity through an eight-gauge passive integrated transponder tag needle, which was inserted through the body cavity wall from the outside proximate to the incision. Surgical staples were used to

close the incisions for the first few fish implanted with transmitters, but I later switched to non-absorbable sutures because staples had a tendency to tear through the incisions in large fish. Fish were returned immediately to the river upon completion of the surgery, restrained until equilibrium was regained, and released. Expected battery life for the transmitters ranged from 500 to 1,100 days.

Tracking of muskellunge began 24 March 2000 and continued approximately weekly until 11 June 2003. Only locations collected after 1 June 2000 were used in assessing habitat selection, which was when selective availability, an intentional degradation of global positioning system (GPS) accuracy by the U.S. Department of Defense (Leva et al. 1996), was discontinued. Fish were relocated only during the daylight hours as it was deemed too dangerous to navigate the study reach at night. Fish were tracked by homing from a boat using an R2000 receiver (Advanced Telemetry Systems, Isanti, Minnesota) and a hand-held loop antenna. As the boat neared a fish's position, only the exposed end of a coaxial cable as an omni-directional antenna to prevent the radiotelemetry signal from overwhelming the receiver (Niemela et al. 1993). When the radiotelemetry signal peaked in amplitude, boat location (and assumingly fish location) was recorded with either a Garmin 48 GPS (GPS 48) receiver or Garmin 76 GPS (GPS 76) receiver (Garmin International Inc., Olathe, Kansas). If fish movement was detected while attempting to locate a fish, tracking was discontinued and no further attempt at locating the fish was made during that week. A previous research study that involved placing test transmitters at known locations and then locating and mapping test transmitter position using these same methods estimated a median accuracy of 4.0 m for this tracking methodology (Chapter 3; Brenden et al. 2004).

#### *Habitat Variable Measurement and Mapping*

Water depth, aquatic vegetation, substrate type, distance to shoreline, and river discharge were variables believed to potentially influence muskellunge habitat use. Water depth, aquatic vegetation, and substrate type within the study reach were measured by hydroacoustic sampling with a DE Series 4000 Echosounder and a 430-kHz single-beam 6.2° transducer (Biosonics, Inc., Seattle, Washington). A GPS Pathfinder® Pro XRS receiver (Trimble Navigation Limited, Sunnyvale, California) interfaced with the echosounder provided geographic locations of the hydroacoustic data. The GPS locations were real-time

differentially corrected through the Wide Area Augmentation System (WAAS; USFAA 2005) or through a subscription to a commercial satellite differential correction provider (OmniSTAR, Inc., Houston, Texas).

Hydroacoustic sampling of habitat was conducted by dividing the study area into several small ( $\approx$  1-rkm) segments. Transects running parallel to the shorelines within each river segment were created in ArcView GIS (ESRI, Redlands, California). Transects were spaced 5 m apart for measuring water depth and aquatic vegetation, and were spaced 25 m apart for measuring substrate type. Transect locations were uploaded to the GPS 76 receiver, which could display boat location and transect location in real time. Hydroacoustic sampling was conducted along these transects, which helped assure a consistent coverage of measurement points within each river segment. A -130 decibel (dB) noise threshold was used when sampling water depth and macrophyte presence/absence. A -70 dB noise threshold was used when measuring substrate type. Sampling of water depth and aquatic vegetation was performed at a rate of 10 pings/s and pulse width of 0.3 milliseconds. Substrate type sampling was performed at a rate of 5 pings/s and pulse width of 0.1 milliseconds.

Water depth was measured from late fall to early spring so aquatic vegetation would not affect depth measurements. Sampling was conducted only when water discharge was between 22 and 84 m<sup>3</sup>/s so fluctuations in water depth stemming from discharge changes would be minimized. Seasonal changes in aquatic vegetation coverage were assessed by measuring aquatic vegetation during both summer and winter. Summer vegetation was measured from June to October, while winter vegetation was measured from November to March. Sampling of aquatic vegetation and substrate type was not standardized by river discharge, although sampling generally could not be conducted when discharge exceeded 226 m<sup>3</sup>/s, because turbulent flows interfered with the hydroacoustic signal.

Hydroacoustic datasets were processed with one of two software programs, EcoSAV and Visual Bottom Typing Seabed Classification (VBT; Biosonics, Inc., Seattle, Washington). The EcoSAV software processes hydroacoustic digital echoes for information related to aquatic vegetation presence/absence, density, height, and water depth. The processing algorithm is premised on vegetation exhibiting a continuous echo return immediately above the bottom echo, and the vegetation echo being weaker than the bottom echo but stronger than ambient water column "noise" (Sabol and Burczinski 1998). Although EcoSAV does estimate density and height of aquatic vegetation, these variables were not included in this

research as sampling could not be completed quickly enough to assure measurement consistency between river segments.

To classify substrate with the VBT software, areas of known substrate type must first be sampled. The digital echo characteristics of these known substrate types then can be identified using the VBT software, and a reference database created to which newly collected data can be compared. For this research, substrate was classified into one of three types: bedrock, gravel/cobble, and sand/mud. Areas in the study region consisting primarily of one of these substrate types were identified and sampled along a total of 20 transects (number of transects: bedrock= 6, gravel/cobble = 7, sand/mud = 7). After processing data from the sampled transects with the VBT software, the output datasets were combined and discriminant analysis [PROC DISCRIM function in SAS (SAS Institute, Inc., Cary, North Carolina)] was used to find a linear combination of the digital echo characteristics that best distinguished among the 3 substrate types. Cross-validation indicated that accuracy in distinguishing among bedrock, gravel/cobble, and sand/mud substrates were 86, 90, and 86%, respectively (Table 4.1).

Bathymetric and aquatic-vegetation maps for the entire 17-rkm study area were created using inverse-distance weighting (IDW) interpolation. When estimating a value at an unobserved location, IDW interpolation assumes that nearby data points will have a stronger influence on the estimated value than more distant points. The IDW interpolation function is

$$Z^* = \frac{\sum_{i=1}^n \left( \frac{1}{d^P} \cdot Z_i \right)}{\sum_{i=1}^n \left( \frac{1}{d^P} \right)},$$

where  $Z^*$  is the location where the variable is to be estimated,  $Z_i$  is a neighboring data point value,  $n$  is the number of neighboring data points,  $d$  is the distance between the data point and the point being interpolated, and  $P$  is a positive-power parameter that determines the influence of neighboring data points on predictions (Mulugeta 1996). As  $P$  approaches zero, predictions approach the average of neighboring points. As  $P$  approaches infinity, predictions approach the value of the nearest data point (Mulugeta 1996). Values for  $n$ ,  $d$ , and  $P$  are selected by the user. One shortcoming of IDW interpolation is that estimation is negatively affected by clustering of observations (Isaaks and Srivastava 1989; Haining 1990). However, clustering of hydroacoustic measurements in this study was not an issue since



sampling was conducted along equally spaced transects. When point patterns are not clustered, IDW interpolation can yield predictions of similar or greater accuracy than other interpolation methods (Weber and Englund 1992).

Bathymetric and aquatic-vegetation maps were interpolated to a 1-m x 1-m spatial resolution grid with  $n$  and  $P$  set equal to ten and one, respectively. The interpolated maps were smoothed by replacing each grid cell with the mean value for its 3-cell x 3-cell surrounding neighborhood. Interpolation, smoothing, and subsequent verification of the winter aquatic vegetation map revealed that aquatic vegetation was essentially absent during winter. As a result, aquatic vegetation was excluded as a habitat variable for assessing winter habitat selection.

Because substrate was classified according to a nominal scale, spatial interpolation could not be used to create a substrate-type map for the entire study area. Instead, a blank 25-m x 25-m spatial resolution grid was overlaid across the entire study reach and individual grid cells were assigned the predominant substrate type that occurred in each cell. Thus, if an individual grid cell overlay 5 sand/mud observations and 1 cobble/gravel observation, that cell was assigned a sand/mud classification. Unclassified grid cells were assigned a substrate type by expanding classified grid cells into empty neighboring cells.

Because existing GIS datasets for the New River shoreline were inaccurate, I created a new shoreline coverage of the study reach by walking the perimeter of the study reach while using the GPS Pathfinder<sup>®</sup> Pro XRS receiver to continuously record location. Real-time differential correction of the recorded shoreline locations was provided by satellite (OmniSTAR, Inc). Positional dilution of precision (PDOP) of the GPS signal was monitored to assure the accuracy of recorded locations. At low PDOPs and with real-time differential correction, the GPS Pathfinder<sup>®</sup> Pro XRS receiver can provide location estimates accurate to within 1 m (Trimble Navigation Limited 2001). Recorded shoreline locations were downloaded to a computer and the Pathfinder<sup>®</sup> Pro Office software program (Trimble Navigation Limited, Sunnyvale, California) was used to create a GIS polygon of study area boundaries. The bathymetric, aquatic-vegetation, and substrate-type maps were clipped to the study area boundaries so that all maps were commensurate.

Real-time river discharge estimates during the time period that muskellunge tracking was conducted were obtained from the Radford, Virginia stream gage (USGS 2004c). Median discharges for the 12 hours before the muskellunge relocations were calculated from the stream gage data. Because the stream gage is located 22 rkm above the study site, it was assumed that it would take an average of seven hours before the discharge measured at the stream gage reached the study area [American Electric Power (AEP), unpublished data]. Thus, if a fish was located at 1400 hours on a Friday, median discharge was calculated from the stream gage measurements recorded from 1900 hours on Thursday to 700 hours on Friday.

#### *Verification of Habitat Map Accuracy*

To verify that delineated habitat maps were accurate, water depth, aquatic vegetation, and substrate type were measured by hand at 200 to 300 points located throughout the study area. Locations where measurements were taken were randomly assigned in ArcView GIS using a random point generator script (Jenness 2004a). Water depth at the random locations was measured using a stadia rod or a SM-5 Depthmate Portable Sounder (Speedtech Instruments, Great Falls, Virginia).

Presence/absence of aquatic vegetation was determined by sight or by sampling with a piece of aluminum conduit that had several 18.7-g galvanized nails protruding from one end. Placing the nailed end of the conduit on the river bottom and twisting it rapidly caused vegetation to entangle in the nails. Presence/absence of aquatic vegetation at a specific location then could be determined based on whether vegetation was entangled in the nails. Substrate type at a specific location was identified by probing the river bottom with a piece of aluminum conduit and classifying the location as consisting primarily of bedrock, gravel/cobble, or sand/mud based on penetration depth and substrate texture.

Within ArcView GIS, I buffered each of the randomly assigned locations with a 10-m radius circular buffer. Delineated habitat maps were used to measure mean water depth, presence/absence of aquatic vegetation, and major substrate type within the buffered locations using Jenness' (2004b) Surface Tools ArcView GIS extension. I then compared the habitat estimates derived from the habitat maps to those estimates obtained in the field. From this verification, I determined that while bathymetric and vegetation presence/absence maps were accurate, accuracy of the substrate-type map was poor.

Absolute deviation of measured water depth at the random locations was  $0.21 \pm 0.03$  m ( $\bar{x} \pm 2 \cdot SE$ ). Eighty-three percent of the random locations were correctly classified in terms of aquatic vegetation presence/absence. In comparison, only 38% of the random locations were correctly classified as to substrate type. Although reducing the substrate-type classification to 2 classes (fine and coarse substrate) increased accuracy slightly (38% to 56% classification accuracy), this was still regarded as too low. Because of the inaccuracies associated with substrate-type identification, substrate type was not considered when assessing habitat selection for telemetered muskellunge.

#### *Home Range Delineation*

For modeling habitat selection, 90% univariate kernel home ranges (Vokoun 2003) were used to define habitat use or habitat availability, depending on the scale of the analysis. Ninety percent probabilistic home ranges were chosen because they provided the best coverage of fish locations, while simultaneously excluding obvious outliers. Kernel density estimation was conducted in S-PLUS 2000 (Mathsoft, Inc., Seattle, Washington) using a Gaussian density function. Bandwidths for the kernel densities were estimated using unbiased cross-validation (Venables and Ripley 1997). Seasonal home ranges and habitat selection models were constructed only if a particular fish had been located at least 20 times during a particular season.

Because not all fish transitioned between summer and winter home ranges at the same time (Figure 4.2), I had to determine the time frame for which to delineate home ranges for each fish individually. Accurate home range delineation is an important aspect of habitat selection studies that use home ranges to define habitat use and/or availability because if home ranges are not correctly delineated, the risk of incorrectly including or excluding certain habitat types and of committing a Type-I or Type-II error increases. Accurate delineation of muskellunge home ranges is particularly problematic because fish sometimes “wander” when transitioning between home ranges (Minor and Crossman 1978). Such “wandering” increases the likelihood of including areas *not* normally used by fish within delineated home ranges, which may significantly bias habitat use and/or habitat availability estimates.

To establish the time frame for delineating summer and winter home ranges for an individual fish, three methods were used. The first method was a nonparametric deviance reduction assessment (Qian et al. 2003), which involved sorting fish longitudinal locations by day of year and then iteratively subsetting the dataset and calculating the reduction in deviance with each possible division. The day of year that resulted in the largest deviance reduction (i.e., the threshold date) was assumed to estimate when a fish abandoned a home range. Bootstrapping (number of iterations = 1,000) was used to calculate 95% confidence intervals for the threshold date (Qian et al. 2003). I then used the upper and lower 95% confidence limits as boundaries for making a subjective decision as to when a fish began occupying a summer or winter home range. Locations from February through August were used to identify the winter-to-summer transition, while locations from September through January were used to identify the summer-to-winter transition.

If the deviance reduction assessment failed to identify obvious transitions between home ranges, I then tried to identify any “wandering” movements that occurred around the time period that other fish were transitioning between summer and winter home ranges. I defined a “wandering” movement as any longitudinal location that was more than 3 times the interquartile range beyond either the 25th or 75th percentiles of the longitudinal locations for that fish. If a “wandering” movement was detected, I then looked for subsequent periods during which the individual fish was sedentary. Such periods of sedentary behavior were identified as the time frame during which fish occupied home ranges. If this method also failed to indicate any obvious transition between summer and winter home ranges, I then simply used 1 April and 15 November as default cut-off dates. These dates correspond roughly to when water temperature in the New River approaches 10°C (T. Brenden, unpublished data), which has been identified as the approximate water temperature at which muskellunge transition between home ranges in other environments (Minor and Crossman 1978).

#### *Muskellunge Habitat Selection*

Muskellunge habitat selection was assessed at both macro- and micro-level scales. For the macro-level habitat selection assessment, I combined the bathymetric (reclassified to 1-m depth

increments) and aquatic-vegetation (summer only) maps into seasonal, thematic habitat maps. The combination of the bathymetric and aquatic-vegetation datasets resulted in 8 and 12 patch classes for the winter and summer habitat maps, respectively (Table 4.2). I then overlaid the 90% kernel home ranges of muskellunge across the seasonal habitat maps and computed a number of “class-level” and “landscape-level” metrics describing landscape pattern and composition within each home range (Table 4.3; see McGarigal et al. 2002). These same metrics also were used to describe landscape pattern and composition within areas randomly identified across the study reach. The total number of randomly delineated areas was 5 times the number of delineated home ranges. Randomly delineated areas were equal in size to the fish home ranges. All landscape pattern and composition metrics were computed using FRAGSTATS (McGarigal et al. 2002).

Several techniques were used to assess the degree of multicollinearity among the landscape pattern and composition metrics and, if necessary, to reduce the habitat variables to an independent set. I initially used two-sample unequal-variance *t*-tests to test whether metric measurements within muskellunge 90% kernel home ranges significantly differed from measurements within random areas. The degrees of freedom for these initial tests were equal to the number of home ranges constructed for each season (subtracted by one) to prevent inflation of the error rate. Metrics that were not different at  $P > 0.20$  were excluded from further analyses. I then conducted a spectral decomposition of the correlation matrix of the retained metrics and calculated the condition index associated with each eigenvalue (Myers 1990). The condition index ( $\phi$ ) for the *j*-th eigenvalue ( $\lambda_j$ ) is calculated as

$$\phi_j = \frac{\lambda_{\max}}{\lambda_j}$$

where  $\lambda_{\max}$  is the maximum eigenvalue. Multicollinearity among the retained metrics was assumed to exist if at least one of the condition indices exceeded 30. If multicollinearity was detected, I determined the variance proportions of the metrics (Myers 1990), and deleted those metrics with variance proportions greater than 60%. I repeated this process (i.e., spectral decomposition of the correlation matrix, calculation of the condition indices, and deletion of variables with variance proportions greater than 30) until all calculated condition indices were less than 30. As a final screening procedure, Pearson correlations were calculated for all pairwise combinations of retained metrics. If the absolute value of the

correlation estimate for a pair of variables exceeded 70%, the variable that appeared the most strongly related to muskellunge habitat selection based on the preliminary *t*-test results was retained while the other variable was deleted.

Habitat selection at a micro-level scale was assessed by comparing habitat use and availability within a fish's 90% kernel home range (Design-III study; Thomas and Taylor 1990). Habitat use was measured by creating 10-m radius buffers around all locations that occurred within the boundaries of a fish's home range. I then determined the mean water depth within each buffered fish location using Jenness' (2004b) Surface Tools ArcView GIS extension. I also determined nearest distances of each buffered fish location to the shoreline, to an aquatic vegetation patch greater than 50-m<sup>2</sup> in area (summer only), and to the 0- to 1-m, 1- to 2-m, 2- to 3-m, 3- to 4-m, and 4- to 5-m depth contours using Jenness' (2004c) Nearest Feature ArcView GIS extension. Such distance measures are advantageous in habitat selection studies because they provide insight as to how fish habitat use may be affected by habitat conditions in surrounding areas, rather than solely focusing on habitat conditions at sites where fish are located (Conner and Plowman 2001; Conner et al. 2003). A 10-m radius was selected because that was the maximum error observed in the previous tracking accuracy assessment (Chapter 3; Brenden et al. 2004).

Habitat availability for the micro-level habitat selection assessment was measured by first creating a 10-m × 10-m spatial resolution grid that covered the entire study reach. The centroid for each grid cell was then identified, which I subsequently buffered with a 10-m radius circle. This resulted in a layer of partially-overlapping circular features (availability circles) that covered the entire study reach. For each availability circle, I determined mean water depth and nearest distances to the shoreline, to an aquatic vegetation patch greater than 50-m<sup>2</sup> in area (summer only), and to the 0- to 1-m, 1- to 2-m, 2- to 3-m, 3- to 4-m, and 4- to 5-m depth contours using the same methods that were used to attribute the buffered fish locations. I then clipped the coverage of availability circles to the spatial extent of each fish's 90% kernel home range.

Only a subset of availability circles was included in the actual habitat selection models because of the disparity between the numbers of availability circles and fish location estimates. Availability circles that were included in the habitat selection models were selected randomly. The number of availability

circles selected was the minimum number required to provide 25% surface area coverage of the home range. Thus, if the surface area of a fish's home range equaled 10 ha, the number of availability circles (surface area of each availability circle  $\approx 314 \text{ m}^2$ ) selected was 80.

Habitat selection probability functions (HSPFs; Manly et al. 2002) were created at both macro- and micro-level habitat scales by modeling observed (use = 1) and random (use = 0) locations as functions of the habitat variables measured at the locations. Two different approaches were used to construct the HSPFs. The first approach was to use logistic regression in combination with model averaging to account for uncertainty between candidate models. The second approach was to use generalized additive modeling (GAM; Hastie and Tibshirani 1990) to explore potential nonlinear relationships among the habitat variables and the HSPFs. Generalized additive modeling is a nonparametric (or semi-parametric) regression procedure, which fits non-specific functions between variables using methods such as spline or loess smoothing. Because users do not need to specify a particular model with GAM, it can be a useful modeling method for studies in which there is insufficient information to suggest a certain model structures. One shortcoming of GAM, though, is that since models lack a specific form, comparison between models is difficult and models cannot be averaged together. Rather, some form of a selection process must be used to identify a single model that performs better than other candidate models. In addition, relationships between dependent and independent variables often must be explored graphically, since statistics that describe variable relationships (i.e., coefficient estimates) are not available (Lehmann 1998). Haas et al. (2001) advocated the dual use of model-averaging and GAM as they felt the two methods combined provided a better understanding of variable relationships than if either method was used separately.

For the macro-level habitat selection assessment, winter and summer HSPFs were constructed based on the landscape metrics measured within home ranges and within randomly identified areas. For the micro-scale habitat selection assessment, HSPFs were constructed based on the habitat variables measured at buffered fish locations and at a random selection of availability circles. For the micro-scale assessment, HSPFs were constructed for each individual fish. The logistic regression models that formed the basis for the model averaging were created using PROC LOGISTIC in SAS, but the generalized additive models were created in S-PLUS 2000 using the Generalized Regression and Spatial Prediction

(GRASP) script of Lehmann et al. (2002). All possible variable combinations were used in the model averaging. Akaike's information criterion (AIC) and Akaike weights were calculated for each candidate logistic regression model. The coefficient estimates for the candidate models were then multiplied by the Akaike weights and summed to produce model-average coefficient estimates (Anderson et al. 2000).

For the macro-scale habitat selection assessment, 95% confidence intervals for the model-average coefficient estimates for the HSPFs were developed by bootstrapping. The involved repeated (number of iterations = 1,000) random selection (with replacement) of observations and recalculation of the HSPFs. With each bootstrap iteration, model-average coefficient estimates for the HSPFs were determined based upon the Akaike weights of the candidate models. This resulted in distributions of model-average coefficient estimates for each landscape pattern metric included in the HSPFs. Ninety-five percent confidence intervals for each the model-average coefficient estimates were determined using the percentile method (Manly 1997). For the micro-scale habitat selection assessment, I averaged the coefficient estimates for each habitat variable across the seasonal HSPFs for all fish and calculated 95% confidence intervals for the coefficient estimates based on a student's-*t* distribution (Erickson et al. 2001).

When constructing the generalized additive models, each habitat variable was allowed to enter the models linearly or as a cubic smoothing spline function with four degrees of freedom (degrees of freedom governs how complex of a function can be fit to the data). Stepwise model selection based on AIC minimization was used to identify the "best" GAM model from the pool of candidate models. The results of the GAM assessment for the micro-scale habitat selection assessment were compared graphically across fish to determine whether any consistent nonlinear relationships between habitat variables and HSPFs were present.

#### *Effect of River Discharge on Habitat Use and Selection*

The effect of river discharge on muskellunge habitat use and selection was assessed using two methods. First, I calculated Pearson pairwise correlations between median river discharge for the 12-hr time period before each fish was located and the habitat variables associated with each buffered fish location. Correlations were calculated for each fish individually, but coefficients were averaged across



individuals to help identify consistent relationships. Ninety-five percent confidence intervals for the mean correlation coefficient were estimated based on a student's-*t* distribution. Correlations were calculated separately for locations occurring 1 April to 15 November (summer), and 16 November and 31 March (winter). Correlations were calculated only for those individuals located > 20 times during these time periods.

In addition to correlating discharge measurements with variables associated with used habitats, I combined the muskellunge locations from the radiotelemetry tracking into summer (1 April – 15 November) and winter (16 November – 31 March) location datasets. I then classified the locations based on whether they were made during high or low discharges. For the purpose of this assessment, I identified locations made during low or high discharges as those locations with median river discharges that were either below or above the median ( $\tilde{x} \approx 45 \text{ m}^3/\text{s}$ ) of all discharge estimates (Figure 4.3). Discharge estimates were again based on the 12-hr time period before fish were relocated during the radiotelemetry tracking. I then constructed separate HSPFs for each discharge and season combination using previously described methods (logistic regression in combination with model averaging and generalized additive modeling), except that models were constructed by comparing habitat use among a pooled group of individuals to a census of habitat availability across the entire study area (i.e. Design-I study; Thomas and Taylor 1990). Habitat availability across the entire study area was estimated by randomly selecting 2,419 availability circles from the coverage of overlapping circular features that were used to census habitat availability for the micro-scale habitat selection assessment. This number of availability circles provided a surface area coverage equal to 25% of the total surface area of the entire study reach. Ninety-five percent confidence intervals for the logistic-regression model-average coefficient estimates were developed using a similar bootstrapping procedure to the procedure described for the macro-scale assessment. It involved repeated random selection of muskellunges and recalculation of the HSPFs. With each bootstrap iteration, a different subset of availability circles was randomly selected. Coefficient estimates for the habitat variables included in the HSPFs were set equal to the mean of the bootstrap coefficient estimates. Ninety-five percent confidence intervals for the coefficient estimates were determined using the percentile method (Manly 1997). Generalized additive models were based on a

single random selection of available habitats because of the difficulty in comparing results of large numbers of models.

## RESULTS

The total number of location estimates for each transmitted muskellunge ranged from 3 to 141 ( $\bar{x} \pm 2 \cdot SE = 43 \pm 11$  locations; Table 4.4). The number of elapsed days between date of transmitter implantation and date of last location ranged from 28 to 1,176 days ( $\bar{x} \pm 2 \cdot SE = 423 \pm 90$  days). Enough locations were collected to delineate home ranges and assess winter and summer habitat selection for 12 and 20 fish, respectively. The lengths of fish for which micro-level habitat selection models were created ranged from 682 to 1,020 mm during winter, and 680 to 1,020 mm during summer.

Of the 42 muskellunge initially outfitted with transmitters, 7 fish still had operable transmitters and were located in the study area when tracking was completed (Table 4.4). Of the remaining 35 fish, 7 fish were occupying sites located outside the study reach boundaries, 5 fish were known to have been harvested by anglers, 3 fish had died from either natural, post-surgical, or post angler-release mortality, 1 fish was euthanized after it was recaptured and found to have an infection at the incision site, and the transmitter of 1 fish was believed to have malfunctioned (the transmitter began emitting a continuous signal and shortly thereafter no signal could be detected). The fates of the remaining 18 fish are unknown, although the transmitters of seven of these fish probably powered down given the expected battery life of the transmitters and the number of elapsed days between transmitter implantation and date of last location (Table 4.4).

Based on the hydroacoustic habitat mapping, water depth in the study reach averaged 1.4 m, with a maximum water depth of approximately 8 m. Surface area coverage of aquatic vegetation patches  $> 50 \text{ m}^2$  in area during the summer was estimated at 0.4 ha, which was approximately 3% of the surface area for the entire study reach.

*Macro-Scale Habitat Selection*

Thirty-five of the 53 landscape metrics initially considered for inclusion in the winter macro-level HSPF were rejected because no significant differences in metrics were detected between fish home ranges and randomly delineated areas ( $P$ -value > 0.20; Table 4.5). Six additional variables were excluded because a high proportion (>60%) of the variance of the coefficients was due to multicollinearity with other variables (Table 4.5). Six other variables were excluded because absolute pairwise correlations with other variables exceeded 0.70 (Table 4.5). The six variables that were used to construct the winter macro-level HSPFs were PARA\_MN (mean of the perimeter-area ratio distribution), PLAND01 (percentage of the landscape consisting of water depths ranging from 0 to 1 m), PLAND05 (percentage of the landscape consisting of water depths ranging from 4 to 5 m), SHAPE\_CV (coefficient of variation of the shape index distribution), SHAPE\_MN (mean of the shape index distribution), and SHDI (Shannon's Diversity Index of patch class types within the landscape). The shape index and perimeter-area ratio are measures of patch shape complexity. Both metrics increase as shape complexity increases, meaning that patches with convoluted perimeters will have larger values than a patch with either a perfectly circular or square perimeter. Shannon's Diversity Index measures how a landscape is composed of different patch classes. A landscape composed of only a few patch classes will have a low SHDI, while a landscape composed of many patch classes will have a high SHDI.

