Spatial and temporal population dynamics of yellow perch (*Perca flavescens*) in Lake Erie

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Dissertation submitted to the faculty of the Virginia Polytechnic Institute and State University in partial fulfillment of the requirements for the degree of

Doctor of Philosophy
In
Fisheries and Wildlife Sciences

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July 14 2010
Blacksburg, Virginia

Keywords: Yellow perch, Lake Erie, catch rate, generalized linear model, generalized additive model, spatial generalized linear model, fishery-independent survey, sampling design, spatial interpolation

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ABSTRACT

Yellow perch (*Perca flavescens*) in Lake Erie support valuable commercial and recreational fisheries critical to the local economy and society. The study of yellow perch's temporal and spatial population dynamics is important for both stock assessment and fisheries management. I explore the spatial and temporal variation of the yellow perch population by analyzing the fishery-independent surveys in Lake Erie. Model-based approaches were developed to estimate the relative abundance index, which reflected the temporal variation of the population. I also used design-based approaches to deal with the situation in which population density varied both spatially and temporally.

I first used model-based approaches to explore the spatial and temporal variation of the yellow perch population and to develop the relative abundance index needed. Generalized linear models (GLM), spatial generalized linear models (s-GLM), and generalized additive models (GAM) were compared by examining the goodness-of-fit, reduction of spatial autocorrelation, and prediction errors from cross-validation. The relationship between yellow perch density distribution and spatial and environmental factors was also studied. I found that GAM showed the best goodness-of-fit shown as AIC and lowest prediction errors but s-GLM resulted in the best reduction of spatial autocorrelation. Both performed better than GLM for yellow perch relative abundance index estimation. I then applied design-based approaches to study the spatial and temporal population dynamics of yellow perch through both practical data analysis and simulation. The currently used approach in Lake Erie is stratified random sampling (StRS). Traditional sampling designs (simple random sampling (SRS) and StRS) and adaptive sampling

designs (adaptive two-phase sampling (ATS), adaptive cluster sampling (ACS), and adaptive two-stage sequential sampling (ATSS)) for fishery-independent surveys were compared. From accuracy and precision aspect, ATS performed better than the SRS, StRS, ACS and ATSS for yellow perch fishery-independent survey data in Lake Erie. Model-based approaches were further studied by including geostatistical models. The performance of the GLM and GAM models and geostatistical models (spatial interpolation) were compared when they are used to analyze the temporal and spatial variation of the yellow perch population through a simulation study. This is the first time that these two types of model- based approaches have been compared in fisheries. I found that arithmetic mean (AM) method was only preferred when neither environment factors nor spatial information of sampling locations were available. If the survey can not cover the distribution area of the population due to biased design or lack of sampling locations, GLMs and GAMs are preferable to spatial interpolation (SI). Otherwise, SI is a good alternative model to estimate relative abundance index. SI has rarely been realized in fisheries.

Different models may be recommended for different species/fisheries when we estimate their spatial-temporal dynamics, and also the most appropriate survey designs may be different for different species. However, the criteria and approaches for the comparison of both model-based and design-based approaches will be applied for different species or fisheries.

ACKNOWLEDGEMENTS

This work was accomplished with many people's help. Firstly, I would like to thank my supervisor, Dr. Yan Jiao. From the beginning to the end, she gave much attention and thoughts to help me finish this work. She guided and encouraged me to conquer all the obstacles I faced during this period. She is an excellent mentor and friend, and I learned a lot from her. I am also deeply grateful to Dr. Laurence W. Carstensen, Dr. Emmanuel A. Frimpong, Dr. Feng Guo, and Dr. Donald J. Orth for their assistance as my committee members. They challenged me to think broadly and critically, answered my questions whenever I needed, and spent a lot of time on evaluating this work.

This research was funded by the Ontario Commercial Fisheries Association (OCFA) and Virginia Tech through the "Decision Analysis and Adaptive Management of Lake Erie Percid Fisheries" project to Y. Jiao as well as Sussman internship funding for supporting my field work. I would like to thank Kevin Reid from OCFA. He helped me with field work, data collecting, and data analysis throughout the entire process. I would like to thank Dr. Andy Cook from Ontario Ministry of Natural Resources and Dr. Zhenming Su from Michigan Department of Natural Resources. They helped me with sampling designs. I also appreciate my lab-mates, Chris Hayes, Robert Leaf, Yan Li, Qing He, Hua Dan, Josh Hatch, Andreas Winter, Mike Errigo, for helping me in data analysis, software application, writing, presentation, and communication. I will never forget the help from all my friends at Virginia Tech. It would not have been possible for me to finish this work without their assistance. I wish to extend my special thanks to my mother and my wife for their love, inspiration, and sacrifices. They did everything they could to support me for chasing my dreams.