The only metric included in the winter habitat selection models that had a negative model-average coefficient estimate was PLAND01 (Table 4.6), which suggests that muskellunge avoided establishing home ranges in predominantly shallow areas (water depth < 1-m deep). Conversely, the model-average coefficient for PLAND05 was positive, meaning that muskellunge home ranges contained higher proportions of areas 4- to 5-m deep than did randomly identified areas. The model-average coefficient estimates for PARA\_MN, SHAPE\_CV, and SHAPE\_MN all were positive as well, suggesting that muskellunge established home ranges in areas of higher and more diverse complexities of patch shape than what might have been expected if fish used areas randomly. The model-average coefficient estimate for SHDI also was positive, suggesting that muskellunge positively selected areas composed of a greater of diversity of patch classes. Since patch classes for winter were defined exclusively by depth, this means that muskellunge positively selected areas that consisted of a wide range of water depths.

However, it should be noted that the only 95% confidence interval for the model-average coefficient estimates that did not encompass zero was the confidence interval calculated for SHAPE\_MN (Table 4.6). The observation that the 95% confidence intervals for the model-average coefficients for the other metrics did encompass zero raises a question as to the statistical significance of the model-average coefficient estimates.

For the winter macro-level GAM assessment, the GAM model with the lowest AIC was comprised of nonlinear functions of PARA\_MN, SHAPE\_CV, and SHDI. The mean of the shape index distribution as a linear function also was contained in the model with the lowest AIC. The relationships between the HSPF and the PARA\_MN, SHAPE\_MN, and SHDI metrics were primarily increasing functions (Figure 4.4); thus, the GAM results supported the model-averaging results. The relationship between the HSPF and SHAPE\_CV was highly curvilinear (Figure 4.4), and suggested no obvious relationship between probability of habitat use and this landscape metric. Of the variables that composed the AIC-selected model, PARA\_MN and SHAPE\_MN had the highest marginal contributions to the final model. Dropping PARA\_MN from the AIC-selected model would have increased the deviance (i.e., worsened model fit) by approximately 66%, while dropping SHAPE\_MN would have increased the deviance by 46%. In comparison, dropping SHAPE\_CV or SHDI would have increased the deviance by 33 and 24%, respectively. The approximate  $r^2$  for the AIC-selected model was 60.5%.

Fifty-two of the 61 landscape metrics initially considered for inclusion in the summer macro-level HSPF were rejected because of insignificant ( $P$ -value > 0.20)  $t$ -tests (Table 4.5). Four additional variables were excluded because absolute pairwise correlations with other variables exceeded 0.70 (Table 4.5). The five variables that were included in the summer macro-level HSPF were ED10 (total edge density created by vegetated areas with water depths ranging from 1 to 2 m), PARA\_RA (range of the perimeter-area ratio distribution), PLAND11 (percentage of the landscape consisting of vegetated areas with water depths ranging from 2 to 3 m), PLAND12 (percentage of the landscape consisting of vegetated areas with water depths ranging from 3 to 4 m), and SHAPE\_MD (median of the shape index distribution). Edge density is a measure of the total density of edge for a particular patch class within a landscape. Edge density increases as the proportion of a landscape consisting of a particular patch class increase and as the complexity of patch class shapes increase.

For the summer macro-level habitat selection assessment, PLAND11, and PLAND12 had model-average coefficient estimates that were negative (Table 4.6), meaning that the proportion of muskellunge home ranges that consisted of vegetated areas ranging in depth from 2 to 4 m was less than what was measured for randomly delineated areas. The coefficient for ED10 also was negative (Table 4.6), meaning that muskellunge home ranges had lower densities of edge created by vegetated areas ranging in depth from 1 to 2 m. The model-average coefficient estimates for SHAPE\_MD and PARA\_RA were positive, thus muskellunge established home ranges with higher and more diverse complexities of patch shape. Only the 95% confidence intervals for the model-average coefficient estimates for ED10, PARA\_RA, and PLAND11 did not encompass zero, which again raises a question as to the statistical significance of the coefficient estimates for the other landscape pattern and composition metrics.

Generalized additive modeling failed to identify any nonlinear relationships between the summer macro-level HSPF and the landscape metrics included in the model. The model with the lowest AIC consisted of ED10, PARA\_RA, and PLAND11 as linear functions. Both ED10 and PLAND11 had negative relationships with the HSPF, while PARA\_RA had a positive relationship (Figure 4.5). Overall, the GAM summer macro-level habitat selection model with the lowest AIC provided a poor fit (approximate  $r^2 = 12.4\%$ ) to the observed data. In terms of marginal contributions of the variables, dropping each term was found to increase model deviance by approximately 50%.

#### *Micro-Scale Habitat Selection*

For the winter micro-level habitat selection assessment, muskellunge exhibited a significant positive selection for mean depth (mean model-average coefficient  $\pm$  95% confidence interval =  $0.53 \pm 0.32$ ). For all other habitat variables that were included in the HSPFs, the 95% confidence intervals calculated for the mean model-average coefficient estimates encompassed zero, meaning that use of was approximately equal to availability (Table 4.7). For each habitat variable that was included in the HSPF, I plotted model-average coefficient estimates versus fish length (at time of transmitter implantation) to determine whether fish ontogeny (length used as a surrogate for age) possibly affected selection of the habitat variables. These plots indicated that selection for some of the habitat variables

possibly did differ with fish ontogeny (Figure 4.6). Smaller muskellunge (< 850 mm) avoided areas located near water depths ranging from 0 to 1 m, while larger muskellunge positively selected such habitats (Figure 4.6). Larger muskellunge (>850 mm) were found to avoid areas located near water depths ranging from 1 to 2 m, while smaller muskellunge positively selected such habitats.

Generalized additive modeling of the winter HSPFs indicated that the habitat variables included in the selected models yielded poor overall fits to the observed data. Approximate  $r^2$ 's for the winter HSPFs constructed for the telemetered fish ranged from 18.5 to 63.4% (average = 37.5%). Mean depth, distance to the shoreline, and distances to the 1- to 2-m and 4- to 5-m depth contours were the only habitat variables that occurred in the AIC-selected models for at least two-thirds of the muskellunge for which winter HSPFs were constructed. Only mean depth and distance to the 1- to 2-m depth contour displayed any consistent selection pattern when compared across fish (see Appendix 5 for response curves for those habitat variables without consistent selection patterns across fish). Comparisons of GAM response curves indicated that probability of habitat use generally increased with mean depth, although probabilities did level-off or decline when mean depth exceeded 4 m for a few fish (Figure 4.7). Probability of habitat use generally declined with increasing distances from the 1- to 2-m depth contour, although this was not the case for all fish (Figure 4.8).

For the summer micro-level habitat selection assessment, mean depth was the only habitat variable with a 95% confidence interval for the mean model-average coefficient estimate that did not encompass zero (Table 4.7). As in winter, the mean model-average coefficient estimate for mean depth was positive (mean model-average coefficient  $\pm$  95% confidence interval =  $0.84 \pm 0.35$ ), meaning that muskellunge positively selected habitats consisting of deeper water. The mean model-average coefficient estimate for mean depth was higher during the summer than in winter; thus, muskellunge selection for deeper areas may be stronger during the summer than in winter. Plots of the model-average coefficient estimates versus fish length for the summer HSPFs again indicated that selection of some habitats variables changed with fish ontogeny. Larger muskellunge exhibited stronger selection for deeper water than smaller fish (Figure 4.9). Larger muskellunge also appeared to select against habitats located close to areas with water depths ranging from 0 to 1 m, while smaller muskellunge positively selected such habitats (Figure 4.9).

As in winter, the GAM approach to fitting the summer HSPFs indicated that the habitat variables did not provide good fits to probability of habitat use for individual muskellunge. Approximate  $r^2$  for AIC-selected models for individual muskellunge ranged from 28 to 63% (average = 38.6%). Mean depth, nearest distance to an aquatic vegetation patch greater than 50 m<sup>2</sup>, and nearest distance to the 4- to 5-m depth contour occurred in the AIC-selected models for at least two-thirds of the telemetered muskellunge. Mean depth was the only habitat variable with any consistent relationship with probability of habitat use when compared across all telemetered fish (see Appendix 5 for response function plots for those habitat variables without consistent selection patterns across fish). Probability of habitat use was generally an increasing function of mean depth for most telemetered muskellunge, although probabilities did level-off or decline somewhat for some fish when water depth exceeded 2 to 3 m (Figure 4.10).

#### *Effect of River Discharge on Habitat Use and Selection*

Sufficient numbers of locations were collected to correlate habitat and river discharge measurements for 15 and 20 fish for winter and summer, respectively. For winter, median river discharge for the 12-hr period before fish were located was significantly related to all habitat variables (Table 4.8). Mean depth and nearest distances to the shoreline and to the 0- to 1-m and 1- to 2-m depth contours had negative relationships with river discharge, while nearest distances to the 2- to 3-m, 3- to 4-m, and 4- to 5-m depth contours had positive relationships. These results suggest that transmitted muskellunge avoided deeper water and moved to shallower areas located closer to the shoreline with increased river discharge. For summer, all habitat variables except nearest distance to an aquatic vegetation patch greater than 50-m<sup>2</sup> in area were significantly related to river discharge (Table 4.8). Summer relationships between river discharge and used habitat variables were similar in direction to those found in winter. However, the winter correlations generally were higher in magnitude than the summer correlations, suggesting that muskellunge habitat use during the winter is more strongly affected by discharge changes than during the summer.

Comparisons of the model-average coefficients for the winter habitat selection probability functions indicated that muskellunge exhibited a stronger positive selection for mean depth during low discharges than during high discharges (Figure 4.11). There were substantial overlaps in the 95%

confidence intervals for the HSPF model-average coefficient estimates for the remaining habitat variables, suggesting no significant differences in habitat selection for high and low discharges.

Generalized additive modeling of the winter HSFPs for low and high discharges indicated remarkably similar selection patterns for habitat variables (Figure 4.12). Slight differences were evident in the HSPF response curves for mean depth and distances to the shoreline and to the 4- to 5-m depth contours. Specifically, probability of habitat use for areas deeper than 3 m declined during high discharges, while probability of use leveled off during low discharges (Figure 4.12). Probability of habitat use also appeared higher for areas located closer to the shoreline during high discharges than during low discharges (Figure 4.12), suggesting that muskellunge may seek refuge from higher water velocities by moving closer to the shoreline. For nearest distance to the 4- to 5-m depth contour, probability of habitat use generally declined of 0 to 750 m for both low and high discharges, but probability of use increased for distances greater than 750 m during high discharges (Figure 4.12), which may again be linked to fish seeking refuge from higher water velocities.

Summer comparisons of the model-average coefficients for the habitat selection probability functions calculated during both low and high discharges yielded similar results to those for winter. Mean depth again was the only habitat variable for which selection differed between low and high discharges (Figure 4.13). Ninety-five percent confidence intervals for the mean coefficient estimates for all other habitat variables overlapped substantially. Generalized additive modeling response curves for low and high discharges also were quite similar for many of the habitat variables (Figure 4.14). As was observed in the winter assessment, probability of habitat use declined for deeper areas during higher discharge relative to the probability observed low discharges, thus suggesting that muskellunge may seek shallower areas during higher discharges (Figure 4.14). The habitat variable with the largest difference in response curves was nearest distance to an aquatic vegetation patch greater than 50 m<sup>2</sup>. During low discharges, probability of habitat use in areas located closer than 150 m to aquatic vegetation patches was highest, but probability of use declined for areas located more than 150 m from such patches (Figure 4.14). During high discharges, probability of habitat use increased as distance from aquatic vegetation patches increased (Figure 4.13).



## DISCUSSION

Native muskellunge populations historically have extended as far south as Alabama, North Carolina, and Tennessee (Crossman 1978). Many of these native southern populations are believed to have been extirpated as a result of chemical pollution and habitat degradation (Parsons 1959; Monaghan and Borawa 1988). Considering that preserving and protecting native muskellunge stocks is a management goal of many fishery management agencies (Hanson et al. 1986), knowledge of muskellunge habitat requirements is critical for maintaining existing populations or re-establishing the species in areas of historical occurrence. Results of this research thus help fill a critical information gap and provide biologists with a method for evaluating sites in terms of habitat suitability and availability.

This research indicates that muskellunge select areas in which to establish home ranges partially based on complexity of habitat patch shape. Measures of patch shape complexity (i.e., mean and median of the shape index distribution, mean and range of the perimeter-area ratio distribution) were the only landscape pattern metrics consistently related to probability of use for the macro-level habitat selection assessment during both summer and winter. Understanding why muskellunge would choose areas with greater complexities of patch shape is difficult to assess at this stage without conducting additional confirmatory research; however, some hypothesis formulation is possible. Muskellunge positive selection for patch shape complexity possibly is related to feeding strategy. The muskellunge is an ambush predator that relies jointly on its lateral line and visual sensory systems when feeding (Webb and Skadsden 1980; New et al. 2001). Vision is the primary sensory system used by muskellunge in orientating towards and in initial pursuit of prey (New et al. 2001). Greater patch shape complexity may afford muskellunge more areas in which to hide and ambush prey. Patch shape complexity might not be beneficial to feeding if muskellunge relied on its lateral line sensory system for orientation and initial prey pursuit, as hiding in recessed areas might affect its lateralis sensory capabilities. Areas with greater patch shape complexity also may result in increased prey densities, which might be an alternative reason why muskellunge select such areas when establishing home ranges.

Other landscape pattern and composition metrics that had predictive value for where muskellunge establish home ranges were patch class diversity, the percentage of the landscape consisting of water 0 to 1-m deep, and the percentage of landscape consisting of vegetated areas ranging

in depth from 2 to 4 m. A positive relationship between patch class diversity and establishment of muskellunge home ranges during the winter was observed in this research, which might be explained in a similar manner to patch shape complexity. A greater diversity of patch classes may provide more areas from which muskellunge can ambush prey. The negative relationship between the percentage of the landscape consisting of areas 0 to 1-m deep and probability of habitat use also indicates that muskellunge may avoid shallow areas. Occupying shallow water may be risky behavior for muskellunge, as such environments may not afford suitable cover for muskellunge to either ambush prey or to hide from their own potential predators. Although the statistical significance of these metrics was generally low, it may be worthwhile for future investigations to consider these variables in order to help clarify their potential influence on muskellunge habitat use.

At a micro-level scale, water depth was the major habitat variable affecting muskellunge habitat use during both winter and summer. In stream fish, there is general tendency for large individuals to occupy deeper water (Power 1987; Harvey and Stewart 1991; Mäki-Petäys et al. 1997); thus, the relationship between habitat use and water depth should have been expected. There also was some evidence to suggest that muskellunge may have occupied sites based on their juxtaposition to deeper water habitats. Even though the statistical significance of selection patterns for habitat variables such as distances to the 1-m to 2-m and 2- to 3-m depth contours were low, similar directions of coefficient estimates during summer and winter suggest that deeper water may serve as a primary or core habitat from which fish activities (e.g., foraging) radiate. The fact that muskellunge exhibited a stronger selection for deeper water during the summer further suggests that muskellunge have a higher affinity for such core habitats than in winter and that there may be temperature issues concerning the use of summer core habitats.

One unexpected result of this research was the apparent lack of selection for vegetated areas. Selection for vegetated habitats has been commonly reported in most muskellunge habitat studies (Minor and Crossman 1978; Miller and Menzel 1986), and it seemed reasonable to assume that this relationship also would hold for southern warmwater rivers. However, only a few telemetered muskellunge in this study positively selected vegetated habitats. Macro-level habitat selection assessment even suggested that fish avoided areas with high densities of aquatic vegetation. There are several factors that possibly

contributed to this unexpected result. First, occupying vegetated areas in rivers may convey less energetic advantage than in lakes. Aquatic vegetation is believed to be important to esocids at all life stages, but for different reasons (Bry 1996). For young fish, vegetation provides cover from predators and attracts prey. For older fish, vegetation can serve as spawning substrate and as cover from which to ambush prey (Casselman 1996). In rivers, greater complexities of bathymetric structure may provide sufficient areas of cover, thus freeing muskellunge to use unvegetated areas with greater frequency. Further, prey items may distribute themselves with regard to current and structures affording refuge from current to a greater degree than that of aquatic vegetation.

Another factor that may explain why muskellunge did not select vegetated areas in this study was because of the scale at which this research was conducted. Although the terms “micro-level” and “macro-level” were used repeatedly throughout this manuscript, these terms as descriptors of the spatial scale at which this research was conducted may be misleading. For a riverine species, a true “macro-level” analysis of habitat selection would focus on comparisons of streams or reaches in which the species occurred relative to the streams or reaches in which the species did not occur. Conversely, a true “micro-level” analysis of habitat selection would concentrate more on focal site comparisons, such as habitat use in relation to individual log jams. In contrast to those scales, this research was conducted at more of a meso-level spatial scale. Selection either for or against aquatic vegetation was based on distance of muskellunge locations to aquatic vegetation patches greater than 50 m<sup>2</sup> in area. My reason for using this approach centered on the potential error associated with location estimates. Previous research indicated that fish location estimates could deviate by as much as 10 m from actual location (Chapter 3; Brenden et al. 2004). This error limited my ability to determine with any degree of confidence whether a fish was using an isolated vegetation patch. In addition, I did not believe that the resolution of the hydroacoustic sampling was sufficiently detailed to be capable of delineating all vegetated patches. As a result, I chose to use aquatic vegetation patches greater than 50 m<sup>2</sup> in area as the smallest level of detail for this variable. While this research indicated that muskellunge did not select such vegetated areas, it still is possible that muskellunge positively select aquatic vegetation, just at a smaller scale than that at which this research was conducted. A research study directed towards evaluating “micro-level” habitat selection by muskellunge in warmwater rivers would help clarify this issue concerning aquatic vegetation; however,

I would not recommend that such a study be based on telemetric tracking for the reasons mentioned above concerning accuracy. Instead, it might prove more useful for research to be based on underwater observations of muskellunge in relation to vegetated areas (Dolloff et al. 1996).

Fit of most habitat selection models in this research was poor, suggesting that muskellunge habitat selection in warmwater rivers is governed by factors not considered in this research. One habitat variable that previous research has identified as being important to muskellunge habitat selection and which may have helped improve model fit was type of substrate. Muskellunge spawning occurs over silt, sand, or organic detritus substrates (Dombeck et al. 1984; Strand 1986; LaPan et al. 1996), and recently hatched and young-of-the-year muskellunge also have been associated with sandy substrate (Craig and Black 1986; Hanson and Margenau 1992). My inability to include substrate in this research possibly stemmed from where transects were established when creating the reference database for classifying substrate type. Most of the sampling transects used to create the reference database were in areas where water depth exceeded 2 m. However, nearly 60% of the study area had a water depth less than 2 m. If the digital echo characteristics used to create the reference substrate type database were affected by water depth, then the classification of newly-sampled data would have involved some extrapolation of the reference database and possibly led to classification errors. For example, the digital echo characteristics for one substrate type (e.g., gravel/cobble) collected along a reference transect at one depth may overlap with the digital echo characteristics for another substrate type (e.g., bedrock) at another water depth, which would result in some confusion as to what the actual substrate type is. Such a scenario seems the most probable explanation given the differences in accuracy between cross-validation accuracy for the reference database (> 86%) and accuracy estimates for newly sampled areas (38%).

The problems that I encountered in creating a substrate type map should serve as a warning for those wishing to create similar maps in rivers. In particular, I suggest that the reference database from which unknown areas will be classified be created using the widest possible range of environmental conditions. This will help assure that substrate-type classification will be based on interpolation rather than extrapolation. My difficulty in creating an accurate substrate-type map also illustrates the importance of verifying delineated habitat maps with independent datasets. If an independent dataset had not been

used to ground-truth map accuracy, then an error-prone map would have been used to explore how muskellunge habitat use was affected by substrate type, which may have resulted in errors that propagated through the scientific literature. For a scientific assessment to be credible, accuracy of delineated maps must be verified (Stehman and Czaplewski 2003).

My findings regarding the effect of river discharge on use of habitat variables suggests that incorporation of river discharge in the habitat selection probability functions also would have helped improve model fit. For most individual muskellunge, I lacked sufficient numbers of observations to calculate separate selection models based on river discharge, thus the only way that I could incorporate discharge into the models was by pooling observations across all fish. This pooling of observations is disadvantageous because it limits inference to the radio-marked sample of fish (Erickson et al. 2001). The type of sampling protocol used in this research (an independent sampling of use and available habitats) also limited my options for incorporating discharge within models. This study was based on an independent sampling of available and used habitats (Manly et al. 2002). Although discharge measurements could have been included in habitat selection models as covariates, no similar measurements could have been included for available habitats. One possible option would have been to generate random discharge measurements for available habitats based on a statistical model that described the probability distribution for measured discharge. Ultimately, I believed this would be too artificial and would raise questions regarding the meaningfulness of study results. The best option for including discharge measurements in habitat selection models would be to use a sampling protocol in which used and unused habitats are identified and sampled or to assure that enough locations are collected at both high and low discharges so that model coefficients can be contrasted.

Other possible explanations for the overall poor fit of the habitat selection models include biased home range estimation and the possibility that habitat use is affected by muskellunge territoriality or social hierarchy. Univariate kernel estimation of home ranges was used in this research because of the inability of bivariate kernel estimators to adequately deal with stream boundaries. When fish home ranges are delineated with a bivariate kernel estimator, home range boundaries often encompass terrestrial areas (Vokoun 2003). Although home ranges can be clipped in a GIS so that water-land boundaries are recognized, this seems an inadequate fix to the problem. Kernel density estimation fits probability density

distributions around individual data points. When a data point is located near a barrier, the mass that would otherwise cross the barrier should be allocated elsewhere. This would result in a probability density distribution that was shifted away from the barrier. From a home range delineation perspective, this would result in longer home ranges that were shifted away from barriers. Because no bivariate kernel home range applications can adequately deal with land-water barriers, Vokoun (2003) developed a univariate kernel home range estimator for use in rivers and streams. Despite its advantages over bivariate kernel density estimation, univariate kernel density estimation may be problematic for identifying habitat availability or use as it could bias estimation by including regions within home ranges that fish may rarely use, particularly when habitats differ laterally across streams. Development of a bivariate kernel home range estimator that is able to adequately deal with stream-land boundaries would be beneficial for studying habitat selection in stream fishes because it would prevent such biases from occurring.

Neither territoriality nor a social hierarchy in muskellunge has been reported in the scientific literature. However, both affect habitat use in salmonids. Harwood et al. (2001, 2002) found that territorial behavior in Atlantic salmon (*Salmo salar*) and brown trout (*Salmo trutta*) affected use of both refugia habitat and deep-water slow-flowing habitat in winter. Arctic grayling (*Thymallus arcticus*) also occupy habitats based upon individual social dominance (Hughes 1992a, Hughes 1992b). If muskellunge are indeed territorial or have a social hierarchy, sub-dominant individuals may be forced into areas where habitat conditions are less than optimal, which would increase variability of results in habitat use and selection research. Overcrowding of muskellunge leading to high levels of agonistic interactions between individuals may be more likely to occur in systems that are stocked, particularly if stocking rates do not match resource availability.

Although few nonlinear relationships between habitat variables and habitat use were detected in this research, I agree with Haas et al. (2001) that the combination of model averaging and generalized additive modeling provides the most insight into variable relationships. Model averaging permits the results from competing models to be joined; thus, modelers do not need to be concerned about excluding models that perform only marginally less well than the selected model. Rather, model averaging allows coefficient estimates from several models to be combined and thus provides the most complete information regarding all candidate variables. Generalized additive modeling provides a convenient

method for initially exploring whether non-linear relationships between variables exist, thus freeing users from the limiting assumption of linearity between variables (Trexler and Travis 1993). Additionally, users do not need to specify a specific functional form for the variable relationships, which can be difficult to do for even well-studied variables. Generalized additive modeling is a fairly recent statistical development (Hastie and Tibshirani 1990), but has already received some use in ecological studies (Forney 2000; Haas et al. 2001; Brosse and Lek 2002). I anticipate that GAM will become more routinely applied in the ecological sciences as its theoretical development continues to include other modeling aspects that ecologists find useful, including model averaging (Anderson et al. 2000) and autocorrelative (spatial or temporal) error structures (Legendre 1993, Lichstein 2002).

The impetus for this research was to fill an information gap regarding muskellunge habitat use and selection in southern warmwater rivers. To this end, patch shape complexity and water depth appear to be the most important habitat variables governing muskellunge habitat use in these systems. River discharge also appears to play a strong mediating role in habitat use and selection, with muskellunge abandoning deeper areas with higher discharges. When either identifying or prioritizing areas in warmwater rivers in which muskellunge will be stocked, biologists should look for areas with juxtaposed patches of shallow and deep water habitats. Even though muskellunge may rarely be found in shallow water, it may offer refuge from increased water velocities. Additionally, shallow water may be important habitat for earlier ontogenetic stages of muskellunge or for items upon which muskellunge feed. Areas consisting exclusively of either shallow or deep-water habitat should not be considered prime areas in which to introduce muskellunge.

Table 4.1. Cross-validation classification accuracies for identifying substrate type with the reference hydroacoustic database via canonical discriminant analysis. Cells along the diagonal are the percent of substrate types correctly identified, while the off-diagonal values are the percent of habitat types incorrectly classified.

True Substrate type	<u>Classified Substrate type</u>		
	Bedrock	Gravel/Cobble	Sand/Mud
Bedrock	86.4%	13.6%	0%
Gravel/Cobble	0.0%	90.2%	9.8%
Sand/Mud	0.4%	13.4%	86.2%



Table 4.2. Description of habitat components for each of the patch classes used in the macro-level habitat selection assessment.

Patch Class	Winter	Summer
1	Depth – 0 to 1 m	Depth – 0 to 1 m, Unvegetated
2	Depth – 1 to 2 m	Depth – 1 to 2 m, Unvegetated
3	Depth – 2 to 3 m	Depth – 2 to 3 m, Unvegetated
4	Depth – 3 to 4 m	Depth – 3 to 4 m, Unvegetated
5	Depth – 4 to 5 m	Depth – 4 to 5 m, Unvegetated
6	Depth – 5 to 6 m	Depth – 5 to 6 m, Unvegetated
7	Depth – 6 to 7 m	Depth – 6 to 7 m, Unvegetated
8	Depth – 7 to 8 m	Depth – 7 to 8 m, Unvegetated
9	-	Depth – 0 to 1 m, Vegetated
10	-	Depth – 1 to 2 m, Vegetated
11	-	Depth – 2 to 3 m, Vegetated
12	-	Depth – 3 to 4 m, Vegetated

Table 4.3. Landscape pattern and composition metrics included in the macro-level habitat selection assessment for muskellunge in the New River and a brief description of each metric.

Variable	Description
<b>Landscape-Level Metrics</b>	
AI	Aggregation Index – measures the ratio of observed number of patch adjacencies to the expected number of patch adjacencies
COHESION	Patch Cohesion Index – measures habitat connectivity within a landscape
CONTAG	Contagion – measures the probability of two adjacent cells being of different patch types
CONTIG <sup>†</sup>	Contiguity Index – measures the spatial connectedness of grid cells within a grid cell patch
DIVISION	Landscape Division Index – measures the probability of randomly placing two objects within the same patch within a landscape
ED	Edge Density – measures total edge density within a landscape
FRAC <sup>†</sup>	Fractal Dimension Index – measures patch shape complexity based on the ratio of the logarithm of patch perimeter and the logarithm of patch area (m <sup>2</sup> )
IJI	Interspersion and Juxtaposition Index – measures the extent to which patch types are interspersed
LPI	Largest Patch Index – measures the percent of a landscape that consists of the largest patch
LSI	Landscape Shape Index – measures the perimeter-area ratio for the landscape as a whole
PARA <sup>†</sup>	Perimeter-Area Ratio – ratio of perimeter distance to total area
PD	Patch Density – measures total patch density within a landscape
PLADJ	Percentage of Like Adjacencies – measures patch contagion as a function of the sum of the diagonal elements of the matrix of pairwise adjacencies divided by the total number of adjacencies
PRD	Patch Richness Density – measures patch richness on a per area basis
SHAPE <sup>†</sup>	Shape Index – measures the complexity of patch shape relative to a perfect or near-perfect square
SHDI	Shannon's Diversity Index – measures patch diversity within a landscape
SIDI	Simpson's Diversity Index – measures patch diversity within a landscape
<b>Class-Level Metrics</b>	
ED <sup>‡</sup>	Edge Density – measures the density of edge in the landscape created by the different patch classes
PLAND <sup>‡</sup>	Percentage of Landscape – measures the percentage of the landscape that consists of the various patch classes

† - Metric was summarized using the following statistics: area-weighted mean (AM), coefficient of variation (CV), median (MD), mean (MN), range(RA), and standard deviation (SD)

‡ - Measured for each patch class (Table 4.2)

Table 4.4. Information concerning the 42 muskellunge implanted with radiotelemetry transmitters and the duration that tracking was conducted.

ID	Length	Weight	Method of Capture	Date Implanted	Date Final Location	Total Number Locations	Elapsed Days	Fate of Fish
48.061 <sup>‡</sup>	905	5,600	Electrofishing	28-Nov-2000	28-Jun-2002	77	577	Harvested
48.101	1,050	9,020	Electrofishing	16-Apr-2001	26-Apr-2002	3	375	Left Study Area
48.111 <sup>†</sup>	1,006	8,700	Electrofishing	11-Apr-2001	4-Oct-2002	70	541	Unknown <sup>a</sup>
48.121 <sup>‡</sup>	725	2,900	Electrofishing	18-Dec-2000	17-Oct-2002	88	668	Unknown <sup>a</sup>
48.311	1,035	8,750	Electrofishing	28-Mar-2001	31-Aug-2001	14	156	Harvested
48.321a	1,143	11,566	Electrofishing	21-Feb-2000	11-May-2000	10	80	Harvested
48.321b <sup>†</sup>	985	6,250	Electrofishing	30-Apr-2002	11-Jun-2003	50	407	Study Ended
48.341 <sup>‡</sup>	880	4,800	Electrofishing	21-Feb-2000	19-Apr-2002	88	788	Unknown
48.381 <sup>‡</sup>	965	6,100	Electrofishing	22-Mar-2000	11-Jun-2003	141	1,176	Study Ended
48.391 <sup>‡</sup>	838	3,200	Angling	25-Feb-2000	13-Jun-2002	101	839	Unknown <sup>a</sup>
48.401 <sup>†</sup>	810	3,300	Electrofishing	22-Mar-2000	03-May-2002	51	772	Unknown <sup>a</sup>
48.411 <sup>‡</sup>	780	2,770	Electrofishing	16-Feb-2000	04-Sep-2002	100	931	Unknown <sup>a</sup>
48.431	1,000	7,850	Electrofishing	22-Mar-2000	11-May-2000	8	50	Unknown
48.451 <sup>‡</sup>	1,020	7,600	Electrofishing	15-Mar-2000	24-May-2000	92	70	Unknown
48.461	796	3,100	Electrofishing	22-Mar-2000	13-Sep-2000	14	175	Unknown
48.571 <sup>‡</sup>	730	2,500	Electrofishing	19-Mar-2001	11-Jun-2003	101	814	Study Ended
48.631a	1,000	8,400	Electrofishing	12-Mar-2001	13-Apr-2001	5	32	Euthanized
48.631b <sup>†</sup>	680	2,000	Electrofishing	16-Jan-2002	21-Nov-2002	39	309	Unknown
48.651	715	2,450	Electrofishing	29-Nov-2000	30-Mar-2001	17	121	Unknown
48.671	655	1,620	Electrofishing	28-Nov-2000	13-Jul-2001	29	227	Unknown
48.691	720	2,400	Electrofishing	22-Jan-2001	13-Jul-2001	20	172	Unknown
48.711	706	2,300	Electrofishing	18-Dec-2000	24-May-2001	21	157	Unknown
48.734 <sup>‡</sup>	682	2,000	Electrofishing	26-Feb-2001	22-Apr-2003	55	785	Left Study Area
48.751	965	6,150	Electrofishing	18-Dec-2000	22-May-2003	15	885	Left Study Area

Table 4.4. Continued

ID	Length	Weight	Method of Capture	Date Implanted	Date Final Location	Total Number Locations	Elapsed Days	Fate
48.774	1,025	9,100	Electrofishing	25-Apr-2001	14-Mar-2003	3	688	Left Study Area
48.814	962	6,400	Electrofishing	11-Apr-2001	10-Aug-2001	15	121	Mortality
48.835	1,256	15,710	Electrofishing	14-Apr-2001	21-Jun-2001	15	68	Harvested
48.855	1,150	13,000	Electrofishing	17-Jan-2001	28-Feb-2002	30	407	Harvested
49.115	826	3,625	Electrofishing	03-Apr-2002	11-Jun-2003	19	434	Left Study Area
49.125a	785	3,250	Angling	16-Jan-2002	05-Apr-2002	10	79	Mortality
49.125b	674	1,950	Electrofishing	2-May-2002	13-Mar-2003	3	315	Unknown
49.135	892	4,300	Angling	17-Jan-2002	26-Feb-2003	27	405	Unknown
49.145	948	5,300	Electrofishing	24-Jan-2002	11-Jun-2003	9	503	Left Study Area
49.155 <sup>‡</sup>	852	4,100	Angling	16-Jan-2002	11-Jun-2003	60	511	Study Ended
49.165 <sup>‡</sup>	884	5,100	Angling	16-Jan-2002	11-Jun-2003	56	511	Study Ended
49.175 <sup>†</sup>	834	4,000	Electrofishing	25-Jan-2002	11-Jun-2003	65	502	Study Ended
49.185 <sup>‡</sup>	847	4,000	Electrofishing	25-Jan-2002	11-Jun-2003	64	502	Study Ended
49.195 <sup>†</sup>	846	3,900	Electrofishing	29-Jan-2002	28-Mar-2003	53	423	Left Study Area
49.211	1,050	9,500	Electrofishing	25-Jan-2002	22-Feb-2002	5	28	Trans. Malfunction
49.231	848	4,500	Angling	17-Jan-2002	02-Aug-2002	28	197	Mortality
49.441 <sup>†</sup>	897	4,600	Electrofishing	18-Apr-2001	25-Jul-2002	62	463	Unknown <sup>a</sup>
49.471 <sup>†</sup>	744	3,000	Electrofishing	22-Jan-2001	28-Jun-2002	70	522	Unknown <sup>a</sup>

<sup>a</sup> Transmitter believed to have powered down.

<sup>†</sup> Summer habitat selection modeled.

<sup>‡</sup> Winter and summer habitat selection modeled.

Table 4.5. Test statistics (*t*-stat.) and *P*-values (winter df = 11, summer df = 19) from the initial tests for differences between landscape pattern and composition metrics defined within muskellunge home ranges and within randomly identified areas for the summer and winter macro-level habitat selection assessment.

Variable	Winter		Summer	
	<i>t</i> -stat.	<i>P</i> -val.	<i>t</i> -stat.	<i>P</i> -val.
<b>Landscape-Level Metrics</b>				
AI	0.78	0.451 <sup>†</sup>	-0.46	0.652 <sup>†</sup>
COHESION	0.59	0.564 <sup>†</sup>	-0.47	0.641 <sup>†</sup>
CONTAG	0.59	0.565 <sup>†</sup>	0.36	0.720 <sup>†</sup>
CONTIG_AM	0.69	0.502 <sup>†</sup>	-0.50	0.623 <sup>†</sup>
CONTIG_CV	-1.63	0.131 <sup>ψ</sup>	-0.28	0.781 <sup>†</sup>
CONTIG_MD	0.05	0.960 <sup>†</sup>	-0.33	0.742 <sup>†</sup>
CONTIG_MN	2.05	0.065 <sup>‡</sup>	0.17	0.866 <sup>†</sup>
CONTIG_RA	-2.85	0.016 <sup>‡</sup>	-2.99	0.008 <sup>ψ</sup>
CONTIG_SD	-1.62	0.133 <sup>‡</sup>	-0.19	0.854 <sup>†</sup>
DIVISION	-0.98	0.350 <sup>†</sup>	-0.81	0.426 <sup>†</sup>
ED	-0.65	0.529 <sup>†</sup>	0.12	0.908 <sup>†</sup>
FRAC_AM	-0.77	0.456 <sup>†</sup>	-0.34	0.735 <sup>†</sup>
FRAC_CV	-1.13	0.284 <sup>†</sup>	-1.17	0.255 <sup>†</sup>
FRAC_MD	-1.32	0.214 <sup>†</sup>	-1.06	0.301 <sup>†</sup>
FRAC_MN	-1.15	0.273 <sup>†</sup>	-1.17	0.255 <sup>†</sup>
FRAC_RA	-0.99	0.343 <sup>†</sup>	-1.15	0.263 <sup>†</sup>
FRAC_SD	-1.15	0.274 <sup>†</sup>	-1.20	0.247 <sup>†</sup>
IJI	-0.41	0.692 <sup>†</sup>	0.37	0.719 <sup>†</sup>
LPI	1.13	0.284 <sup>†</sup>	1.08	0.292 <sup>†</sup>
LSI	-1.22	0.247 <sup>†</sup>	0.26	0.797 <sup>†</sup>
PARA_AM	-0.79	0.448 <sup>†</sup>	0.42	0.679 <sup>†</sup>
PARA_CV	-0.37	0.722 <sup>†</sup>	-0.04	0.971 <sup>†</sup>
PARA_MD	-0.85	0.412 <sup>†</sup>	0.41	0.684 <sup>†</sup>
PARA_MN	-1.99	0.072	-0.24	0.812 <sup>†</sup>
PARA_RA	-2.92	0.014 <sup>ψ</sup>	-2.47	0.023
PARA_SD	-1.44	0.177 <sup>‡</sup>	-0.23	0.817 <sup>†</sup>
PD	-0.59	0.570 <sup>†</sup>	0.60	0.554 <sup>†</sup>
PLADJ	0.79	0.448 <sup>†</sup>	-0.42	0.679 <sup>†</sup>
PRD	-0.55	0.592 <sup>†</sup>	-0.05	0.957 <sup>†</sup>
SHAPE_AM	-0.47	0.650 <sup>†</sup>	-0.53	0.605 <sup>†</sup>
SHAPE_CV	-1.57	0.145	-0.30	0.765 <sup>†</sup>
SHAPE_MD	-0.43	0.678 <sup>†</sup>	-1.43	0.170
SHAPE_MN	-2.04	0.066	-0.87	0.395 <sup>†</sup>
SHAPE_RA	-0.81	0.438 <sup>†</sup>	-0.19	0.850 <sup>†</sup>
SHAPE_SD	-2.34	0.039 <sup>‡</sup>	-0.74	0.468 <sup>†</sup>
SHDI	-2.74	0.019	-0.33	0.747 <sup>†</sup>
SIDI	-2.07	0.062 <sup>‡</sup>	-0.89	0.385 <sup>†</sup>

Variable	Winter		Summer	
	<i>t</i> -stat.	<i>P</i> -val.	<i>t</i> -stat.	<i>P</i> -val.
<b>Class-Level Metrics</b>				
ED01	0.60	0.558 <sup>†</sup>	1.14	0.269 <sup>†</sup>
ED02	-0.54	0.599 <sup>†</sup>	0.20	0.840 <sup>†</sup>
ED03	-1.34	0.208 <sup>†</sup>	-0.62	0.540 <sup>†</sup>
ED04	-1.92	0.081 <sup>ψ</sup>	-0.64	0.529 <sup>†</sup>
ED05	-1.96	0.075 <sup>ψ</sup>	-0.55	0.586 <sup>†</sup>
ED06	-1.23	0.246 <sup>†</sup>	-1.11	0.279 <sup>†</sup>
ED07	-0.80	0.441 <sup>†</sup>	-1.25	0.225 <sup>†</sup>
ED08	-0.90	0.386 <sup>†</sup>	-1.32	0.203 <sup>†</sup>
ED09	N/A	N/A	1.46	0.161 <sup>ψ</sup>
ED10	N/A	N/A	2.20	0.040
ED11	N/A	N/A	2.34	0.030 <sup>ψ</sup>
ED12	N/A	N/A	2.20	0.041 <sup>ψ</sup>
PLAND01	2.32	0.041	-0.02	0.983 <sup>†</sup>
PLAND02	0.64	0.535 <sup>†</sup>	0.59	0.562 <sup>†</sup>
PLAND03	-1.88	0.086 <sup>ψ</sup>	-0.89	0.384 <sup>†</sup>
PLAND04	-2.31	0.041 <sup>ψ</sup>	0.01	0.992 <sup>†</sup>
PLAND05	-1.81	0.098	-0.32	0.756 <sup>†</sup>
PLAND06	-1.06	0.312 <sup>†</sup>	-0.27	0.791 <sup>ψ</sup>
PLAND07	-0.50	0.629 <sup>†</sup>	-0.97	0.345 <sup>†</sup>
PLAND08	-0.83	0.426 <sup>†</sup>	-1.36	0.188 <sup>†</sup>
PLAND09	N/A	N/A	0.59	0.562 <sup>ψ</sup>
PLAND10	N/A	N/A	0.90	0.381 <sup>†</sup>
PLAND11	N/A	N/A	3.45	0.003
PLAND12	N/A	N/A	2.77	0.012

<sup>†</sup> - Excluded because of insignificant (*P*-value > 0.20) *t*-test.

<sup>‡</sup> - Excluded because variance proportions > 0.60.

<sup>ψ</sup> - Excluded because Pearson pairwise correlation with other variable > 0.70.

<sup>N/A</sup> - Variables were not included in the selection models constructed for that season.

Table 4.6. Coefficient estimates for the landscape pattern and composition metrics included in the macro-level habitat selection models. Coefficients are the AIC model-average estimates of the metrics. Also shown are the lower (LCL) and upper 95% confidence limits (UCL) for the coefficients, which were estimated by bootstrapping. See Table 4.3 for a description of the metrics.

Metric	Coefficient	LCL	UCL
<b>Winter</b>			
PARA_MN	1.71E-04	-7.56E-05	1.84E-03
PLAND01	-2.29	-17.38	2.29
PLAND05	1.18	-199.05	30.13
SHAPE_CV	9.03E-03	-3.36E-02	2.90E-01
SHAPE_MN	1.90	0.22	27.32
SHDI	1.48	-5.05	22.06
<b>Summer</b>			
ED10	-0.04	-0.15	-0.01
PARA_RA	1.02E-03	1.08E-04	5.09E-03
PLAND11	-285.61	-1407.14	116.72
PLAND12	-35307.61	-918158.00	-3198.00
SHAPE_MD	0.06	-5.18	7.44

Table 4.7. Coefficient estimates and 95% confidence limits for the habitat variables used in determining the micro-level habitat selection probability functions. Estimates were calculated by averaging the AIC model-average coefficient estimates across all telemetered muskellunge. Confidence limits are based on a student's-*t* distribution. The number of telemetered muskellunge among which coefficients were averaged are shown for each season.

Model Coefficient	Winter ( <i>n</i> = 12)	Summer ( <i>n</i> = 20)
	Mean ± 95% CI	Mean ± 95% CI
Intercept	-3.17 ± 0.71	-2.92 ± 2.36
Mean Depth	0.53 ± 0.32	0.84 ± 0.35
Shoreline	4.82E-03 ± 5.82E-03	-0.04 ± 0.09
Vegetation Patch (> 50 m <sup>2</sup> )	N/A	-8.36E-03 ± 1.39E-02
Depth Contour (0 to 1 m)	-4.72E-04 ± 8.46E-03	0.04 ± 0.07
Depth Contour (1 to 2 m)	4.86E-04 ± 1.11E-02	5.10E-03 ± 4.32E-02
Depth Contour (2 to 3 m)	-0.09 ± 0.15	-0.05 ± 0.07
Depth Contour (3 to 4 m)	-0.15 ± 0.26	-0.07 ± 0.11
Depth Contour (4 to 5 m)	6.54E-04 ± 3.39E-03	-1.07E-04 ± 3.61E-03

N/A - Variables were not included in the selection models constructed for that season.



Table 4.8. Average correlation coefficients and the upper (UCL) and lower (LCL) 95% confidence limits relating muskellunge use of winter and summer habitat variables to median river discharge for the 12-hr period before fish were located. The numbered of telemetered muskellunge among which coefficients were averaged are shown for each season.

Habitat Variable	Winter ( <i>n</i> = 15)			Summer ( <i>n</i> = 20)		
	Correlation	LCL	UCL	Correlation	LCL	UCL
Mean Depth	-0.464	-0.547	-0.383	-0.250	-0.327	-0.173
Distance to Shore	-0.232	-0.373	-0.091	-0.104	-0.193	-0.016
Distance to Vegetation	N/A	N/A	N/A	0.069	-0.038	0.176
Distance to 0- to 1-m Contour	-0.241	-0.353	-0.130	-0.155	-0.233	-0.077
Distance to 1- to 2-m Contour	-0.156	-0.253	-0.059	-0.104	-0.188	-0.020
Distance to 2- to 3-m Contour	0.219	0.143	0.296	0.161	0.054	0.268
Distance to 3- to 4-m Contour	0.338	0.240	0.435	0.146	0.039	0.253
Distance to 4- to 5-m Contour	0.267	0.148	0.385	0.112	0.029	0.195

N/A - Variables were not included in the selection models constructed for that season.

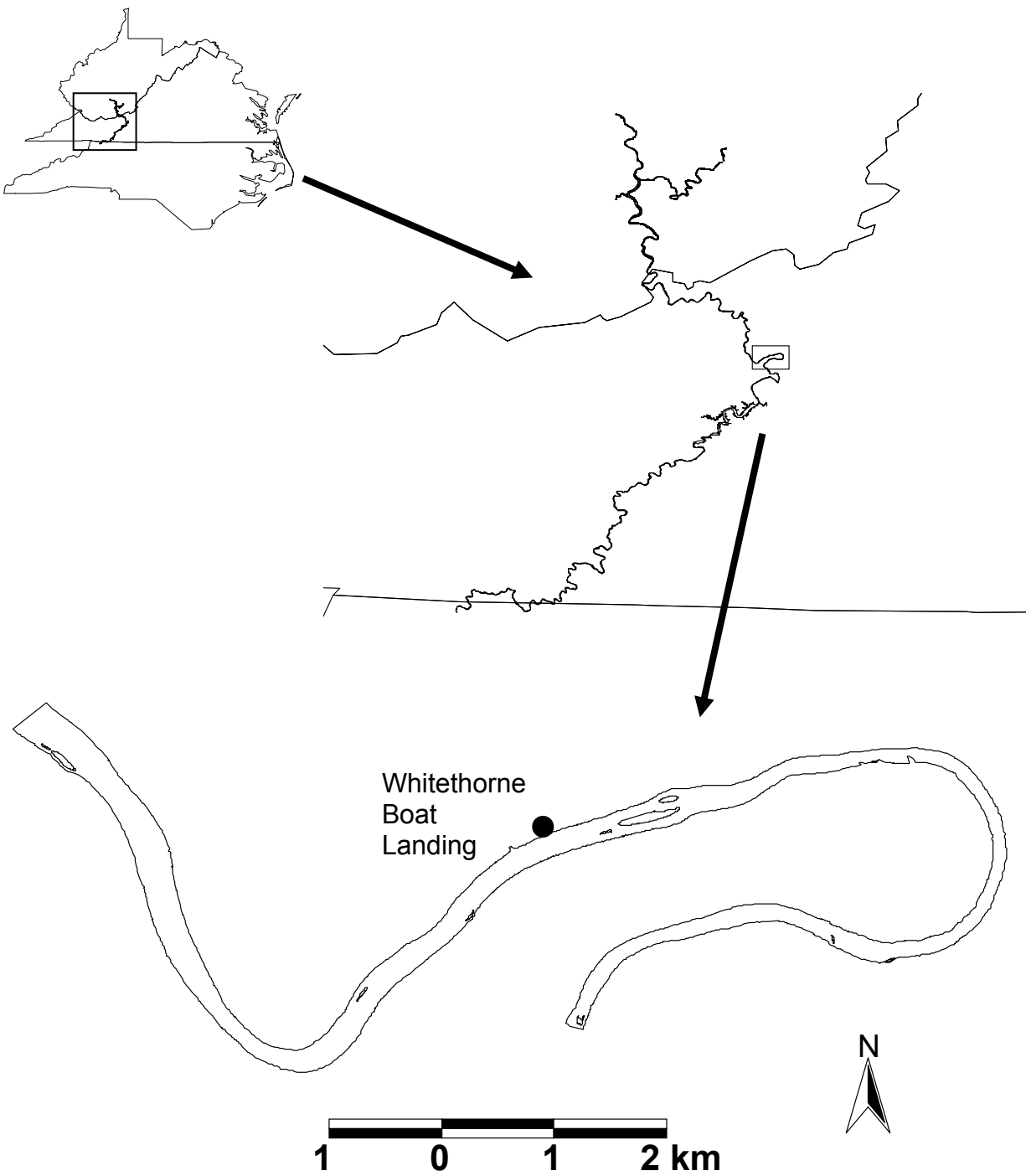


Figure 4.1. The 17-km study reach and its location in the New River where muskellunge habitat selection was evaluated.

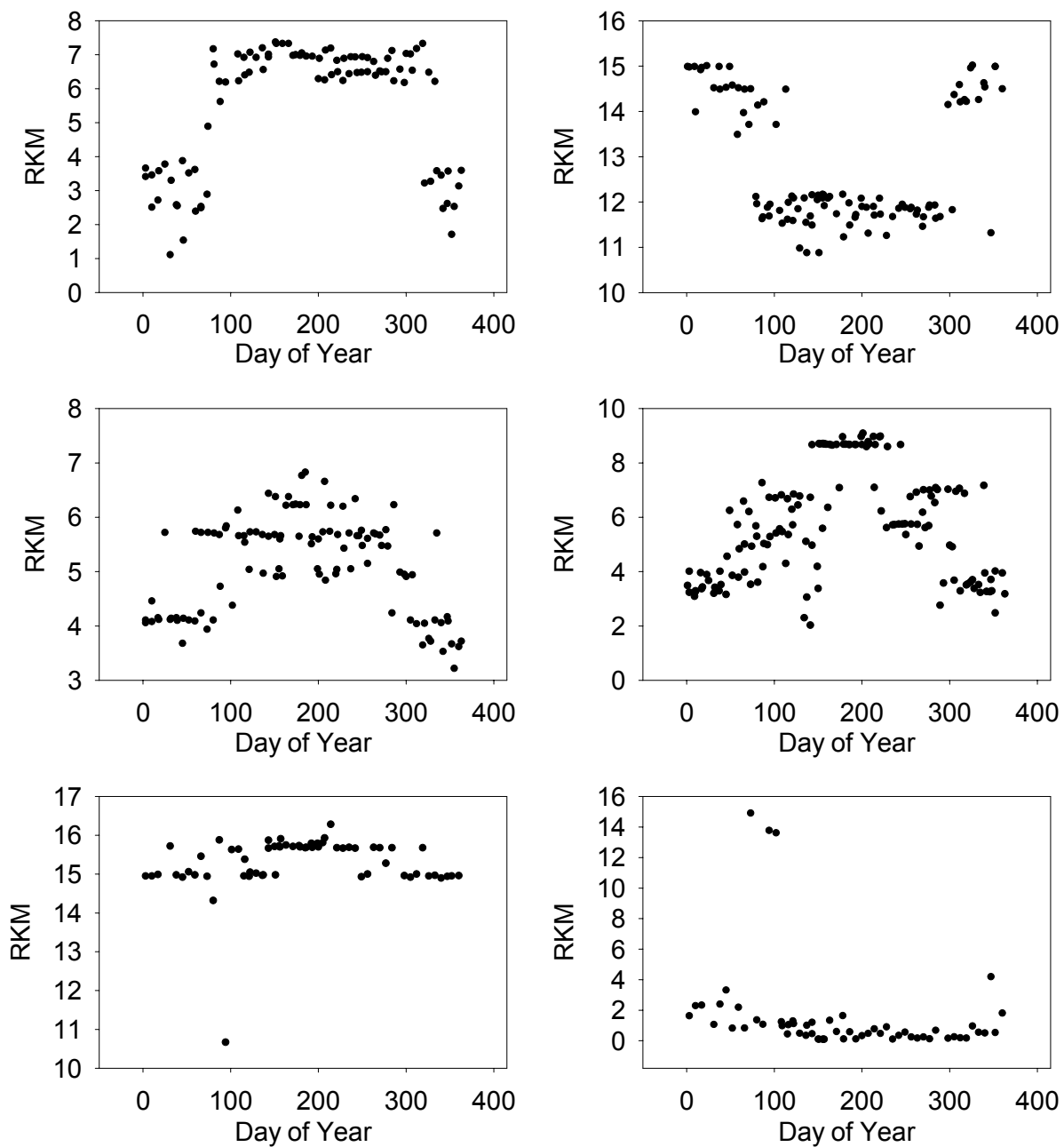


Figure 4.2. Scatterplots showing fish longitudinal location in the study reach (RKM) in relation to day of the year. The plots on the top row show fish that exhibited clear transition between summer and winter home ranges. The plots on the middle row show less clear transitions, while the plots on the bottom row show no clear transition between summer and winter home ranges.