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LIST OF ABBREVIATIONS

ACS	Adaptive cluster sampling
AIC	Akaike information criterion
AM	Arithmetic mean
ATS	Adaptive two-phase sampling
ATSS	Adaptive two-stage sequential sampling
B	Bias
CPUE	Catch per unit effort
CV	Coefficient of variation
DO	Dissolved oxygen
EBLUP	Empirical best linear unbiased predictions
GAM	Generalized additive model
GIS	Geographic information systems
GLM	Generalized linear model
LEMU	Lake Erie Fisheries Association
LOOCV	Leave-one-out-cross-validation
MAE	Mean absolute error
MI	Moran's I
MSE	Mean squared error
OCFA	Ontario Commercial Fisheries' Association
OMNR	Ontario Ministry of Natural Resources
RAI	Relative abundance index
RE	Relative efficiency
s-GLM	Spatial generalized linear model
SACS	Stratified adaptive cluster sampling
SI	Spatial interpolation
StRS	Stratified random sampling
SRS	Simple random sampling
V	Variance of the mean
VIF	Variance inflation factor
VPA	Virtual population analysis

INTRODUCTION

Yellow perch (*Perca flavescens*) form the basis of one of the most important fisheries in Lake Erie, one which is critical to the local economy and society (Baldwin and Saalfeld 1962; Regier and Hartman 1973). The abundance of yellow perch varies both spatially and temporally in Lake Erie (YPTG 2008). The study of its spatial and temporal population dynamics plays an important role in its stock assessment and fisheries management. However current stock assessments of yellow perch in Lake Erie are based on arbitrary political management units, only consider temporal factors, and rarely take spatial effects into account.

Lake Erie is the shallowest, warmest, most southern and most biologically productive of all the Great Lakes (Hartman 1972). The surface of the lake is approximately evenly divided between the United States and Canada. The current study area is only within the Canadian side of Lake Erie as that is where the fishery independent surveys were conducted. Many factors can influence the dynamics of the fish species in Lake Erie. The water levels in Lake Erie change on short-term (daily and seasonally) and on long-term (annual and decadal) scales (Lenters 2001; Quinn 2002; Lofgren et al. 2002). Changing water levels could have a large impact on aquatic systems (Chubb and Liston 1985) and could also affect food web dynamics, structure, and abundance of fish communities in Lake Erie (Casselman et al. 2002). Water temperature could also cause changes in both lake chemistry and lake ecology (EOSC 2005). Water transparency is also considered as an important factor affecting the distribution of habitat and the fish community in Lake Erie (Ryder 1977).

Yellow perch density distribution shows apparent spatial characteristics (YPTG 2008). Ignoring these spatial trends results in improper interpretations of the biological characteristics of yellow perch, such as its distribution, growth, reproductive and feeding patterns (Booth 2000), provides inaccurate relative abundance estimates (Swartzman et al. 1992) and incorrect fishery status evaluation, and leads to incorrect management inferences.

Currently, yellow perch relative abundance index estimation does not consider the possible influences from spatial heterogeneity and other environmental factors. The current fishery independent sampling survey design is a stratified based on water depth variation and the stratified mean or arithmetic mean is commonly used for stock assessment purposes. Current studies of spatial dynamics of yellow perch are very limited, and they have not been incorporated into the population dynamics studies. It is important to consider both spatial and temporal population dynamics for yellow perch in Lake Erie. I investigated both the spatial and temporal dynamics of the yellow perch fisheries based on the fishery independent gillnet survey data.