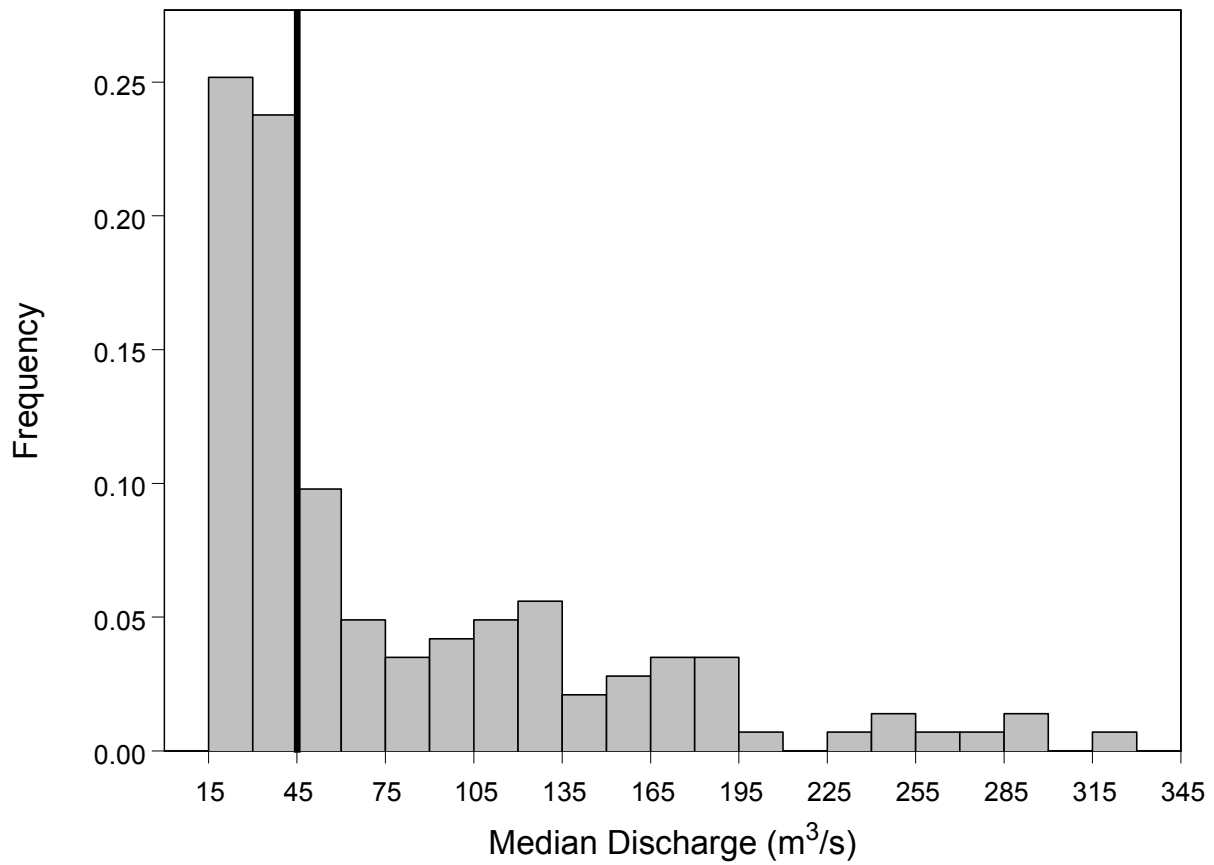


Figure 4.3. Frequency histogram of median river discharge measurements for the 12-hours prior to each muskellunge location estimate. Locations associated with high and low discharges were classified based on the overall median (solid vertical line:  $\tilde{x} = 45.3 \text{ m}^3/\text{s}$ ) of the discharge measurements.

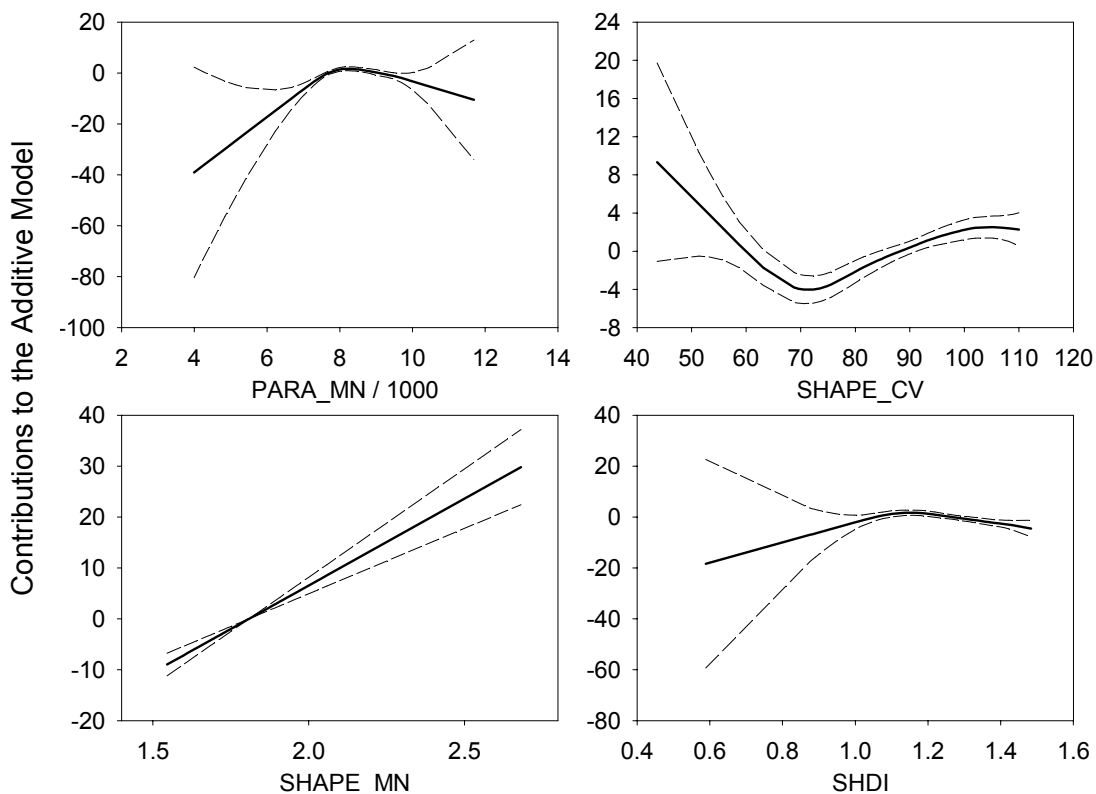


Figure 4.4. Response curves for the landscape pattern and composition metrics (PARA\_MN: mean of the perimeter-area ratio distribution, SHAPE\_CV: coefficient of variation of the shape index distribution, SHAPE\_MN: mean of the shape index distribution, SHDI: Shannon's diversity index of patch classes) that comprised the AIC-selected model for the winter-macro-level habitat selection probability function fit by generalized additive modeling. The vertical axes, expressed in logits, indicate the relative influence of each habitat variable on predicted probability of habitat use based on partial residuals. Dashed lines represent two standard error bands.

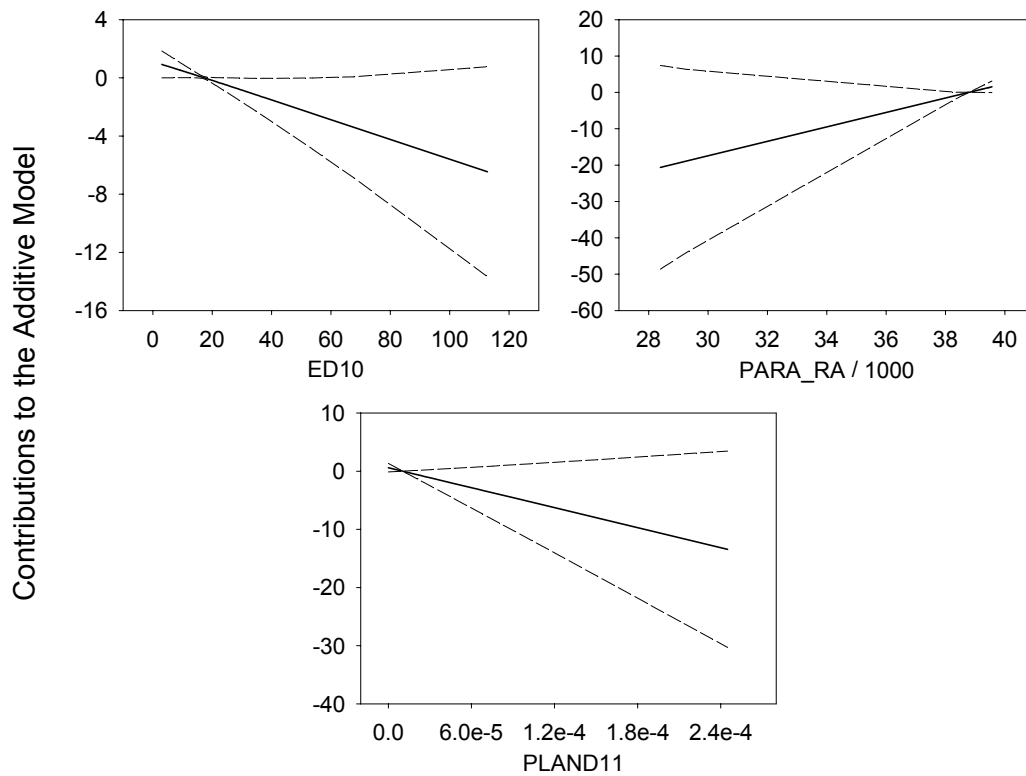


Figure 4.5. Response curves for the landscape pattern and composition metrics (ED10: edge density of vegetated habitats ranging in depth from 1 to 2 m; PARA\_RA: range of the perimeter-area ratio distribution; PLAND11: percentage of the landscape consisting of vegetated habitats ranging in depth from 2 to 3 m) that comprised the AIC-selected model for the summer-macro-level habitat selection probability function fit by generalized additive modeling. The vertical axes, expressed in logits, indicate the relative influence of each habitat variable on predicted probability of habitat use based on partial residuals. Dashed lines represent two standard error bands.

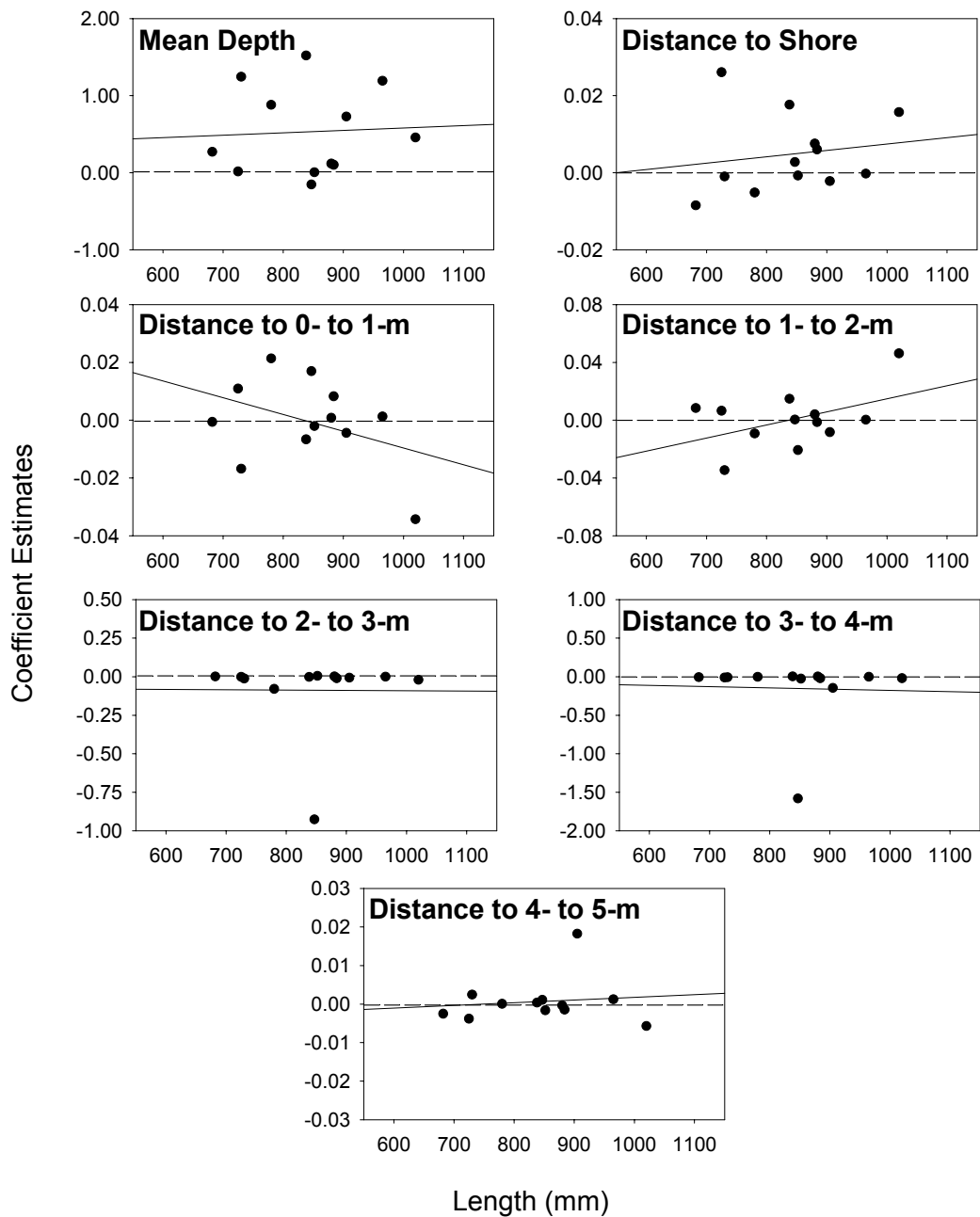


Figure 4.6. Scatterplot of model-average coefficient estimates in relation to fish length for the habitat variables included in the winter habitat selection probability functions. The solid lines on the figures are least-squares linear regression lines fit to the coefficient-fish length relationships. The dashed lines are reference lines (slope = 0).

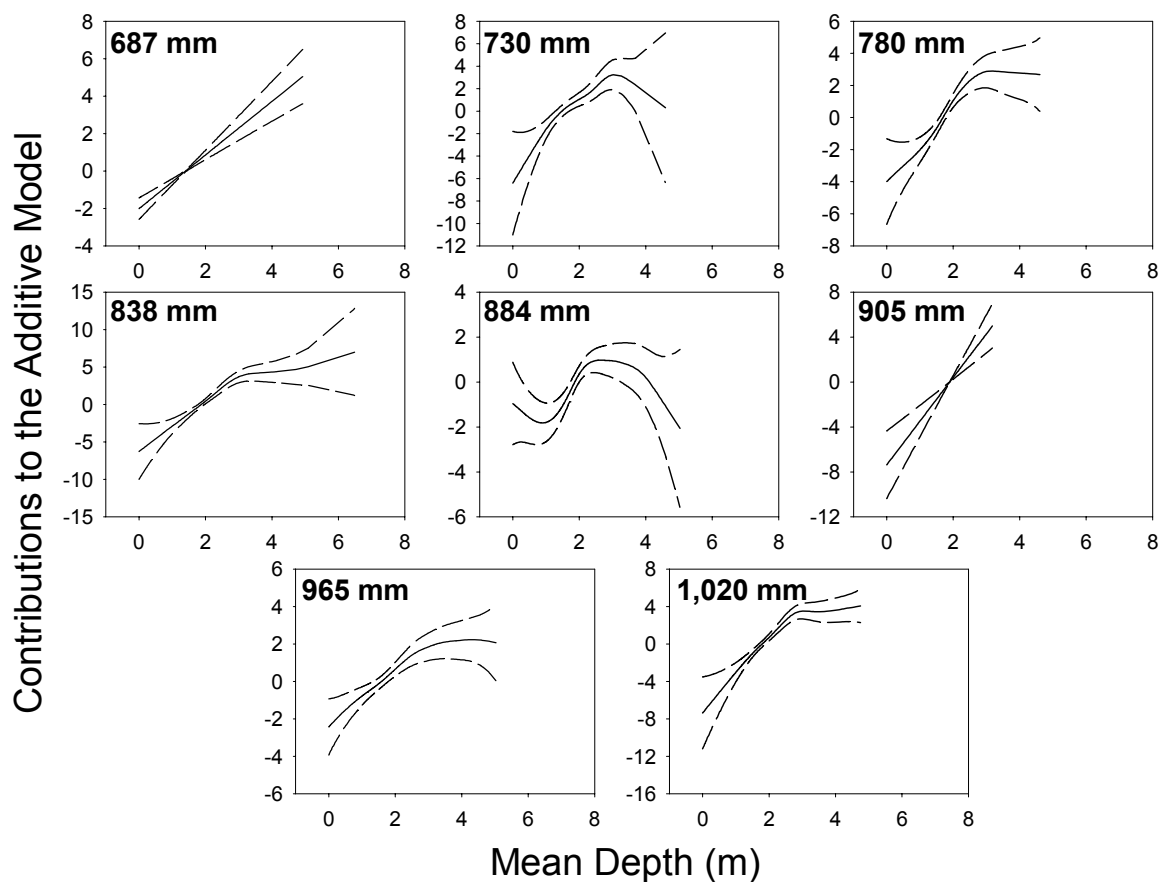


Figure 4.7. Response curves of habitat selection probability functions to mean depth for those fish in which mean depth was among the variables included in the AIC-selected generalized additive model for winter. The vertical axes, expressed in logits, indicate the relative influence on probability of habitat use predictions based on partial residuals. Dashed lines represent two standard error bands. Lengths of fish when first equipped with transmitters are shown on each graph.



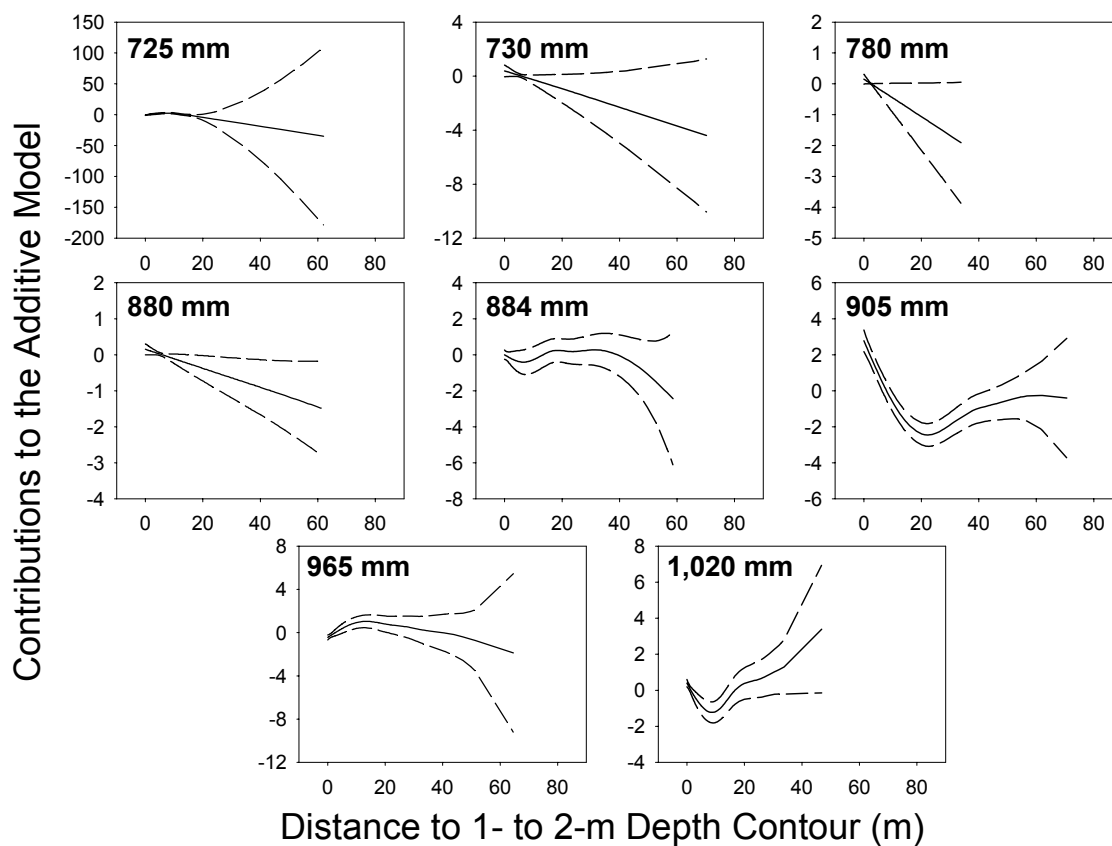


Figure 4.8. Response curves of habitat selection probability functions to nearest distance to the 1- to 2-m depth contour for those fish in which this habitat variable was among those included in the AIC-selected generalized additive model for winter. The vertical axes, expressed in logits, indicate the relative influence on predictions of probability of habitat use based on partial residuals. Dashed lines represent two standard error bands. Lengths of fish when first equipped with transmitters are shown on each graph.

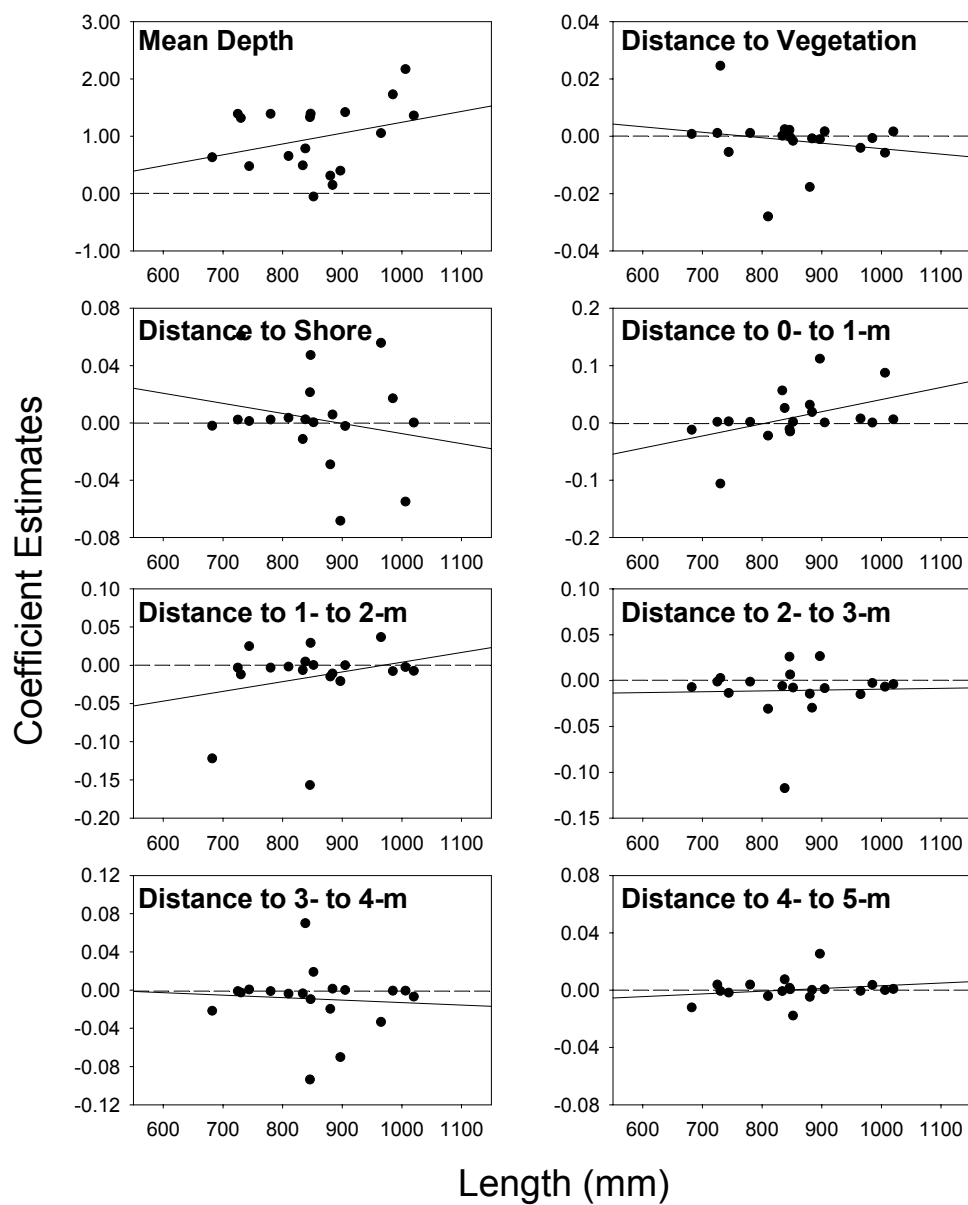


Figure 4.9. Scatterplot of model-average coefficient estimates in relation to fish length for the habitat variables included in the summer habitat selection probability functions. The solid lines on the figures are least-squares linear regression lines fit to the coefficient-fish length relationships. The dashed lines are reference lines (slope = 0).

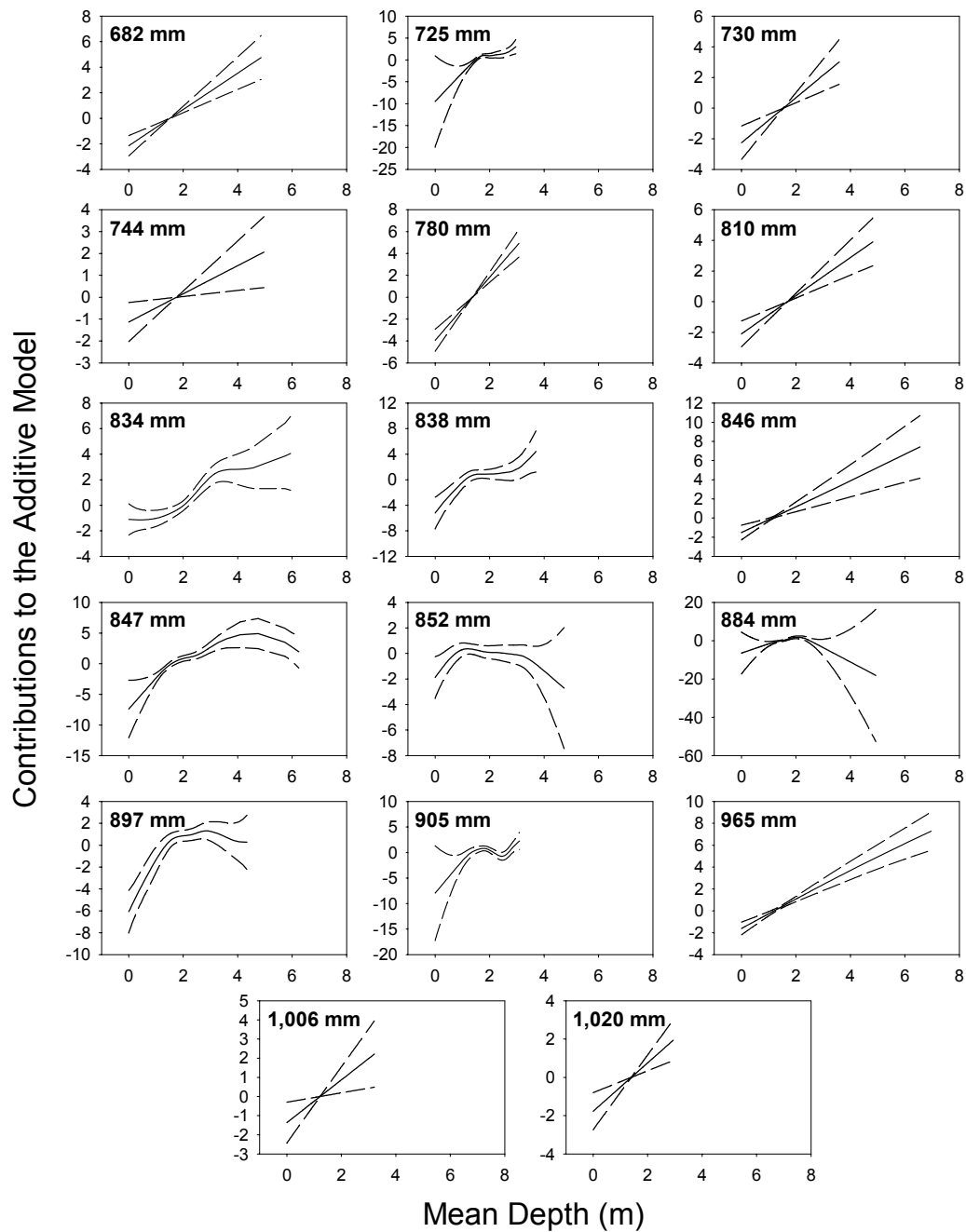


Figure 4.10. Response curves of habitat selection probability functions to mean depth for those fish in which this habitat variable was among those included in the AIC-selected generalized additive model for summer. The vertical axes, expressed in logits, indicate the relative influence on predictions of probability of habitat use based on partial residuals. Dashed lines represent two standard error bands. Lengths of fish when first equipped with transmitters are shown on each graph.