The central null hypothesis that I tested through this study is that yellow perch population varies spatially and temporally in Lake Erie. The corresponding alternative hypothesis is yellow perch population stays constant over time and locations in Lake Erie. I also tested hypotheses on sampling method and post data analyses. The corresponding null hypotheses are the current method to estimate the relative abundance index of yellow perch, AM, is the best method; the current sampling design (StRS) is the best design. The corresponding alternative hypotheses are the current method to estimate yellow perch relative abundance index needs to be improved and GLM, GAM and S-GLM perform better; currently used sampling design is not appropriate for yellow perch fishery-independent survey and adaptive sampling designs perform better. Other hypotheses that I tested include environmental factors influence the distribution and density of yellow perch in Lake Erie.

Models and approaches to simulate the spatial and temporal dynamics of yellow perch are greatly needed to better manage this species in Lake Erie. There are usually two types of approaches in analyzing the spatial and temporal trends of aquatic species: model-based approaches such as generalized linear model, and design-based approaches such as stratified random sampling design (Maunder and Punt 2004; Rago 2005). Both of them try to capture the spatial and temporal variation of the species of interest. Geostatistical analysis is also a possible approach designed to capture the spatial variation of the fish distribution (Petitgas 2001). It has the potential to help us to improve the data usage in subsequent stock assessment models by considering their spatial coverage and influence from other environmental and survey factors.

The general goal of this study was to better describe the population dynamics of yellow perch and to improve our understanding of this fishery. The objectives of this study were to synthesize and analyze the geostatistical data of the catch rate from the fishery independent survey to develop and compare geostatistical methods with the currently used model-based approaches in assessing this fishery through empirical data analyses and simulation studies, and to evaluate current sampling methods and improve sampling survey efficiency through simulation studies. I plotted yellow perch density distribution maps in the study area and explored the relationship between catch rates and spatial and environmental factors. I also simulated the variation of fish densities over time and space, and explored the effects of the variation on relative abundance indices estimation. This work will improve our understanding of this fishery.

Simulation studies are often used when seeking appropriate models/approaches in natural resource modeling (Bolker 2008). Besides using real survey data, I developed simulation studies based on the geographic heterogeneity from the real data to evaluate different models and approaches, e.g., to compare different models that are currently used, and to compare the current survey design with adaptive sampling designs, which are usually better in capturing different patterns of spatial heterogeneity. Possible uncertainties caused by sample size variation are also evaluated through this study.

I compared the currently widely used models in simulating the spatial and temporal dynamics of aquatic species in developing relative abundance indices for fisheries stock assessment purposes based on the model goodness-of-fit, reduction of spatial autocorrelation, and prediction errors from cross-validation. Standardized catch rate is usually used as the relative abundance index for many fisheries in practice (Quinn and Deriso 1999; Maunder and Punt 2004). However what standardization approach is the best choice for fish relative abundance index estimation? A large number of papers have attempted to answer this question (Gavaris 1980; Lo et al. 1992; Harley et al. 2001; Walsh and Kleiber 2001; Bishop et al. 2004; Maunder and Punt 2004; Shono 2008). Thus far there is not a generally accepted model that is suitable for every species analyzed. Generalized linear models (GLMs) and generalized additive models (GAMs) are commonly applied for catch rate standardization (O'Brien and Mayo 1988; Ye et al. 2001; Campbell 2004; Nishida and Chen 2006; Damalas et al. 2007). Currently researchers are using the arithmetic mean (AM) of catch rate data from fishery independent surveys to estimate yellow perch relative abundance index in Lake Erie, but new models/approaches to better consider the spatial and temporal dynamics of yellow perch are urgently needed. Fishery-independent survey data have their own characteristics, i.e., the catch data are spatially autocorrelated, which causes difficulties in catch rate standardization. When GLMs or GAMs are fitted with the correlated catch data, the residuals were usually autocorrelated too, violating one of the basic assumptions of GLMs or GAMs: that the residuals are independently and identically distributed (iid) (Montgomery et al. 2006). Spatial generalized linear models (s-GLMs) proved practical to solve this problem for Yellow Tuna longline catch rate standardization (Nishida and Chen 2006). I compared the performance of GLM, GAM, and s-GLM for Yellow Perch catch rate standardization. This study is first to analyze the performance of three models on yellow perch catch rate standardization. In addition, ridge regression was applied in this study to select multicollinear independent variables in GLM, and cross-validation was used to test the models' prediction ability.

I explored the possible ways to improve the relative abundance index estimation from sample-based approaches. The survey data used in this study came from the fishery independent survey, which is a partnership survey between the Ontario Commercial Fisheries' Association (OCFA) and the Ontario Ministry of Natural Resources (OMNR) Lake Erie Fisheries Management Unit (LEMU). This survey was conducted under a stratified random sampling design (StRS) and the number of strata was 14. However, yellow perch were observed to be heterogeneously distributed in each stratum and this heterogeneity varied over time, which violated the fundamental assumption of StRS, i.e., measurements within strata are homogeneous (Scheaffer et al. 2006). Adaptive sampling designs are thought to be more suitable for surveying heterogeneous populations, but different sampling designs have various requirements for survey areas and sample sizes (Jolly and Hampton 1990; Bez 2002; Brown 2003; Kimura and Somerton 2006; Jardim and Ribeiro Jr. 2007; Poulard and Trenkel 2007; Link et al. 2008; Morrison et al. 2008). The performance comparison between traditional sampling designs and adaptive sampling designs or among adaptive sampling designs is necessary for a successful survey design. In this dissertation, the best sampling design was selected through three scenarios. In the first scenario, simple random sampling (SRS), StRS, and adaptive two-phase sampling (ATS) were compared; in the second scenario, adaptive cluster sampling design (ACS), adaptive two stage sequential sampling design (ATSS), and ATS were compared; in the third scenario, current sampling design and ATS were compared. This is the first time that the efficiencies of ACS, ATSS and ATS were compared through a simulation study. This study should also be helpful for other field survey designs and fishery-independent surveys besides yellow perch fishery independent survey in Lake Erie.

I compared the traditional model-based methods with the geostatistical method through a simulation study. There are many practical limitations when using GLMs and GAMs, such as lack of record of needed explanatory variables, model selection uncertainty, error structure assumption, high percentage of zero catches and methods in dealing with intersection terms (Maunder and Punt 2004). An improved fishery-independent survey provides us with high quality survey data. Therefore, geostatistical approaches may be applied for relative abundance index estimation rather than model-based approaches. In this dissertation, a geostatistical method was used to estimate the yellow perch abundance index in addition to GLMs and GAMs. Spatial interpolation (SI) is one of the applications of geostatistical methods, and ordinary kriging is one commonly used SI method (Rahel 2004). The application of geostatistical methods in fisheries has a relatively short history but has developed rapidly in recent years (Simard et al. 1992; Maynou et al. 1996; Rivoirard et al. 2000; Wyatt 2003). However, there has been no SI application toward yellow perch relative abundance index estimation in Lake Erie and there are no comparisons of this method with the commonly used model-based approaches. This study explored the feasibility of using the model based approaches and the geostatistical method by comparing the performance of AM, GLM, GAM and SI through simulation studies. When we use GLMs and GAMs, we are to eliminate the other factors' effects (e.g., environmental factors and spatial autocorrelation) on population abundances, but SI is using the spatial autocorrelation to generate a smooth surface of the relative abundance index. They have the same goal, i.e., to estimate an accurate index of population relative abundance, but based on contrary ideas. Three simulation scenarios were used to test the performances of AM, GLM, GAM and SI. In each scenario, the “true” data came from the predicted values of GLM, GAM and SI respectively. Correlation coefficient (*r*) and AIC were used for model comparison in each scenario.

Chapter 1

[1]Catch Rate Standardization of Yellow Perch in Lake Erie: A Comparison among the Generalized Linear Model, Spatial Generalized Linear Model, and Generalized Additive Model

Abstract.-Various statistical models have been used to standardize catch rates of fish populations for stock assessment. The generalized linear model (GLM) is one of the most commonly used approaches. However, response variables in fisheries data are often spatially autocorrelated or show a nonlinear relationship with explanatory variables, violating the underlying assumption of GLM. The generalized linear model with spatial autocorrelation (s-GLM) and the generalized additive model (GAM) may be better suited to dealing with autocorrelated data and nonlinear data, respectively. In this study, catch rates of yellow perch from a fishery-independent gillnet survey in Lake Erie during 1990-2003 were estimated using GLM, s-GLM and GAM. A ridge regression analysis selected year, month, set duration, gear depth, temperature at gear depth, dissolved oxygen, water transparency and latitude as significant explanatory variables for these models. By comparing the goodness-of-fit, reduction of spatial autocorrelation, and prediction errors from cross-validation, I found that GAM had the best goodness-of-fit and lowest prediction errors but s-GLM resulted in the best reduction of spatial autocorrelation for catch rate standardization of yellow perch in Lake Erie. I recommend that GAM and s-GLM should be considered when the fish distribution and density are spatially autocorrelated.