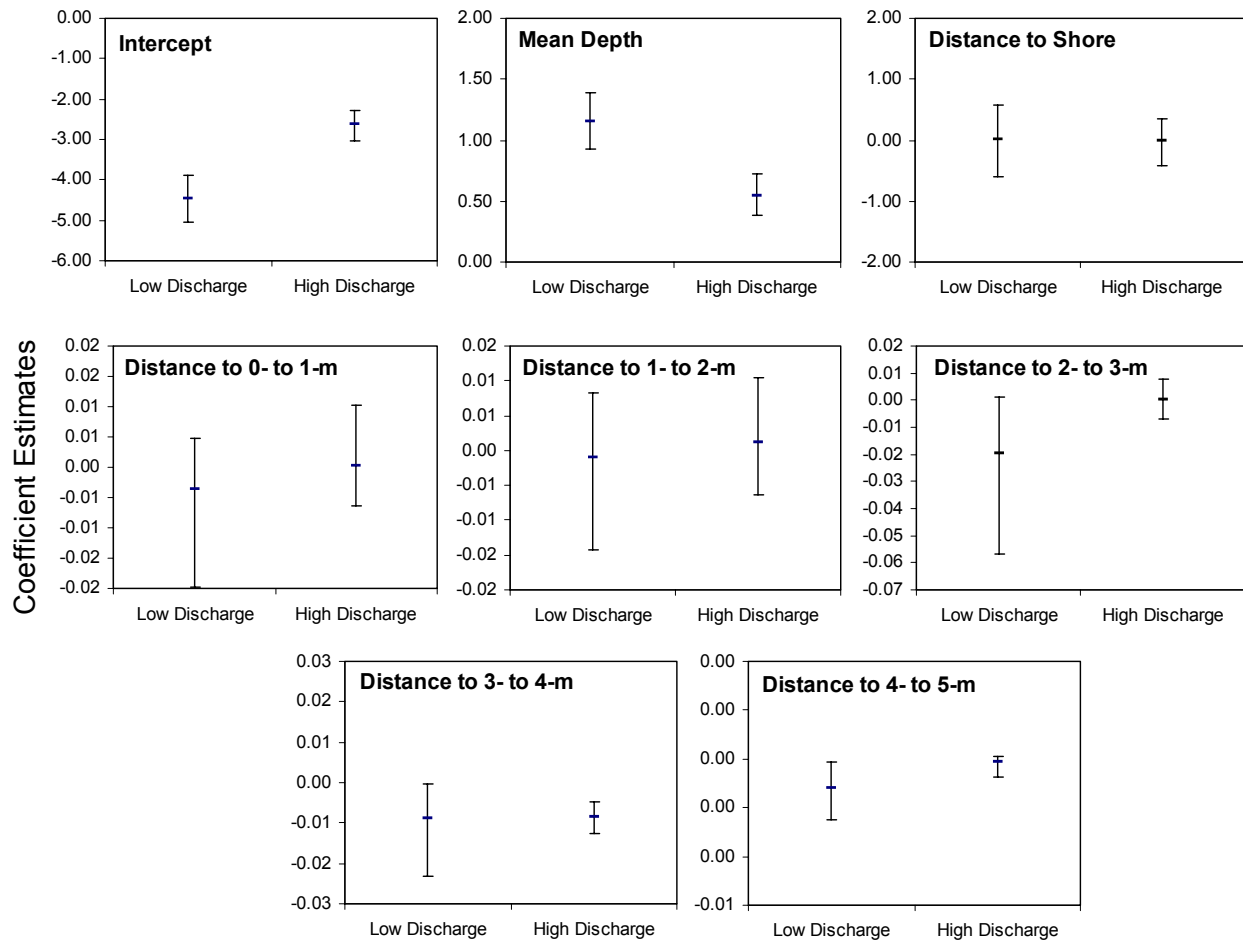


Figure 4.11. Comparisons of mean coefficient estimates ( $\pm$  95% bootstrap confidence intervals) between low and high discharges for winter habitat selection probability functions.

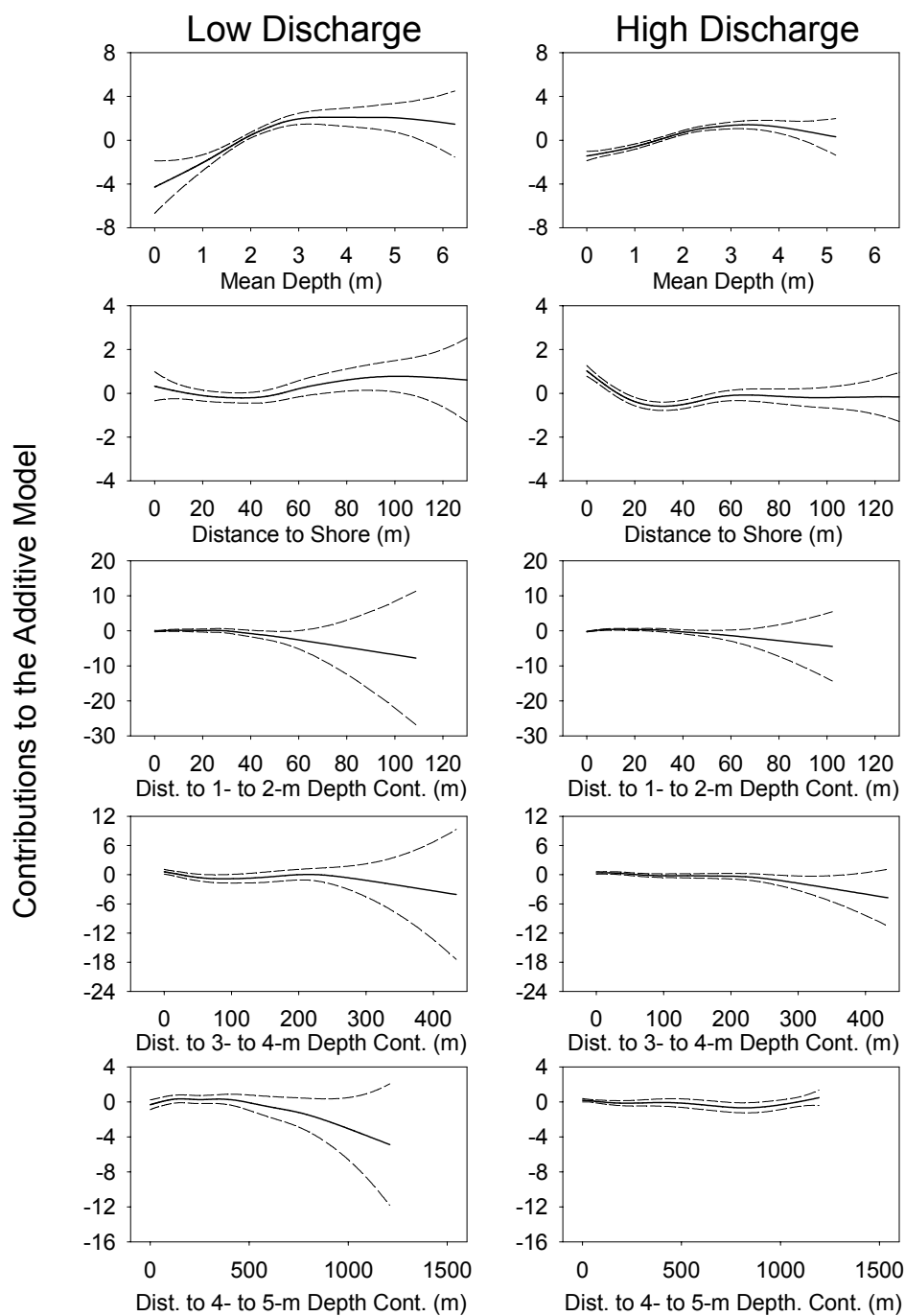


Figure 4.12. Comparisons of response curves for the winter habitat selection probability functions fit by generalized additive modeling for fish locations associated with low and high river discharges. The vertical axes, expressed in logits, indicate the relative influence on predictions of probability of habitat use for each of the habitat variables based on partial residuals. Dashed lines represent two standard error bands.

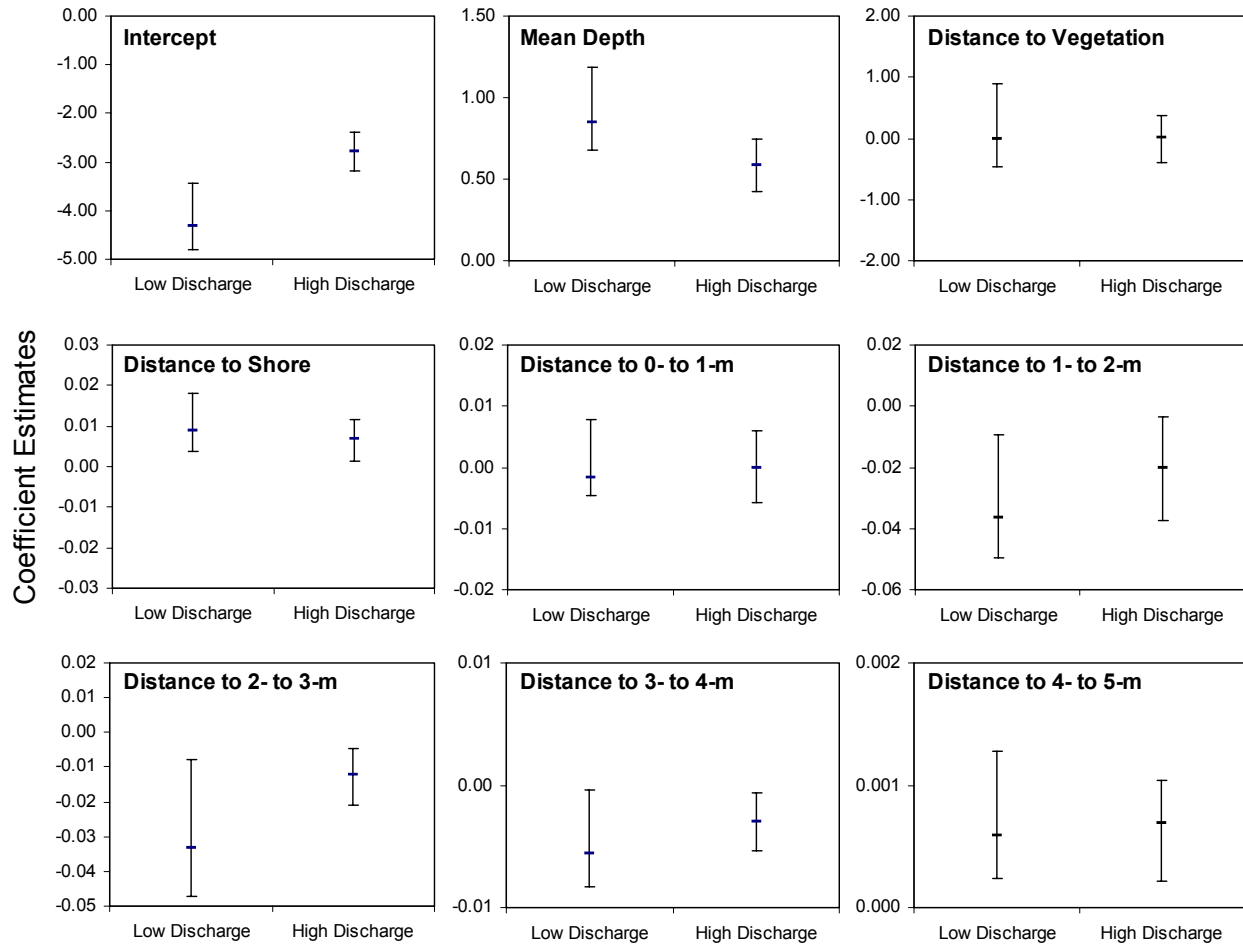


Figure 4.13. Comparisons between mean coefficient estimates ( $\pm$  95% bootstrap confidence intervals) of summer habitat selection probability functions calculated for low and high discharges.

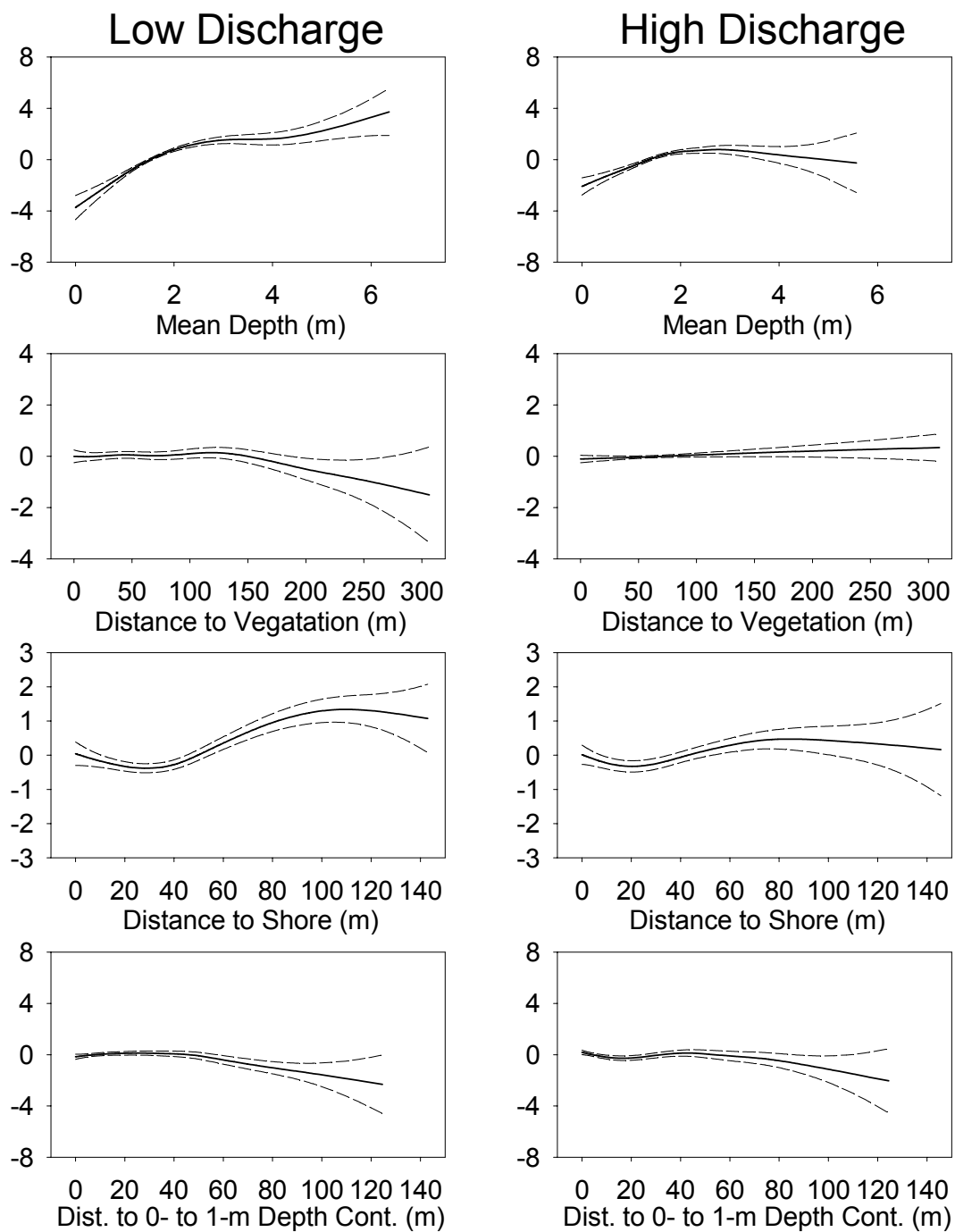


Figure 4.14. Comparisons of response curves for the summer habitat selection probability functions fit by generalized additive modeling for fish locations associated with low and high river discharges. The vertical axes, expressed in logits, indicate the relative influence on predictions of probability of habitat use for each of the habitat variables based on partial residuals. Dashed lines represent two standard error bands.

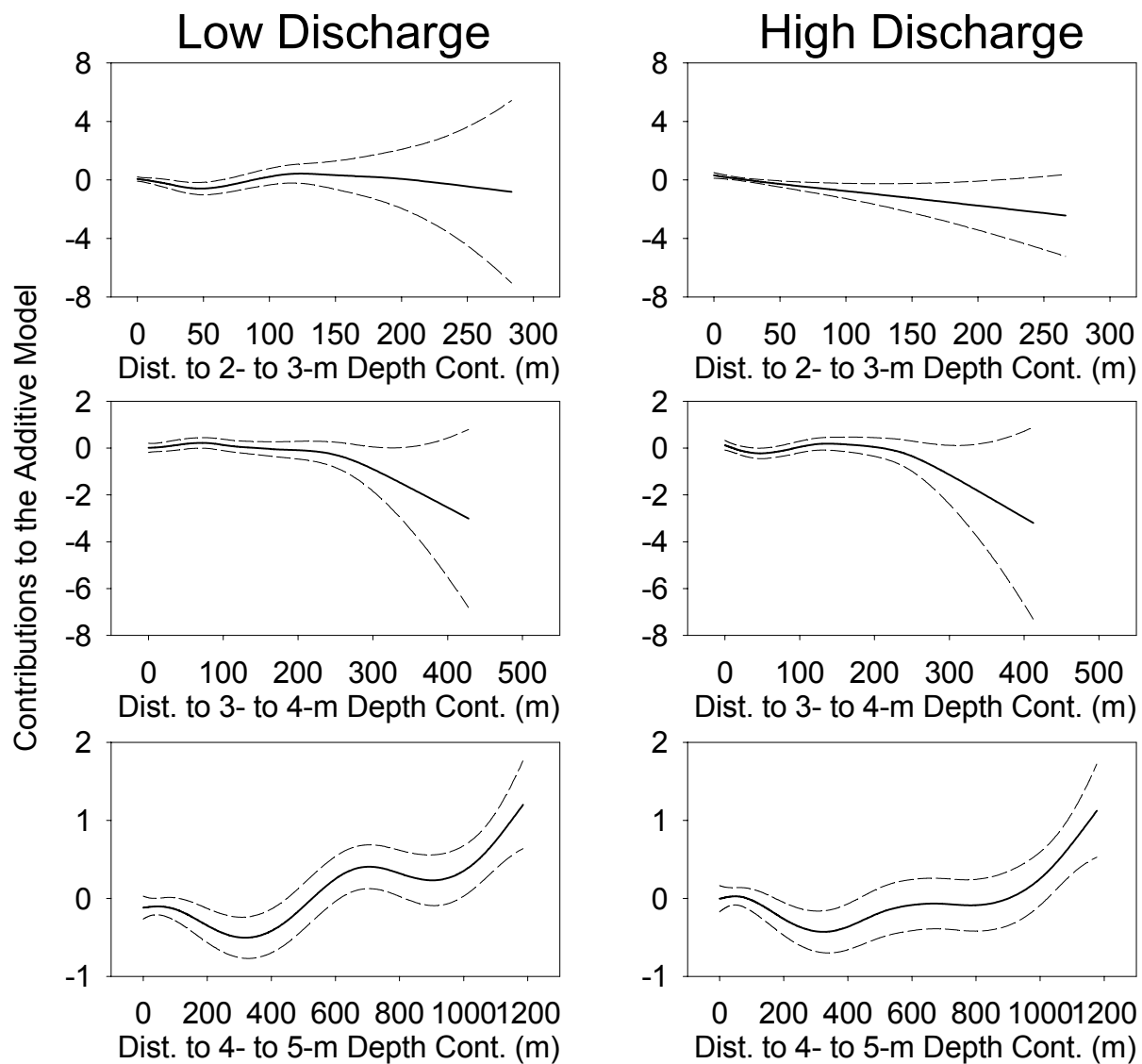


Figure 4.14. (continued).



**CONCLUSIONS/MANAGEMENT RECOMMENDATIONS/FUTURE INVESTIGATIONS**

Management of the New River, Virginia, muskellunge fishery by the Virginia Department of Game and Inland Fisheries primarily is directed towards the production of “trophy” fish and secondarily to provide “rough” fish control (J. Williams, Virginia Department of Game and Inland Fisheries, personal communication). Annual stocking of fingerling muskellunge and enforcement of a 762-mm minimum length limit and 2 fish/day creel limit are the primary management activities used to achieve these goals. The fact that the New River supports Virginia’s premier muskellunge fishery provides some anecdotal evidence of the success of these management activities. However, the results of this research also suggest that the quality of the fishery and cost-effectiveness of management actions could be increased by slight alteration of the management approaches.

Given the fast growth of muskellunge to lengths in excess of 1,000 mm and the fact that most New River anglers identify “trophy” muskellunge to be fish greater than 1,050 mm in length, an increase in the minimum length limit to between 965 and 1,067 mm (38 and 42 inches) would substantially improve the trophy-producing potential of the New River fishery. Although raising the limit to even larger lengths (>1,143 mm) might seem a worthwhile approach for maximizing abundance of large fish, such a drastic change in the size limit seems unnecessary given angler opinions concerning “trophy” lengths of muskellunge. The observation that a minority of even the most dedicated muskellunge anglers rarely identified “trophy” muskellunge to be greater than 1,270 mm means that few anglers may be supportive of length limits that exceed 1,100 mm. Even winning support for a 965 to 1,067 mm size limit might prove difficult given the low percentage of anglers that believe the minimum length limit needs to be changed. Support for a length limit change possibly could be increased by publicizing the fast growth rates of muskellunge and explaining how higher limits will result in a greater abundance of “trophy” fish.

I also recommend that the current creel limit of 2 fish per day be reduced to 1 fish per day. Although reducing the creel limit to 1 fish per day will likely have little direct impact on fishing mortality rates given the limited number of anglers that actually creel 2 fish in a single day, reducing the creel limit may impart to anglers a more conservative mindset regarding the muskellunge fishery. A more conservative mindset by anglers may lead to higher incidences of voluntary catch-and-release angling,

which could alleviate the need to implement even more restrictive harvest regulations in the future (e.g., closed seasons, catch-and-release only sections of the river).

Future investigations that would assist in formulating appropriate management strategies for the New River muskellunge fishery include a large-scale age validation study to assess the accuracy of pelvic fin rays as a non-lethal aging structure, additional monitoring of muskellunge mortality rates to assure that stocks are not being overharvested, and an assessment of the relative contributions of stocked and naturally reproduced muskellunge to the fishery. Many of my findings in Chapter 2 are predicated on the assumption that age estimates from sectioned pelvic fin rays were accurate. Although I found high agreement between cleithrum and pelvic fin ray age estimates, such a comparison does not truly validate fin rays as an aging structure. A true validation study would involve aging known-age fish so that age estimates could be compared to actual ages. Such a study could be conducted in a number of ways. Muskellunge could be raised in an aquaculture facility and aged at various time periods. Fish also could be marked and released into a natural environment. Age estimates for fish subsequently recaptured could then be compared to known ages. Johnson's (1971) pelvic fin ray age validation study for muskellunge followed the latter protocol. Johnson (1971) marked, recaptured, and aged more than 1,700 muskellunge using different fin clip combinations. I recommend that researchers attempting an age-validation study for muskellunge in southern U.S. regions refer to his study, as well as to similar validation studies that have been conducted for other fish species (Rossiter et al. 1995; Buckmeier and Howells 2003).

If the minimum length limit for muskellunge in the New River is raised as I have suggested, this may lead to increased fishing pressure as anglers may be attracted by the uniqueness of the harvest regulation, which could lead to higher mortality rates (Margenau and AveLallemant 2000). To assure that the New River muskellunge fishery does not become overharvested, I recommend that a monitoring program be implemented so that changes in fishing pressure and mortality rates can be measured. This could take the form a reward-based tagging program in which a certain number of fish are tagged annually with tags visible to anglers. Monetary rewards would then be given to anglers that harvested tagged fish and returned the tags. Such a program would allow temporal trends in exploitation rates to be

assessed, and would allow early detection of increased harvest rates. Fishery biologists could then respond with more restrictive harvest regulations as needed to prevent overharvest from occurring.

Future investigations should also be directed towards determining how much of the muskellunge fishery is supported by stocking and how much is supported by natural reproduction. A limited amount of natural reproduction has been suspected in the New River, but it has been difficult to detect because of the annual stocking of muskellunge by the Virginia Department of Game and Inland Fisheries. My collection of 14 young muskellunge in the unstocked section of the New River supports the hypothesis that at least some natural reproduction is indeed occurring. The next logical step then is to determine the extent to which naturally reproduced fish are contributing to the fishery. Because muskellunge currently are stocked as fingerlings ( $\approx 100$  mm), there is a chance that a high percentage ( $>90\%$ ) of stocked fish are consumed by *Micropterus* spp. shortly after stocking (Serns and Andrews 1986; Szendrey and Wahl 1995; Wahl 1999) and that the muskellunge fishery consists primarily of naturally reproduced fish. If this is the case, then the stocking of muskellunge may be a waste of resources (i.e., hatchery space, money to provide forage fish). If stocked fish are not lost to predation, the combination of stocking and natural reproduction increases the chances of muskellunge become overcrowded at small sizes, leading to intra- or inter-specific competition and reduced growth rates. Contributions by stocked and naturally reproduced muskellunge could be assessed by simply staggering fish stocking to an every-other-year time frame while monitoring relative abundance of muskellunge yearly.

With regards to habitat use and selection, this research found that patch shape complexity and water depth were the primary habitat variables that influenced site selection in muskellunge. I also found that muskellunge ontogeny affected habitat selection and that increased river discharge resulted in muskellunge moving out of deep water habitats and closer to the shoreline and shallower water. These findings have important implications for the New River muskellunge fishery from a management standpoint. First, it suggests that basing the muskellunge stocking rate on a single, large-scale habitat variable such as pool surface area may not accurately gauge its capacity to support fish. Pools often are identified based simply on the degree of laminar surface-water flow, which may misrepresent availability of deep-water habitat or complexity of patch habitat shapes. Rather than identifying areas in which to stock muskellunge based on pool surface area, biologists should distinguish areas based on deep-water

habitat availability and juxtaposition of deep- and shallow-water habitat patches. The effect of river discharge on habitat use and selection also has important implications on muskellunge management, given the manner by which American Electric Power operates Claytor Hydroelectric Dam. From approximately mid-April to mid-October, Claytor Dam is operated on a “run-of-the river” release schedule to protect spawning habitat for fish in the upstream impoundments. During the rest of the year, Claytor Dam is operated on a hydro-peaking release schedule. When hydropeaking, river discharge typically is increased to 125 to 200 m<sup>3</sup>/s (Figure 5.1), which is more than 3 times the discharge that was used to assess the effect of increased discharge on muskellunge habitat selection. When the dam is operated on a hydro-peaking release schedule, muskellunge may continually be displaced from core habitats and need to seek refuge in shallower habitats located closer to the shoreline.

Future research into muskellunge habitat use and selection should be directed towards understanding how river discharge affects muskellunge biology and ecology. Such research might entail laboratory experimentation to determine energy requirements for maintaining holding positions at various water velocities, as well as possible field experimentation in which individual fish are tracked at both low and high discharges. Research into true micro-scale habitat selection also would be fruitful in that it may help determine whether muskellunge habitat use is not affected by aquatic vegetation, as this research suggests. As previously stated, direct observation of muskellunge through scuba diving may be the best method for conducting such research, as it is unlikely that telemetry would provide sufficient resolution to determine focal site habitat use.

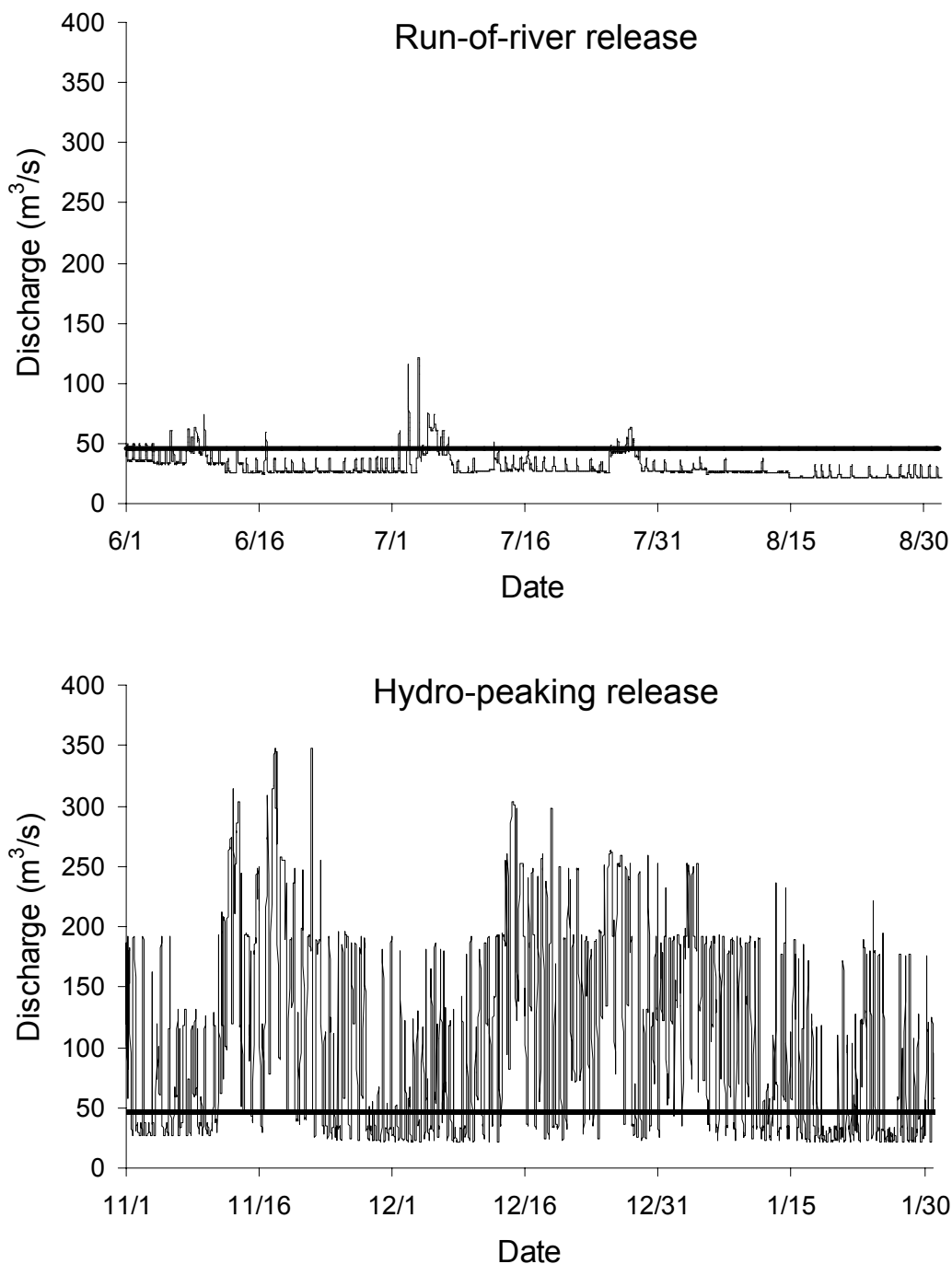


Figure 5.1 Comparison of real-time river discharge measurements for the New River when water is released from Claytor Hydroelectric Dam according to a run-of-river and hydropeaking release schedule. The horizontal line on each graph demarks the discharge measurement used to distinguish between low and high discharges in the habitat selection assessment for muskellunge.

### SUMMARY

- 1) Data generated from the relative weight ( $W_r$ ) index are neither independent nor identically distributed (i.i.d.) when estimates of standard weight are developed from the regression-line-percentile technique. Consequently, statistical tests that assume i.i.d. may lead to incorrect conclusions regarding condition when they are used to test differences in condition between and within fish populations.
- 2) A statistical test that can account for the non-i.i.d. structure of  $W_r$  data is the  $R$  test, which is a likelihood ratio test that incorporates delta-method derived variance-covariance estimates of  $W_r$  data. Pairwise comparisons can be conducted in the  $R$  test using linear contrasts. Comparison of the  $R$  test with other statistical tests of location (ANOVA, Student's- $t$ , Kruskal-Wallis, Wilcoxon rank-sum tests) using  $W_r$  data for largemouth bass, black crappie, and muskellunge populations indicated that the  $R$  test yielded more conservative test results and thus should help prevent management biologists from making management decisions that are not biologically supported.
- 3) One factor that contributes to the conservatism of the  $R$  test is its incorporation of uncertainty as to the accuracy of the standard weight equation. Other statistical tests assume that the standard weights are estimated without error, which is an unrealistic assumption. The incorporation of standard weight equation uncertainty provides a check for assuring that standard weight equations developed from too few populations or that involve excessive extrapolation of length-weight relationships do not play a major role in making management decisions.
- 4) Comparison of pelvic fin ray and cleithrum age estimates for 21 muskellunge indicated a high rate of agreement between the structures. Equal age estimates were obtained for 76% of the fish that were aged with both structures, and age estimate agreement within one year was 100%. This high rate of agreement between pelvic fin ray and cleithrum age estimates suggests that fin rays may provide an accurate and non-lethal structure for aging muskellunge in southern U.S. regions.
- 5) Growth rates of New River muskellunge were fast, with fish reaching current harvestable lengths (762 mm) in as little as 2 to 3 years. By age 5, New River muskellunge can be in excess of 1,000 mm in length. This is one of the fastest growth rates that has been reported to date, suggesting

that the New River may provide near-optimal conditions (i.e., appropriate thermal conditions, high prey availability, long growing season) for muskellunge growth.

- 6) Conditional natural and fishing mortality for muskellunge estimated from the relocation history of 47 radiotelemetry tagged muskellunge and catch-curve analysis of sectioned fin-ray aged fish equaled 12.6 and 15.2% respectively. Annual exploitation was estimated at 14.2%. Annual exploitation rates in excess of 25% generally are believed to be too high to manage a quality muskellunge fishery; thus, it seems unlikely that the New River muskellunge fishery is currently being overharvested.
- 7) A creel survey of anglers that fished the New River indicated that 2.2% of angling parties specifically targeted muskellunge. Most anglers, regardless of how often they fished for muskellunge, defined a “trophy” fish to approximately 1,050 to 1,100 mm in length.
- 8) Angler support for changing harvest regulation differed between anglers depending on their muskellunge angling experience. Fifty-six percent of anglers that fished most often for muskellunge supported changing the regulation, with 79% supporting a creel limit change and 71% supporting a size limit change. In comparison, 10% of anglers that had never fished for muskellunge supported a regulation change, with 83% supporting a creel limit change and 33% supporting a size limit change. Anglers that fished most often for muskellunge were more likely to support a lower creel limit and higher size limit.
- 9) Alternative harvest regulation modeling indicated that total abundance of memorable-length ( $\geq 1,070$  mm) muskellunge would increase under a 914-, 1,016-, or 1,143-mm length limit. Yield would remain fairly stable under a 914- or 1,016-mm minimum length limit, but would decline dramatically with a 1,143-mm minimum length limit due to the inability of male muskellunge to reach lengths exceeding 1,100 mm.
- 10) Based on the results of the creel survey and alternative harvesting regulation modeling, increasing the minimum length limit from 762 mm to approximately 965 to 1,067 mm (38 to 42 inches) would result in the greatest benefit to the muskellunge fishery. Although increasing the minimum length limit to larger lengths would protect more of the population, angler support for such an increase might be low.

- 11) An anchor design consisting of cement, PVC pipe, and rebar was adequate for preventing entrainment of test transmitters at discharges less than 920 m<sup>3</sup>/s. The use of such test transmitter anchors at the beginning of a radiotelemetry tracking study permits the quantitative evaluation of accuracy associated with locating and mapping transmitters.
- 12) An accuracy assessment that involved placing radiotelemetry transmitters at known locations and attempting to locate and map transmitter position by homing and global positioning system (GPS) receivers estimated a median distance error of 4 m. Greater than 95% of all locations were within 10 m of actual location. This accuracy assessment suggests that radiotelemetry tracking may not be an appropriate method for assessing micro-habitat use and selection since the associated locating and mapping error would limit the ability to determine focal site habitat use or selection. Consequently, radiotelemetry may be best suited for assessing habitat use and selection at meso-habitat scales.
- 13) Although hydroacoustic mapping of habitat availability in rivers was accurate for water depth and aquatic vegetation, accuracy in creating a habitat map for substrate type was low. The bottom-typing inaccuracy possibly stems from shallow water effecting characteristics of hydroacoustic echoes. In order to increase bottom-typing accuracy, reference databases that will be used to classify newly sampled data need to be developed from hydroacoustic data collected across a large range of environmental conditions so that substrate-type estimation is based on interpolation rather than extrapolation.
- 14) At large scales, muskellunge selection of habitats appears partially based on complexity of patch shape. Probability of habitat use increased in areas with greater patch shape complexities, which may be linked to complex patch shapes providing suitable areas from which fish can ambush prey.
- 15) At small scales, probability of habitat use during both summer and winter was most significantly related to mean depth. For most telemetered muskellunge for which habitat selection was assessed, probability of habitat use increased linearly with mean depth, although for some fish probabilities leveled-off or declined as water depth exceeded 4 m. Based on this assessment, deep water habitat appears to be a primary or core habitat from which fish activities (e.g.,



foraging) radiate. Because muskellunge during summer exhibited a stronger positive selection for mean depth during summer than in winter, it may be that muskellunge's association with deep water areas is related to thermal tolerances in the species.

- 16) The lack of selection for other habitat variables that were included in the habitat selection probability functions possibly was related to selection patterns shifting with fish ontogeny. Plots of model-average coefficient estimates versus fish length, which was used as a surrogate for age, indicated that small (<850 mm) and large (>850 mm) individuals differed in their selection area based on distances to the 1- to 2-m and 2- to 3-m depth contours. There also appeared to be size-related differences in selection of areas based on mean depth, with larger muskellunge more strongly selecting areas based on mean depth than smaller fish.
- 17) Habitat use and selection also appeared to be affected by changes in discharge. Higher discharge was correlated with muskellunge moving away from deeper water and closer to shallower areas located near the shoreline. It seems likely that fish may be moving to such habitats because they provide refuge from higher water velocities, which is energetically advantageous to muskellunge. Comparisons of habitat selection probability functions constructed for high and low discharges also indicated that muskellunge were less likely to be found in deeper habitats during high discharges. These results suggest that optimal habitats for muskellunge consist of areas with juxtaposition of deep and shallow habitat patches. Areas that consist predominantly of shallow or deep water should not be considered prime areas in which to introduce muskellunge.

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### APPENDIX 1: TECHNICAL DESCRIPTION OF DERIVATION RESULTS

The derivations of the statistical properties of the allometric growth model,  $W_s$ , and  $W_r$  relied heavily upon the  $\bar{\delta}$  method, expectation operator rules, and theorems pertaining to the variances and covariances of random variables. I recommend that readers refer to Kendall and Stuart (1969) and Hoel et al. (1971) for additional background on this method, operator rules, and theorems.

#### *Expectation and Variance of the Allometric Growth Model*

The allometric growth model assuming a multiplicative error structure is given by

$$W_i = \alpha^* L_i^{\beta^*} 10^{\varepsilon_i^*} \quad (\text{A.1})$$

I assumed that the random errors in equation A.1 were i.i.d. with expectation 0 and variance  $\sigma_w^2$ . A first-order Taylor series expansion of equation A.1 around the expectation of  $\varepsilon_i^*$  gave

$$W_i \approx \alpha^* L_i^{\beta^*} + (\varepsilon_i^* - 0) \left( \frac{\partial \left[ \alpha^* L_i^{\beta^*} 10^{\varepsilon_i^*} \right]}{\partial \varepsilon_i^*} \right), \quad (\text{A.2})$$

while a second-order Taylor series expansion yielded

$$W_i \approx \alpha^* L_i^{\beta^*} + (\varepsilon_i^* - 0) \left( \frac{\partial \left[ \alpha^* L_i^{\beta^*} 10^{\varepsilon_i^*} \right]}{\partial \varepsilon_i^*} \right) + \frac{(\varepsilon_i^* - 0)^2}{2} \left( \frac{\partial^2 \left[ \alpha^* L_i^{\beta^*} 10^{\varepsilon_i^*} \right]}{\partial \varepsilon_i^{*2}} \right). \quad (\text{A.3})$$

Applying the expectation operator to equation A.3 resulted in

$$E(W_i) \approx \alpha^* L_i^{\beta^*} + E(\varepsilon_i^* - 0) \left( \frac{\partial \left[ \alpha^* L_i^{\beta^*} 10^{\varepsilon_i^*} \right]}{\partial \varepsilon_i^*} \right) + \frac{E(\varepsilon_i^* - 0)^2}{2} \left( \frac{\partial^2 \left[ \alpha^* L_i^{\beta^*} 10^{\varepsilon_i^*} \right]}{\partial \varepsilon_i^{*2}} \right), \quad (\text{A.4})$$

which simplified to

$$E(W_i) \approx \alpha^* L_i^{\beta^*} + \frac{\text{Var}(\varepsilon_i^*)^2}{2} \left( \alpha^* L_i^{\beta^*} (\log_e 10)^2 \right). \quad (\text{A.5})$$

Squaring equation A.2 and taking its expectation resulted in

$$E((W_i)^2) \approx \left( \alpha^* L_i^{\beta^*} \right)^2 + \text{Var}(\varepsilon_i^*) \left( \alpha^* L_i^{\beta^*} (\log_e 10) \right)^2. \quad (\text{A.6})$$

Subtracting the square of the expectation of equation A.2 from equation A.6 and simplifying gave a variance of  $W_i$  equal to

$$\text{Var}(W_i) \approx \sigma_w^2 \left( \alpha^* L_i^{\beta^*} (\log_e 10) \right)^2. \quad (\text{A.7})$$

#### *Expectation, Variance, and Covariance of the Standard Weight Equation*

The standard weight for a fish of a particular length can be found using the equation

$$\hat{W}_{s_i} = \hat{\alpha} L_i^{\hat{\beta}}, \quad (\text{A.8})$$

where  $\hat{W}_{s_i}$  is the predicted standard weight for a fish of length  $L_i$  and  $\hat{\alpha}$  and  $\hat{\beta}$  are the parameter estimates of the  $W_s$  equation (Anderson and Neumann 1996). A second-order Taylor series expansion of equation A.8 around the expectations of  $\hat{\alpha}$  and  $\hat{\beta}$  yielded

$$\begin{aligned} \hat{W}_{s_i} \approx & \alpha L_i^{\beta} + (\hat{\alpha} - \alpha) \left( \frac{\partial [\hat{\alpha} L_i^{\hat{\beta}}]}{\partial \hat{\alpha}} \right) + (\hat{\beta} - \beta) \left( \frac{\partial [\hat{\alpha} L_i^{\hat{\beta}}]}{\partial \hat{\beta}} \right) + \frac{(\hat{\alpha} - \alpha)^2}{2} \left( \frac{\partial^2 [\hat{\alpha} L_i^{\hat{\beta}}]}{\partial \hat{\alpha}^2} \right) + \\ & \frac{(\hat{\beta} - \beta)^2}{2} \left( \frac{\partial^2 [\hat{\alpha} L_i^{\hat{\beta}}]}{\partial \hat{\beta}^2} \right) + (\hat{\alpha} - \alpha)(\hat{\beta} - \beta) \left( \frac{\partial^2 [\hat{\alpha} L_i^{\hat{\beta}}]}{\partial \hat{\alpha} \hat{\beta}} \right) \end{aligned} \quad (\text{A.9})$$

Applying the expectation operator to equation A.9 and simplifying resulted in

$$E(\hat{W}_{s_i}) \approx \alpha L_i^\beta + \frac{\text{Var}(\hat{\alpha})}{2} L_i^\beta + \frac{\text{Var}(\hat{\beta})}{2} \alpha L_i^\beta (\log_e L_i)^2 + \text{Cov}(\hat{\alpha}, \hat{\beta}) L_i^\beta (\log_e L_i). \quad (\text{A.10})$$

Because the parameter estimates of  $\alpha$  and  $\beta$  obtained by regression are not independent, the final term in equation A.10 does not necessarily equal zero.

A first-order Taylor series expansion of equation A.8 around the expectations of  $\hat{\alpha}$  and  $\hat{\beta}$  gave

$$\hat{W}_{s_i} \approx \alpha L_i^\beta + (\hat{\alpha} - \alpha) \left( \frac{\partial [\hat{\alpha} L_i^\beta]}{\partial \hat{\alpha}} \right) + (\hat{\beta} - \beta) \left( \frac{\partial [\hat{\alpha} L_i^\beta]}{\partial \hat{\beta}} \right). \quad (\text{A.11})$$

Subtracting the square of the expectation of equation A.11 from the expectation of its square gave a variance of

$$\text{Var}(\hat{W}_{s_i}) \approx \text{Var}(\hat{\alpha}) \left( L_i^\beta \right)^2 + \text{Var}(\hat{\beta}) \left( \alpha L_i^\beta (\log_e L_i) \right)^2 + 2 \text{Cov}(\hat{\alpha}, \hat{\beta}) \alpha \left( L_i^\beta \right)^2 (\log_e L_i). \quad (\text{A.12})$$

To find the covariance of  $\hat{W}_{s_i}$  and  $\hat{W}_{s_{i'}}$ , where  $\hat{W}_{s_i}$  refers to the standard weight of a fish of length  $L_i$

( $i' \neq i$ ), I first multiplied the product of the first-order Taylor series expansions of  $\hat{W}_{s_i}$  and  $\hat{W}_{s_{i'}}$ , which

gave

$$\begin{aligned} \hat{W}_{s_i} \cdot \hat{W}_{s_{i'}} \approx & \alpha^2 (L_i L_{i'})^\beta + (\hat{\alpha} - \alpha)^2 \frac{\partial [\hat{\alpha} L_i^\beta]}{\partial \hat{\alpha}} \frac{\partial [\hat{\alpha} L_{i'}^\beta]}{\partial \hat{\alpha}} + (\hat{\beta} - \beta)^2 \frac{\partial [\hat{\alpha} L_i^\beta]}{\partial \hat{\beta}} \frac{\partial [\hat{\alpha} L_{i'}^\beta]}{\partial \hat{\beta}} + \\ & (\hat{\alpha} - \alpha)(\hat{\beta} - \beta) \frac{\partial [\hat{\alpha} L_i^\beta]}{\partial \hat{\alpha}} \frac{\partial [\hat{\alpha} L_{i'}^\beta]}{\partial \hat{\beta}} + (\hat{\alpha} - \alpha)(\hat{\beta} - \beta) \frac{\partial [\hat{\alpha} L_{i'}^\beta]}{\partial \hat{\alpha}} \frac{\partial [\hat{\alpha} L_i^\beta]}{\partial \hat{\beta}}. \end{aligned} \quad (\text{A.13})$$

Applying the expectation operator to equation A.13 yielded

$$\begin{aligned} E(\hat{W}_{s_i} \cdot \hat{W}_{s_{i'}}) \approx & \alpha^2 (L_i L_{i'})^\beta + \text{Var}(\hat{\alpha}) \left( (L_i L_{i'})^\beta \right) + \text{Var}(\hat{\beta}) \left( (\alpha^2) (L_i L_{i'})^\beta (\log_e L_i) (\log_e L_{i'}) \right) + \\ & \text{Cov}(\hat{\alpha}, \hat{\beta}) \left( (\alpha) (L_i L_{i'})^\beta (\log_e L_i + \log_e L_{i'}) \right). \end{aligned} \quad (\text{A.14})$$

Subtracting the product of the expectations of  $\hat{W}_{s_i}$  and  $\hat{W}_{s_r}$  from equation A.14 to find the covariance of

$\hat{W}_{s_i}$  and  $\hat{W}_{s_r}$  resulted in

$$\begin{aligned} \text{Cov}(\hat{W}_{s_i} \cdot \hat{W}_{s_r}) \approx & \text{Var}(\hat{\alpha}) \left( (L_i L_{i'})^\beta \right) + \text{Var}(\hat{\beta}) \left( (\alpha^2) (L_i L_{i'})^\beta (\log_e L_i) (\log_e L_{i'}) \right) + \\ & \text{Cov}(\hat{\alpha}, \hat{\beta}) \left( (\alpha) (L_i L_{i'})^\beta (\log_e L_i + \log_e L_{i'}) \right). \end{aligned} \quad (\text{A.15})$$

#### Expectation, Variance, and Covariance of $W_r$

The relative weight index was rewritten as

$$W_{r_i} = \frac{W_i}{\hat{\alpha} L_i^{\hat{\beta}}} \cdot 100. \quad (\text{A.16})$$

A first- and second-order Taylor series expansion of equation A.16 gave

$$\begin{aligned} W_{r_i} \approx & \left( \frac{\alpha^* L_i^{\beta^*}}{\alpha L_i^\beta} \cdot 100 \right) + (W_i - \alpha^* L_i^{\beta^*}) \frac{\partial \left[ \frac{W_i}{\hat{\alpha} L_i^{\hat{\beta}}} \cdot 100 \right]}{\partial W_i} + (\hat{\alpha} - \alpha) \frac{\partial \left[ \frac{W_i}{\hat{\alpha} L_i^{\hat{\beta}}} \cdot 100 \right]}{\partial \hat{\alpha}} + \\ & (\hat{\beta} - \beta) \frac{\partial \left[ \frac{W_i}{\hat{\alpha} L_i^{\hat{\beta}}} \cdot 100 \right]}{\partial \hat{\beta}}, \end{aligned} \quad (\text{A.17})$$

and

$$\begin{aligned}
W_{r_i} \approx & \left( \frac{\alpha^* L_i^{\beta^*}}{\alpha L_i^\beta} \cdot 100 \right) + (W_i - \alpha^* L_i^{\beta^*}) \frac{\partial \left[ \frac{W_i}{\hat{\alpha} L_i^{\hat{\beta}}} \cdot 100 \right]}{\partial W_i} + (\hat{\alpha} - \alpha) \frac{\partial \left[ \frac{W_i}{\hat{\alpha} L_i^{\hat{\beta}}} \cdot 100 \right]}{\partial \hat{\alpha}} + \\
& (\hat{\beta} - \beta) \frac{\partial \left[ \frac{W_i}{\hat{\alpha} L_i^{\hat{\beta}}} \cdot 100 \right]}{\partial \hat{\beta}} + \frac{(W_i - \alpha^* L_i^{\beta^*})^2}{2} \frac{\partial^2 \left[ \frac{W_i}{\hat{\alpha} L_i^{\hat{\beta}}} \cdot 100 \right]}{\partial W_i^2} + \frac{(\hat{\alpha} - \alpha)^2}{2} \frac{\partial^2 \left[ \frac{W_i}{\hat{\alpha} L_i^{\hat{\beta}}} \cdot 100 \right]}{\partial \hat{\alpha}^2} + \\
& \frac{(\hat{\beta} - \beta)^2}{2} \frac{\partial^2 \left[ \frac{W_i}{\hat{\alpha} L_i^{\hat{\beta}}} \cdot 100 \right]}{\partial \hat{\beta}^2} + (W_i - \alpha^* L_i^{\beta^*})(\hat{\alpha} - \alpha) \frac{\partial^2 \left[ \frac{W_i}{\hat{\alpha} L_i^{\hat{\beta}}} \cdot 100 \right]}{\partial W_i \hat{\alpha}} + \\
& (W_i - \alpha^* L_i^{\beta^*})(\hat{\beta} - \beta) \frac{\partial^2 \left[ \frac{W_i}{\hat{\alpha} L_i^{\hat{\beta}}} \cdot 100 \right]}{\partial W_i \hat{\beta}} + (\hat{\alpha} - \alpha)(\hat{\beta} - \beta) \frac{\partial^2 \left[ \frac{W_i}{\hat{\alpha} L_i^{\hat{\beta}}} \cdot 100 \right]}{\partial \hat{\alpha} \hat{\beta}}. \tag{A.18}
\end{aligned}$$

Applying the expectation operator to equation A.18, substituting in equation A.7, and assuming that a fish's weight is independent of the standard weight for the species, which is a reasonable assumption except when  $W_r$  is computed for a population that was used in determining the standard weight equation, resulted in

$$\begin{aligned}
E(W_{r_i}) \approx & \left( \frac{\alpha^* L_i^{\beta^*}}{\alpha L_i^\beta} \cdot 100 \right) + \frac{\sigma_w^2 (\alpha^* L_i^{\beta^*} \log_e 10)^2}{2} \left( \frac{100}{\alpha L_i^\beta} \right) + \text{Var}(\hat{\alpha}) \left( \frac{(\alpha^* L_i^{\beta^*}) 100}{\alpha^3 L_i^\beta} \right) + \\
& \frac{\text{Var}(\hat{\beta})}{2} \left( \frac{(\alpha^* L_i^{\beta^*}) (\log_e L_i)^2 100}{\alpha L_i^\beta} \right) + \text{Cov}(\hat{\alpha}, \hat{\beta}) \left( \frac{(\alpha^* L_i^{\beta^*}) (\log_e L_i) 100}{\alpha^2 L_i^\beta} \right). \tag{A.19}
\end{aligned}$$

The expectation of the squared first-order Taylor series expansion of equation A.16 was



$$\begin{aligned}
E(W_{r_i}^2) \approx & \left( \frac{\alpha^* L_i^{\beta^*}}{\alpha L_i^\beta} \cdot 100 \right)^2 + \text{Var}(W_i) \left( \frac{100}{\alpha L_i^\beta} \right)^2 + \text{Var}(\hat{\alpha}) \left( \frac{\alpha^* L_i^{\beta^*} 100}{\alpha^2 L_i^\beta} \right)^2 + \\
& \text{Var}(\hat{\beta}) \left( \frac{\alpha^* L_i^{\beta^*} \log_e L_i 100}{\alpha L_i^\beta} \right)^2 + 2 \text{Cov}(\hat{\alpha}, \hat{\beta}) \left( \frac{(\alpha^*)^2 (L_i^{\beta^*})^2 (\log_e L_i) 10,000}{\alpha^3 L_i^{2\beta}} \right). \quad (\text{A.20})
\end{aligned}$$

The variance of the relative weight index was found by subtracting from equation A.20 the squared expectation of the first-order Taylor series expansion of equation A.16 and substituting in equation A.7, which resulted in

$$\begin{aligned}
\text{Var}(W_{r_i}) \approx & \sigma_w^2 (\alpha^* L_i^{\beta^*} \log_e 10)^2 \left( \frac{100}{\alpha L_i^\beta} \right)^2 + \text{Var}(\hat{\alpha}) \left( \frac{\alpha^* L_i^{\beta^*} 100}{\alpha^2 L_i^\beta} \right)^2 + \quad (\text{A.21}) \\
& \text{Var}(\hat{\beta}) \left( \frac{\alpha^* L_i^{\beta^*} \log_e L_i 100}{\alpha L_i^\beta} \right)^2 + 2 \text{Cov}(\hat{\alpha}, \hat{\beta}) \left( \frac{(\alpha^*)^2 (L_i^{\beta^*})^2 (\log_e L_i) 10,000}{\alpha^3 L_i^{2\beta}} \right).
\end{aligned}$$

The approximate expectation of the product of the first-order Taylor series expansion of  $W_{r_i}$  and  $W_{r_{i'}}$ ,

where  $W_{r_{i'}}$  refers to the relative weight of fish  $i'$  ( $i' \neq i$ ), equaled

$$\begin{aligned}
E(W_{r_i} \cdot W_{r_{i'}}) \approx & \left( \frac{\alpha^* L_i^{\beta^*}}{\alpha L_i^\beta} \cdot 100 \right) \left( \frac{\alpha^* L_{i'}^{\beta^*}}{\alpha L_{i'}^\beta} \cdot 100 \right) + \text{Cov}(W_i, W_{i'}) \left( \frac{10,000}{\alpha^2 (L_i L_{i'})^\beta} \right) + \\
& \text{Var}(\hat{\alpha}) \left( \frac{(\alpha^*)^2 (L_i L_{i'})^{\beta^*} 10,000}{\alpha^4 (L_i L_{i'})^\beta} \right) + \\
& \text{Var}(\hat{\beta}) \left( \frac{(\alpha^*)^2 (L_i L_{i'})^{\beta^*} (\log_e L_i) (\log_e L_{i'}) 10,000}{\alpha^2 (L_i L_{i'})^\beta} \right) + \\
& \text{Cov}(\hat{\alpha}, \hat{\beta}) \left( \frac{(\alpha^*)^2 (L_i L_{i'})^{\beta^*} 10,000}{\alpha^3 (L_i L_{i'})^\beta} \right) ((\log_e L_i) + (\log_e L_{i'})). \quad (\text{A.22})
\end{aligned}$$

By subtracting the product of the approximate expectations of the first-order Taylor series expansion of equation A.16 from equation A.22 and because I assumed that the weight of fish  $i$  was independent from the weight of fish  $i'$ , the covariance of  $W_{r_i}$  and  $W_{r_{i'}}$  was found to equal

$$\begin{aligned} \text{Cov}(W_{r_i} \cdot W_{r_{i'}}) \approx & \text{Var}(\hat{\alpha}) \left( \frac{(\alpha^*)^2 (L_i L_{i'})^\beta 10,000}{\alpha^4 (L_i L_{i'})^\beta} \right) + \\ & \text{Var}(\hat{\beta}) \left( \frac{(\alpha^*)^2 (L_i L_{i'})^\beta (\log_e L_i)(\log_e L_{i'}) 10,000}{\alpha^2 (L_i L_{i'})^\beta} \right) + \\ & \text{Cov}(\hat{\alpha}, \hat{\beta}) \left( \frac{(\alpha^*)^2 (L_i L_{i'})^\beta 10,000}{\alpha^3 (L_i L_{i'})^\beta} \right) \left( (\log_e L_i) + (\log_e L_{i'}) \right). \end{aligned} \quad (\text{A.23})$$

Equation (A.23) can be modified to yield the covariance between fish from two different populations.

Letting subscript  $j$  and  $j'$  indicate fish from populations  $j$  and  $j'$ , respectively, the covariance in  $W_r$  between fish from different populations equals,

$$\begin{aligned} \text{Cov}(W_{r_j} \cdot W_{r_{j'}}) \approx & \text{Var}(\hat{\alpha}) \left( \frac{(\alpha_j^*)(\alpha_{j'}^*)(L_j)^\beta (L_{j'})^\beta 10,000}{\alpha^4 (L_j L_{j'})^\beta} \right) + \\ & \text{Var}(\hat{\beta}) \left( \frac{(\alpha_j^*)(\alpha_{j'}^*)(L_j)^\beta (L_{j'})^\beta (\log_e L_j)(\log_e L_{j'}) 10,000}{\alpha^2 (L_j L_{j'})^\beta} \right) + \\ & \text{Cov}(\hat{\alpha}, \hat{\beta}) \left( \frac{(\alpha_j^*)(\alpha_{j'}^*)(L_j)^\beta (L_{j'})^\beta 10,000}{\alpha^3 (L_j L_{j'})^\beta} \right) \left( (\log_e L_j) + (\log_e L_{j'}) \right). \end{aligned} \quad (\text{A.24})$$

**APPENDIX 2: SAS PROGRAMMING CODE FOR THE R TEST**

The following SAS (SAS Institute, Inc., Cary, North Carolina) code is provided for those unfamiliar with programming matrix-vector operations. This is the exact session that I used to find the maximum likelihood estimates of mean  $W_r$  and to test for differences in  $W_r$  for the muskellunge sample using the overall test and the multiple comparison procedure outlined in the text. Thus, this example is for 5 groups with the sizes of the groups equal to 28, 27, 23, 20, and 3. Users will need to modify the code to fit their own situation. These modifications may include changing the number of fish in each group as well as the total number of groups. Text preceded by */\** and followed by *\*/* is commentary and does not need to be programmed.

*/\** PROC IMPORT is a procedure that can be used to input a spreadsheet file created using other software into a SAS data set. In this case, the file *Wr.xls* is a Microsoft® Excel file located directly on the C:\ drive. This file consists only of the 101×1 vector of  $W_r$  values for all fish in the muskellunge sample.  $W_r$  values are sorted by fish length so that the first and last entries are for the smallest and longest fish in the sample, respectively. There is no header row associated with this file. The file gets written to the SAS data set *WORK.WR*. *\*/*

```
PROC IMPORT OUT= WORK.WR
    DATAFILE="C:\Wr.xls"
    DBMS=EXCEL2000 REPLACE;
    GETNAMES=NO;
RUN;
```

*/\** The following PROC IMPORT command inputs the 101×101 variance-covariance matrix of  $W_r$  for the muskellunge sample into the SAS data set *WORK.COV*. Again, there is no header row with this file. Both the rows and columns of the matrix are sorted by fish length, thus the element in the 5th row and 5th column is the variance in  $W_r$  for the 5th smallest fish and the element in the 5th row and 6th column is the covariance in  $W_r$  for the 5th and 6th smallest fish.*\*/*

```

PROC IMPORT OUT= WORK.COV
    DATAFILE= "C:\Covariance.xls"
    DBMS=EXCEL2000 REPLACE;
    GETNAMES=NO;
RUN;

```

*/\** The calculation of the maximum likelihood estimates of mean  $W_r$  for all fish combined and for each group and the calculation of  $R$  and  $R_i$  is done using PROC IML, which is both a SAS procedure and a programming language. The basic data elements in IML are matrices, which includes both vectors and scalars. *\*/*

```

PROC IML;
USE WORK.WR;           /* Reads the SAS data set WORK.WR into the 101x1 vector WR */
READ ALL INTO WR;
CLOSE WORK.WR;
USE WORK.COV;         /* Reads the SAS data set WORK.COV into the 101x101 matrix V. */
READ ALL INTO V;
CLOSE WORK.COV;
GX=J(101,1,1);       /* Creates a 101x1 vector with all elements = 1. */
G1X1=J(28,1,1);      /* Creates a 28x1 vector with all elements = 1. */
G2X1=J(27,1,1);      /* Creates a 27x1 vector with all elements = 1. */
G3X1=J(23,1,1);      /* Creates a 23x1 vector with all elements = 1. */
G4X1=J(20,1,1);      /* Creates a 20x1 vector with all elements = 1. */
G5X1=J(3,1,1);       /* Creates a 3x1 vector with all elements = 1. */
G1X0=J(28,1,0);      /* Creates a 28x1 vector with all elements = 0. */
G2X0=J(27,1,0);      /* Creates a 27x1 vector with all elements = 0. */
G3X0=J(23,1,0);      /* Creates a 23x1 vector with all elements = 0. */
G4X0=J(20,1,0);      /* Creates a 20x1 vector with all elements = 0. */

```

```

G5X0=J(3,1,0);          /* Creates a 3x1 vector with all elements = 0. */
X1=G1X1||G1X0||G1X0||G1X0||G1X0; /* Creates the first column of the X matrix. */
X2=G2X0||G2X1||G2X0||G2X0||G2X0; /* Creates the second column of the X matrix. */
X3=G3X0||G3X0||G3X1||G3X0||G3X0; /* Creates the third column of the X matrix. */
X4=G4X0||G4X0||G4X0||G4X1||G4X0; /* Creates the fourth column of the X matrix. */
X5=G5X0||G5X0||G5X0||G5X0||G5X1; /* Creates the fifth column of the X matrix. */
X=X1//X2//X3//X4//X5;    /*Creates the X matrix by horizontally pasting its columns. */
MLE0=(INV(GX`*INV(V)*GX))*GX`*INV(V)*WR; /* MLE of mean Wr for all fish. */
MLE1=(INV(X`*INV(V)*X))*X`*INV(V)*WR;    /* The MLE of mean Wr for each group. */
MLE11=MLE1[1,];          /* Isolates the MLE of mean Wr for the 1st group. */
MLE12=MLE1[2,];          /* Isolates the MLE of mean Wr for the 2nd group. */
MLE13=MLE1[3,];          /* Isolates the MLE of mean Wr for the 3rd group. */
MLE14=MLE1[4,];          /* Isolates the MLE of mean Wr for the 4th group. */
MLE15=MLE1[5,];          /* Isolates the MLE of mean Wr for the 5th group. */

/* The next 17 lines of code simply creates the print statements for printing out the MLEs of mean Wr and
prints the MLEs. */
A='THE MLE OF OVERALL MEAN RELATIVE WEIGHT EQUALS';
B='THE MLE OF MEAN RELATIVE WEIGHT FOR GROUP 1 EQUALS';
C='THE MLE OF MEAN RELATIVE WEIGHT FOR GROUP 2 EQUALS';
D='THE MLE OF MEAN RELATIVE WEIGHT FOR GROUP 3 EQUALS';
E='THE MLE OF MEAN RELATIVE WEIGHT FOR GROUP 4 EQUALS';
F='THE MLE OF MEAN RELATIVE WEIGHT FOR GROUP 5 EQUALS';
PRINT A MLE0;
PRINT ";
PRINT B MLE11;
PRINT ";
PRINT C MLE12;

```

```

PRINT ";
PRINT D MLE13;
PRINT ";
PRINT E MLE14;
PRINT ";
PRINT F MLE15;

MU0=J(101,1,MLE0);      /* Creates the 101x1 vector  $\hat{\mu}_0$  . */
G1MU=J(28,1,MLE11);    /* Creates a 28x1 vector of mean  $W_r$  for the 1st group. */
G2MU=J(27,1,MLE12);    /* Creates a 27x1 vector of mean  $W_r$  for the 2nd group. */
G3MU=J(23,1,MLE13);    /* Creates a 23x1 vector of mean  $W_r$  for the 3rd group. */
G4MU=J(20,1,MLE14);    /* Creates a 20x1 vector of mean  $W_r$  for the 4th group. */
G5MU=J(3,1,MLE15);     /* Creates a 3x1 vector of mean  $W_r$  for the 5th group. */
MU1=G1MU//G2MU//G3MU//G4MU//G5MU; /* Creates the 101x1 vector  $\hat{\mu}_1$  . */

R=(MU1-MU0)*INV(V)*(MU1-MU0)*(1/4); /* Calculates R for the overall hypothesis test. */

/* The next two lines of code set up the print statement and prints R. */
G='THE TEST STATISTIC R FOR TESTING NO DIFFERENCES BETWEEN GROUPS EQUALS';
PRINT G R;

/* The next 10 lines of code create the contrast vectors for the 10 pairwise comparisons. */
C1 = {1 -1 0 0 0};      /* Contrast to compare Groups 1 & 2. */
C2 = {1 0 -1 0 0};     /* Contrast to compare Groups 1 & 3. */
C3 = {1 0 0 -1 0};     /* Contrast to compare Groups 1 & 4. */
C4 = {1 0 0 0 -1};     /* Contrast to compare Groups 1 & 5. */
C5 = {0 1 -1 0 0};     /* Contrast to compare Groups 2 & 3. */
C6 = {0 1 0 -1 0};     /* Contrast to compare Groups 2 & 4. */

```

```

C7 = {0 1 0 0 -1};      /* Contrast to compare Groups 2 & 5. */
C8 = {0 0 1 -1 0};     /* Contrast to compare Groups 3 & 4. */
C9 = {0 0 1 0 -1};     /* Contrast to compare Groups 3 & 5. */
C10 = {0 0 0 1 -1};    /* Contrast to compare Groups 4 & 5. */

R1 = (C1*MLE1)`*INV(C1*INV(X`*INV(V)*X)*C1`)*(C1*MLE1); /* R1 for comparing Groups 1 & 2. */
R2 = (C2*MLE1)`*INV(C2*INV(X`*INV(V)*X)*C2`)*(C2*MLE1); /* R2 for comparing Groups 1 & 3. */
R3 = (C3*MLE1)`*INV(C3*INV(X`*INV(V)*X)*C3`)*(C3*MLE1); /* R3 for comparing Groups 1 & 4. */
R4 = (C4*MLE1)`*INV(C4*INV(X`*INV(V)*X)*C4`)*(C4*MLE1); /* R4 for comparing Groups 1 & 5. */
R5 = (C5*MLE1)`*INV(C5*INV(X`*INV(V)*X)*C5`)*(C5*MLE1); /* R5 for comparing Groups 2 & 3. */
R6 = (C6*MLE1)`*INV(C6*INV(X`*INV(V)*X)*C6`)*(C6*MLE1); /* R6 for comparing Groups 2 & 4. */
R7 = (C7*MLE1)`*INV(C7*INV(X`*INV(V)*X)*C7`)*(C7*MLE1); /* R7 for comparing Groups 2 & 5. */
R8 = (C8*MLE1)`*INV(C8*INV(X`*INV(V)*X)*C8`)*(C8*MLE1); /* R8 for comparing Groups 3 & 4. */
R9 = (C9*MLE1)`*INV(C9*INV(X`*INV(V)*X)*C9`)*(C9*MLE1); /* R9 for comparing Groups 3 & 5. */
R10 = (C10*MLE1)`*INV(C10*INV(X`*INV(V)*X)*C10`)*(C10*MLE1); /* R10 for comparing Groups 4 & 5.
*/

/* The next 30 lines of code creates the print statements and prints the test statistics for the multiple
comparison procedure. */
AA = 'THE TEST STATISTIC R1 FOR TESTING GROUPS 1 & 2 EQUALS';
AB = 'THE TEST STATISTIC R2 FOR TESTING GROUPS 1 & 3 EQUALS';
AC = 'THE TEST STATISTIC R3 FOR TESTING GROUPS 1 & 4 EQUALS';
AD = 'THE TEST STATISTIC R4 FOR TESTING GROUPS 1 & 5 EQUALS';
AE = 'THE TEST STATISTIC R5 FOR TESTING GROUPS 2 & 3 EQUALS';
AF = 'THE TEST STATISTIC R6 FOR TESTING GROUPS 2 & 4 EQUALS';
AG = 'THE TEST STATISTIC R7 FOR TESTING GROUPS 2 & 5 EQUALS';
AH = 'THE TEST STATISTIC R8 FOR TESTING GROUPS 3 & 4 EQUALS';
AI = 'THE TEST STATISTIC R9 FOR TESTING GROUPS 3 & 5 EQUALS';

```

AJ = 'THE TEST STATISTIC R10 FOR TESTING GROUPS 4 & 5 EQUALS';

PRINT AA R1;

PRINT ";

PRINT AB R2;

PRINT ";

PRINT AC R3;

PRINT ";

PRINT AD R4;

PRINT ";

PRINT AE R5;

PRINT ";

PRINT AF R6;

PRINT ";

PRINT AG R7;

PRINT ";

PRINT AH R8;

PRINT ";

PRINT AI R9;

PRINT ";

PRINT AJ R10;

QUIT;



## APPENDIX 3: VARIANCE-COVARIANCE ESTIMATES FOR STANDARD WEIGHT EQUATION COEFFICIENTS FOR 58 SPECIES AND

## PURPOSEFUL HYBRIDS

Family	Scientific Name	Common Name	Var <sub>B</sub>		Cov <sub>B</sub>	Source
			(log <sub>10</sub> α)	Var <sub>B</sub> (β)	(log <sub>10</sub> α, β)	
Acipenseridae	<i>Acipenser transmontanus</i>	White sturgeon	0.02066	0.00217	-0.00667	Beamesderfer 1993
	<i>Scaphirhynchus platyrhynchus</i>	Shovelnose sturgeon	0.00114	0.00015	-0.00041	Quist et al. 1998
Catostomidae	<i>Carpiondes carpio</i>	River carpsucker	0.00469	0.00074	-0.00185	Bister et al. 1999
	<i>Catostomus commersoni</i>	White sucker	0.00370	0.00052	-0.00139	Bister et al. 1999
	<i>Catostomus latipinnis</i>	Flannelmouth sucker	0.01266	0.00157	-0.00341	Didenko et al. 2004
	<i>Ictiobus bubalus</i>	Smallmouth buffalo	0.00348	0.00049	-0.00130	Bister et al. 1999
	<i>Ictiobus cyprinellus</i>	Bigmouth buffalo	0.00137	0.00019	-0.00050	Bister et al. 1999
	<i>Moxostoma macrolepidotum</i>	Shorthead redhorse	0.00666	0.00101	-0.00259	Bister et al. 1999
	<i>Xyrauchen texanus</i>	Razorback sucker	0.04525	0.00502	-0.01500	Didenko et al. 2004
Centrarchidae	<i>Ambloplites rupestris</i>	Rock bass	0.00692	0.00127	-0.00295	Bister et al. 1998
	<i>Lepomis cyanellus</i>	Green sunfish	0.02375	0.00535	-0.01125	Bister et al. 1999
	<i>Lepomis gibbosus</i>	Pumpkinseed	0.00970	0.00219	-0.00458	Liao 1994
	<i>Lepomis gulosus</i>	Warmouth	0.00771	0.00164	-0.00354	Bister et al. 1999
	<i>Lepomis microlophus</i>	Redear sunfish	0.00750	0.00141	-0.00323	Unpublished <sup>a</sup>
	<i>Micropterus dolomieu</i>	Smallmouth bass	0.01029	0.00166	-0.00412	Kolander et al. 1993
	<i>Micropterus salmoides</i>	Largemouth bass	0.00166	0.00025	-0.00064	Henson 1991
	<i>Pomoxis annularis</i>	White crappie	0.01129	0.00196	-0.00469	Neumann and Murphy 1991
	<i>Pomoxis nigromaculatus</i>	Black crappie	0.01228	0.00224	-0.00521	Neumann and Murphy 1991
Cyprinidae	<i>Cyprinus carpio</i>	Common carp	0.00377	0.00052	-0.00139	Bister et al. 1999
	<i>Gila cypha</i>	Humpback chub	0.00982	0.00180	-0.00416	Didenko et al. 2004

## Appendix 3 (cont.)

Family	Scientific Name	Common Name	Var <sub>B</sub>		Cov <sub>B</sub>	Source
			(log <sub>10</sub> α)	Var <sub>B</sub> (β)	(log <sub>10</sub> α, β)	
Cyprinidae	<i>Gila robusta</i>	Roundtail chub	0.00982	0.00180	-0.00416	Didenko et al. 2004
	<i>Notemigous crysoleucas</i>	Golden shiner	0.01506	0.00335	-0.00707	Liao 1994
Esocidae	<i>Esox lucius</i>	Northern pike	0.00132	0.00019	-0.00050	Unpublished <sup>b</sup>
	<i>Esox lucius</i> × <i>Esox masquinongy</i>	Tiger muskellunge	0.00255	0.00030	-0.00087	Rogers and Koupal 1997
	<i>Esox masquinongy</i>	Muskellunge	0.01266	0.00157	-0.00444	Neumann and Willis 1994
	<i>Esox niger</i>	Chain pickerel	0.00356	0.00058	-0.00143	Unpublished <sup>c</sup>
Gadidae	<i>Lota lota</i>	Burbot	0.00432	0.00060	-0.0016	Fisher et al. 1996
Ictaluridae	<i>Ameiurus catus</i>	White catfish	0.00524	0.00084	-0.00209	Bister et al. 1999
	<i>Ameiurus melas</i>	Black bullhead	0.00888	0.00162	-0.00378	Bister et al. 1999
	<i>Ameiurus natalis</i>	Yellow bullhead	0.00445	0.00078	-0.00185	Bister et al. 1999
	<i>Ameiurus nebulosus</i>	Brown bullhead	0.01019	0.00162	-0.00405	Bister et al. 1999
	<i>Ictalurus punctatus</i>	Channel catfish	0.00119	0.00018	-0.00046	Unpublished <sup>d</sup>
	<i>Pylodictis olivaris</i>	Flathead catfish	0.00135	0.00020	-0.00051	Bister et al. 1999
Lepisosteidae	<i>Lepisosteus oculatus</i>	Spotted gar	0.01085	0.00144	-0.00395	Bister et al. 1999
	<i>Lepisosteus osseus</i>	Longnose gar	0.01674	0.00207	-0.00586	Bister et al. 1999
Percichthyidae	<i>Morone americana</i>	White perch	0.01591	0.00324	-0.00714	Bister et al. 1999
	<i>Morone chrysops</i>	White bass	0.00651	0.00107	-0.00263	Brown and Murphy 1991
	<i>Morone mississippiensis</i>	Yellow bass	0.00938	0.00153	-0.00377	Bister et al. 1999
	<i>Morone saxatilis</i>	Striped bass	0.00577	0.00082	-0.00216	Brown and Murphy 1991
	<i>Morone saxatilis</i> × <i>Morone chrysops</i>	Palmetto bass	0.00728	0.00107	-0.00278	Brown and Murphy 1991
Percidae	<i>Perca flavescens</i>	Yellow perch	0.01487	0.00255	-0.00612	Willis et al. 1991

## Appendix 3 (cont.)

Family	Scientific Name	Common Name	Var <sub>B</sub>		Cov <sub>B</sub>	Source
			(log <sub>10</sub> α)	Var <sub>B</sub> (β)	(log <sub>10</sub> α, β)	
Percidae	<i>Sander vitreus</i>	Walleye (adult)	0.00438	0.00081	-0.00188	Murphy et al. 1990
	<i>Sander vitreus</i>	Walleye (juvenile)	0.03458	0.00747	-0.01603	Flammang et al. 1999
	<i>Sander vitreus</i> × <i>Sander canadensis</i>	Saugeye	0.00410	0.00062	-0.00159	Flammang et al. 1993
	<i>Sander canadensis</i>	Sauger	0.00533	0.00078	-0.00204	Unpublished <sup>b</sup>
Polyodontidae	<i>Polyodon spathula</i>	Paddlefish (combined)	0.03365	0.00369	-0.01110	Brown and Murphy 1993
	<i>Polyodon spathula</i>	Paddlefish (female)	0.14318	0.01523	-0.04661	Brown and Murphy 1993
	<i>Polyodon spathula</i>	Paddlefish (male)	0.07609	0.00929	-0.02650	Brown and Murphy 1993
Salmonidae	<i>Coregonus artedi</i>	Lake herring	0.00792	0.00140	-0.00330	Fisher and Fielder 1998
	<i>Oncorhynchus aguabonita</i>	Golden trout	0.00371	0.00071	-0.00161	Hyatt 2000
	<i>Oncorhynchus mykiss</i>	Rainbow trout (lentic)	0.00508	0.00084	-0.00206	Unpublished <sup>e</sup>
	<i>Oncorhynchus mykiss</i>	Rainbow trout (lotic)	0.00252	0.00038	-0.00098	Unpublished <sup>e</sup>
	<i>Oncorhynchus nerka</i>	Kokanee	0.00976	0.00146	-0.00376	Hyatt 2000
	<i>Oncorhynchus tshawytscha</i>	Chinook salmon	0.00735	0.00090	-0.00256	Halseth et al. 1990
	<i>Prosopium williamsoni</i>	Mountain whitefish	0.01238	0.00218	-0.00518	Rogers et al. 1996
	<i>Salmo trutta</i>	Brown trout (lentic)	0.00765	0.00130	-0.00315	Hyatt 2000
	<i>Salmo trutta</i>	Brown trout (lotic)	0.00587	0.00093	-0.00233	Milewski and Brown 1994
	<i>Salvelinus confluentus</i>	Bull trout	0.00027	0.00003	-0.00008	Hyatt 2000
	<i>Salvelinus fontinalis</i>	Brook trout (combined)	0.00445	0.00075	-0.00182	Hyatt 2000
	<i>Salvelinus fontinalis</i>	Brook trout (lentic)	0.00545	0.00099	-0.00231	Hyatt 2000
	<i>Salvelinus fontinalis</i>	Brook trout (lotic)	0.00686	0.00118	-0.00283	Hyatt 2000
<i>Salvelinus fontinalis</i> × <i>Salvelinus namaycush</i>	Splake	0.02535	0.00486	-0.01109	Hyatt 2000	

## Appendix 3 (cont.)

Family	Scientific Name	Common Name	Var <sub>B</sub>		Cov <sub>B</sub>	Source
			(log <sub>10</sub> α)	Var <sub>B</sub> (β)	(log <sub>10</sub> α, β)	
Salmonidae	<i>Salvelinus namaycush</i>	Lake trout	0.00338	0.00046	-0.00124	Piccolo et al. 1993
	<i>Thymallus arcticus</i>	Arctic grayling	0.00625	0.00176	-0.00320	Hyatt 2000
Sciaenidae	<i>Aplodinotus grunniens</i>	Freshwater drum	0.0022	0.00037	-0.00090	Blackwell et al. 1995

<sup>a</sup> K. Pope, Texas Tech University

<sup>b</sup> D. Willis, South Dakota State University

<sup>c</sup> R. Neumann, University of Connecticut

<sup>d</sup> M. Brown, South Dakota State University

<sup>e</sup> D. Simpkins, Colorado Cooperative Fish and Wildlife Research Unit

## APPENDIX 4: SAS CODE FOR FINDING VARIANCE AND COVARIANCE ESTIMATES OF $W_s$

### EQUATION PARAMETERS

```

%MACRO BOOTSTRAP(ITERATIONS,POPSIZE,SEED);
/*START OF THE ITERATIVE PROCESS*/
%DO I=1 %TO &ITERATIONS;

/*ADDS THE INITIAL SEED VALUE TO THE CURRENT ITERATION NUMBER. OTHERWISE PROC
SURVEYSELECT WILL RESAMPLE THE SAME DATA SET*/
%LET A=%EVAL(&SEED+&I);

PROC SURVEYSELECT DATA=WORK.PARMS NOPRINT METHOD=URS OUT=SURVSEL OUTHITS
SAMPsize=&POPSIZE SEED=&A;
RUN;
QUIT;

DATA WORK.BootPARMS (KEEP=F1 F2);
    SET WORK.SURVSEL;
RUN;

PROC IML;
    LOAD;
/*READS THE PARAMETER ESTIMATES INTO A MATRIX CALLED PARMS. */
    USE WORK.BootPARMS;
    READ ALL INTO BootPARMS;
    CLOSE WORK.BootPARMS;

    LOGBWEIGHT=BootPARMS*DATA;

    PBWEIGHT=10**LOGBWEIGHT;

    PBWEIGHTVEC=COLVEC(PBWEIGHT');

    DATA2 = PBWEIGHTVEC||LLLVEC||IDVEC;

    VARNAMES={WEIGHT LENGTH ID};

    CREATE WORK.BootDATA FROM DATA2 [COLNAME=VARNAMES];
        APPEND FROM DATA2;

    STORE;

    QUIT;

PROC MEANS DATA=WORK.BootDATA NOPRINT;
    BY LENGTH;
    VAR WEIGHT;
    OUTPUT OUT=WORK.BootQUART Q3(WEIGHT)=WEIGHT;
RUN;
QUIT;

DATA WORK.BootQUART (KEEP=LENGTH WEIGHT);
    SET WORK.BootQUART;
RUN;

```

```
DATA WORK.BootQuart;  
  SET WORK.BootQuart;  
  LOGWEIGHT=LOG10(WEIGHT);  
  LOGLENGTH=LOG10(LENGTH);  
RUN;  
  
PROC REG DATA=WORK.BootQuart OUTEST=BOOTPARMS NOPRINT;  
  MODEL LOGWEIGHT=LOGLENGTH;  
RUN;  
QUIT;  
  
PROC APPEND BASE=OUTPARMS DATA=BOOTPARMS;  
RUN;  
  
/*ENDS THE ITERATIONS*/  
%END;  
  
/*END OF THE MACRO*/  
%MEND BOOTSTRAP;  
  
PROC IMPORT OUT= WORK.parms  
  DATAFILE= "C:\MyDocuments\PubsinPrep\WsVariance\Data\muskycomb.xls"  
  DBMS=EXCEL2000 REPLACE;  
  GETNAMES=NO;  
RUN;  
  
PROC IML;  
/*READS THE PARAMETER ESTIMATES INTO A MATRIX CALLED PARMs. */  
  USE WORK.PARMS;  
  READ ALL INTO PARMs;  
  CLOSE WORK.PARMS;  
  
/*SETS THE LENGTH CATEGORIES FOR WHICH THE STANDARD WEIGHT EQUATION IS USED. */  
  LENGTH=DO(380,1640,10);  
  
/*PARAMETER ESTIMATES OF THE WS EQUATION BASED ON THE RLP TECHNIQUE*/  
  RLPSLOPE=3.325;  
  RLPINTER=-6.066;  
  
/*COUNTS THE NUMBER OF LENGTH INTERVALS*/  
  NLEN=NCOL(LENGTH);  
  
/*COUNTS THE NUMBER OF POPULATIONS (N) USED IN THE RLP TECHNIQUE*/  
  NPOPS=NROW(PARMS);  
  
/*CREATES A 1*K (K=NUMBER OF LENGTH CATEGORIES) VECTOR WITH ALL ELEMENTS =1*/  
  ONES=J(1,NLEN,1);  
  
/*LOG BASE 10 TRANSFORMS THE LENGTH CATEGORIES*/  
  LOGLEN=LOG10(LENGTH);  
  
/*CREATES A 2*K MATRIX BY VERTICALLY PASTING THE VECTORS ONES AND LOGLEN*/  
  DATA=ONES//LOGLEN;  
  
/*CREATES AN N*K MATRIX OF PREDICTED LOG10 WEIGHT AT THE LENGTH CATEGORIES FOR
```

```
THE POPULATIONS USED IN THE RLP TECHNIQUE*/
LOGPWEIGHT=PARMS*DATA;

/*ANTILOG TRANSFORMS THE MATRIX OF PREDICTED LOG10 WEIGHT TO
ACTUAL WEIGHT FOR THE LENGTH CATEGORIES*/
PWEIGHT=10**LOGPWEIGHT;

/*CREATES A 1xN:K VECTOR OF PREDICED WEIGHTS*/
PWEIGHTVEC=COLVEC(PWEIGHT`);

/*CREATES AN INDEX OF ID VARIABLES RANGING FROM 1 TO THE NUMBER OF LENGTH
CATEGORIES*/
XX=1:NLEN;

/*CREATES A MATRIX OF THESE ID VARIABLES*/
XXX=REPEAT(XX,NPOPS,1);

/*CREATES A VECTOR OF THE ID VARIABLES*/
IDVECTOR=COLVEC(XXX`);

/*CREATES A MATRIX OF LENGTH CATGEORIES */
LLL=REPEAT(LENGTH,NPOPS,1);

/*CREATES A VECTOR OF THE LENGTH CATEGORIES*/
LLLVEC=COLVEC(LLL`);

/*CREATES A MATRIX OF THE ORIGINAL PREDICTED WEIGHTS OF THE POPULATIONS USED
IN THE RLP TECHNIQUE AND THE LENGTH CATEGORIES*/
ORIG=IDVECTOR||LLLVEC||PWEIGHTVEC;

/*NAMES THAT WILL BE USED FOR THE COLUMNS WHEN CREATING THE SAS DATA SET*/
VARNAMES={ID LENGTH WEIGHT};

/*CREATES THE FOLLOWING SAS DATA SETS BASED ON ABOVE MATRICES*/
CREATE WORK.ORIG FROM ORIG [COLNAME=VARNAMES];
APPEND FROM ORIG;

/*STORES ALL OF THE CREATED MATRICES IN THIS IML SESSION*/
STORE;

QUIT;

/*FINDS THE 75TH PERCENTILE OF PREDICTED WEIGHTS FOR THE ORIGINAL POPULATION
DATA*/
PROC MEANS DATA=WORK.ORIG NOPRINT;
  BY ID LENGTH;
  VAR WEIGHT;
  OUTPUT OUT=WORK.ORIGQUART Q3(WEIGHT)=WEIGHT;
RUN;
QUIT;

/*REMOVES UNNECESSARY INFORMATION*/
DATA WORK.ORIGQUART (KEEP=ID LENGTH WEIGHT);
  SET WORK.ORIGQUART;
RUN;
```

```
/*LOG BASE 10 TRANSFORMS THE 75TH PERCENTILE OF PREDICTED WEIGHTS*/  
DATA WORK.ORIGQUART;  
    SET WORK.ORIGQUART;  
    LOGWEIGHT=LOG10(WEIGHT);  
    LOGLENGTH=LOG10(LENGTH);  
RUN;
```

```
/*PERFORMS THE FINAL REGRESSION OF THE RLP TECHNIQUE*/  
PROC REG DATA=ORIGQUART OUTEST=OUTPARMS NOPRINT;  
    MODEL LOGWEIGHT=LOGLENGTH;  
RUN;  
QUIT;
```

```
/*IMPLEMENTS THE BOOTSTRAP MACRO*/  
%BOOTSTRAP(1000,45,518855)  
QUIT;
```

```
PROC EXPORT DATA=WORK.OUTPARMS  
OUTFILE="C:\MyDocuments\PubsinPrep\WsVariance\Revision\muskycomb.xls"  
DBMS=EXCEL2000;  
RUN;
```



**APPENDIX 5: GENERALIZED ADDITIVE MODELING RESPONSE CURVES FOR WINTER AND  
SUMMER MICRO-LEVEL HABITAT SELECTION PROBABILITY FUNCTIONS FOR THOSE HABITAT  
VARIABLES WITHOUT CONSISTENT PATTERNS ACROSS MUSKELLUNGE**

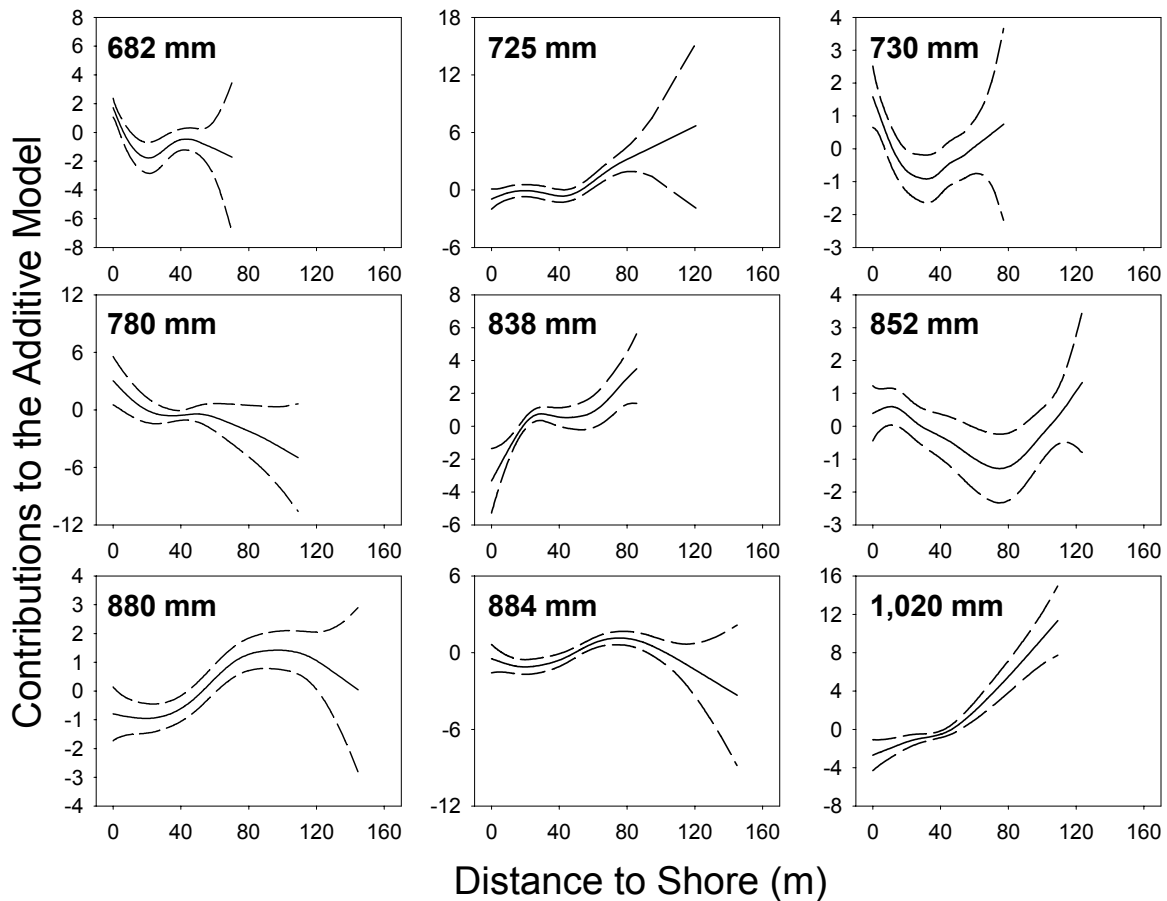


Figure A5.1. Winter HSPF response curves of individual muskellunge to nearest distance to shore for those fish in which this habitat variable was among those included in the AIC-selected model. The vertical axes, expressed in logits, represent the variable's relative influence on probability of habitat use predictions based on partial residuals. Dashed lines represent two standard error bands. Lengths of fish when equipped with transmitters are shown on the graphs.

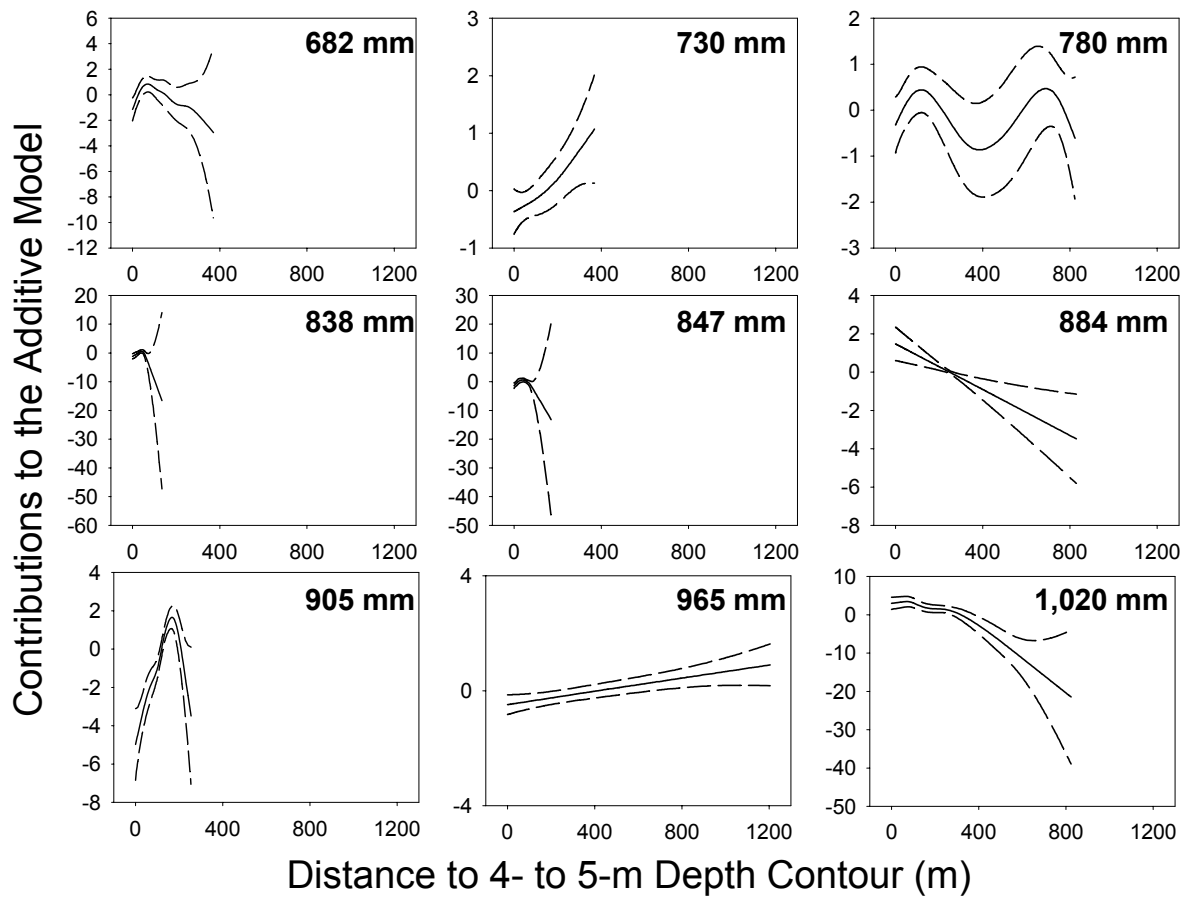


Figure A5.2. Winter HSPF response curves of individual muskellunge to nearest distance to the 4- to 5-m depth contour for those fish in which this habitat variable was among those included in the AIC-selected model. The vertical axes, expressed in logits, represent the variable's relative influence on probability of habitat use predictions based on partial residuals. Dashed lines represent two standard error bands. Lengths of fish when equipped with transmitters are shown on the graphs.

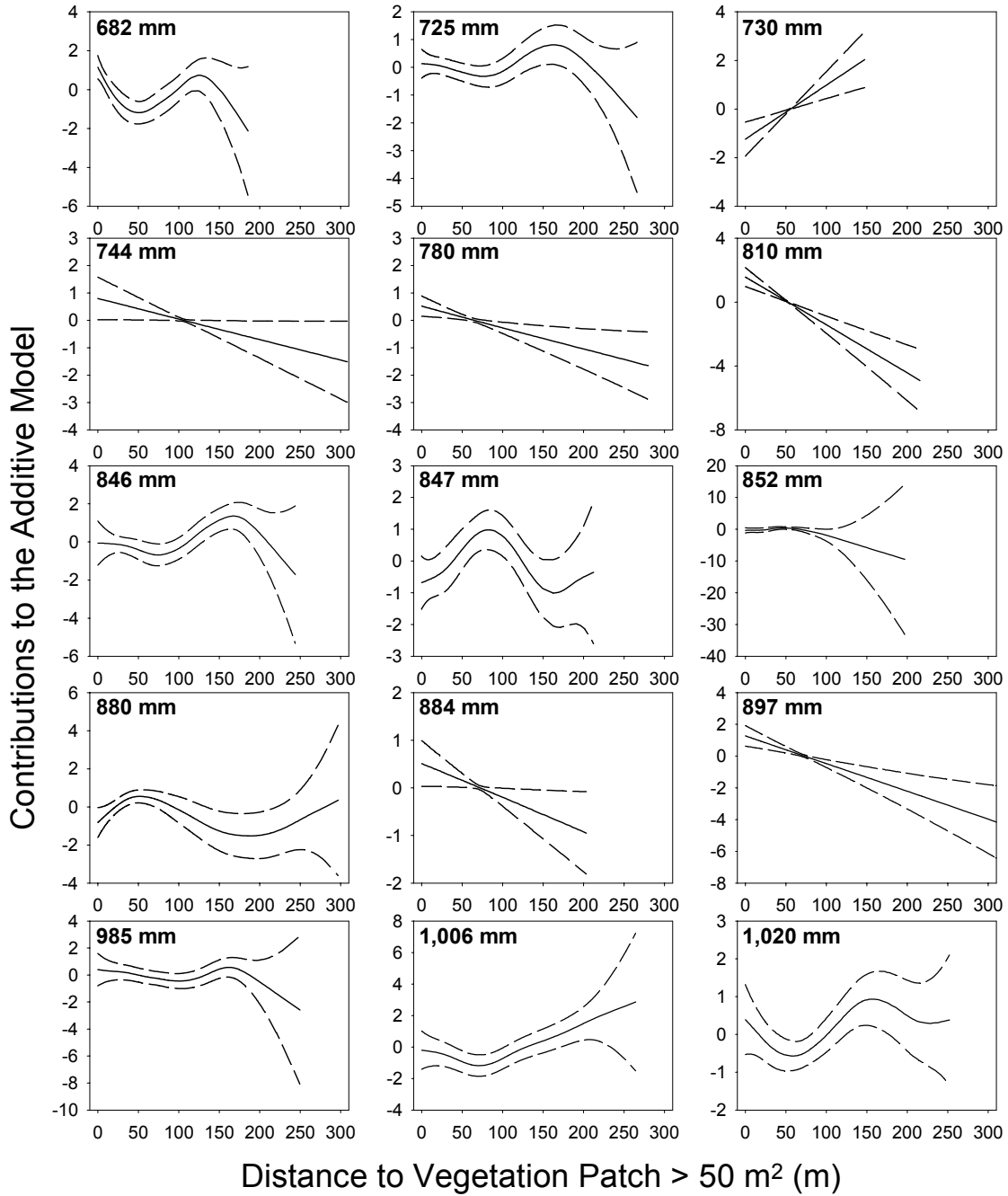


Figure A5.3. Summer HSPF response curves of individual muskellunge to nearest distance to aquatic vegetation patch > 50 m<sup>2</sup> for those fish in which this habitat variable was among those included in the AIC-selected model. The vertical axes, expressed in logits, represent the variable's relative influence on probability of habitat use predictions based on partial residuals. Dashed lines represent two standard error bands. Lengths of fish when equipped with transmitters are shown on the graphs.

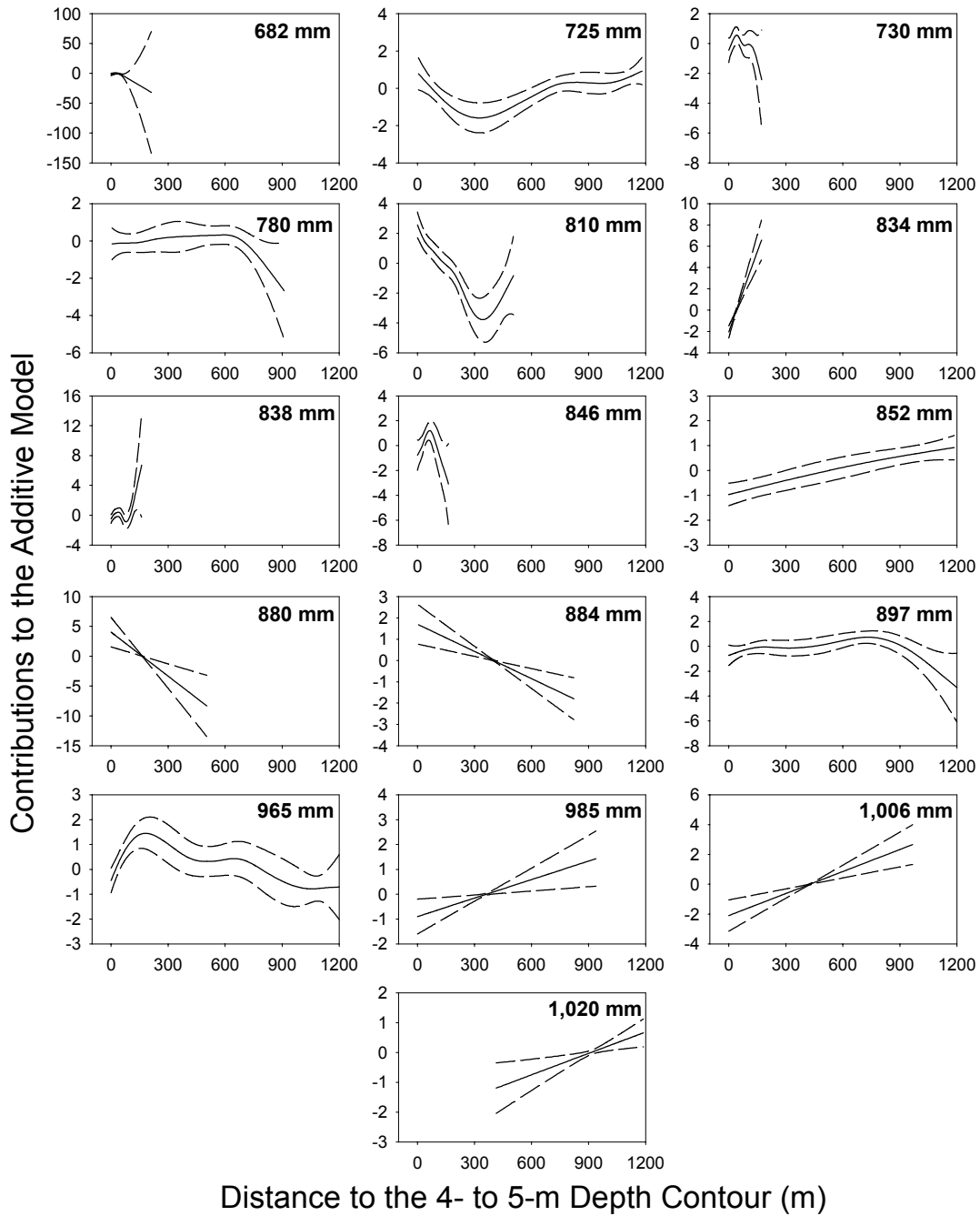


Figure A5.4. Summer HSPF response curves of individual muskellunge to nearest distance to the 4- to 5- m depth contour for those fish in which this habitat variable was among those included in the AIC-selected model. The vertical axes, expressed in logits, represent the variable’s relative influence on probability of habitat use predictions based on partial residuals. Dashed lines represent two standard error bands. Lengths of fish when equipped with transmitters are shown on the graphs.

**VITA**

Travis Owen Brenden was born in Beach, North Dakota on April 2, 1973. He grew up in Rapid City, South Dakota, in the shadow of the Black Hills. He graduated from Stevens High School in 1991 and worked for several years in Rapid City as an Assistant Curator of reptiles for Reptile Gardens. He attended South Dakota School of Mines and Technology, Western Washington University, and University of South Dakota before finally declaring a major while in attendance at South Dakota State University. He graduated with highest honors from SDSU in 1996 with a major in Biological Sciences (Emphasis: Wildlife and Fisheries Sciences) and a minor in Criminal Justice. Although his original intention was to gain employment as a Conservation Officer, he moved to Blacksburg, Virginia in January 1997 to pursue an M.S. degree in Fisheries and Wildlife Sciences at Virginia Polytechnic Institute and State University. Upon completion of the M.S. degree in 1999, he continued his academic pursuit at Virginia Tech by enrolling in both the Ph.D. program in the Department of Fisheries and Wildlife Sciences and the M.S. program in the Department of Statistics. He received his M.S. in Statistics in 2001. Shortly before the completion of his Ph.D. degree in 2005, he was hired as a Research Associate at the School of Natural Resources and Environment at the University of Michigan.