Keywords: GLM; spatial-GLM; GAM; Yellow perch; Lake Erie

[1]Formatted for submission to the Transactions of the American Fisheries Society

Introduction

Catch rate data are commonly used as indicators for stock assessments of many commercial and recreational fish species (Quinn and Deriso 1999; Maunder and Punt 2004). Improper use of catch rates can bias a stock assessment and result in mismanagement of the corresponding fisheries (Maunder et al. 2006). Numerous studies have recognized this problem and concluded that catch rate standardization is needed before catch rates can be used as an indicator of population size in stock assessment models (Gavaris 1980; O'Brien and Mayo 1988; Harley et al. 2001; Hinton and Maunder 2004; Shono 2008).

The most common approach for standardizing catch and effort data is the use of generalized linear models (GLMs) (Ye et al. 2001; Bishop et al. 2004; Cheng and Gallinat 2004; Maunder and Punt 2004; Carlson et al. 2007). GLMs are particularly suitable for analyzing complex data structures, such as non-Gaussian distributed dependent variables (Guisan et al. 2002). However, generalized additive models (GAMs) have been reported to perform better in some situations, such as those in which relationships are nonlinear or non-monotonic (Swartzman et al. 1992; Guisan et al. 2002). Conversely, nonlinear relationships inferred from a GAM may be more difficult to interpret than linear relationships from a GLM. Both GLM and GAM assume that residuals and response variables are independent, and spatial autocorrelation is sometimes ignored when these models are used. But spatial autocorrelation often exists among ecological variables (Legendre 1993) and may cause serious errors in data analyses if neglected. In these situations, generalized linear models with spatial autocorrelation (s-GLM) have been reported to perform better (Nishida and Chen 2004; Zhang et al. 2005).

With any model, catch rate standardization of a time series must be designed to include only independent (explanatory) variables that significantly influence the dependent variable

(Maunder and Punt 2004). Too few explanatory variables will cause variation in catch rate to be wrongly attributed to the time series, while too many explanatory variables will over-fit the model (Hinton and Maunder 2004). Potential explanatory variables may be highly collinear, resulting in poor estimates of the model parameters even if the fitted model is a good predictor (Ryan 1997; Montgomery et al. 2006). Selection of explanatory variables is commonly performed with standard hypothesis testing methods (e.g. *F*-test), information-theoretic methods (e.g. AIC) (Akaike 1973), or with stepwise regression procedures (Efroymson et al. 1960; Whittingham et al. 2006). However, these methods can become time consuming and inconsistent when there are many independent variables to choose from. The variance Inflation Factor (VIF) has often been used to test collinear explanatory variables (Marquardt 1970; Graham 2003). If VIFs exceeds 5 or 10, the associated regression coefficients should be excluded. Ridge regression (Hoerl 1962; Hoerl and Kennard 1970; Montgomery et al. 2006) has also been used to select the best combination of explanatory variables that are correlated. A recent study through a simulation suggested that ridge regression could select appropriate variables in linear regression when several independent variables were highly correlated (Dorugade and Kashid 2009). In this study, nine independent variables were used to build the original model, and many of them were highly correlated. Ridge regression is more convenient here than VIF to select the optimal independent variable combination. Ridge regression adds a ridge parameter to the diagonal of the variance-covariance matrix, yielding a modified estimator which decreases the mean square error and avoids a singular matrix which can be caused by presence of highly collinear variables (Ryan 1997). Inspection of regression coefficients versus the ridge parameter then allows variables to be selected simultaneously and with less sensitivity to random data variations than, for example, *F*-tests among nested models (Ryan 1997).

In this study, I used ridge regression and standard hypothesis testing methods to select variables for catch rate standardization from a 14-year time series of gillnet survey data. The catch rate standardization was calculated with GLM, s-GLM and GAM, and the three models were compared for their goodness-of-fit and efficiency at reducing autocorrelation. Specifically, I applied this model comparison to the catch rates of yellow perch in Lake Erie.

Yellow perch (*Perca flavescens*) is a cool-water species widely distributed throughout North America, and most abundant in the open waters of lakes with moderate vegetation and clear water (Craig 1987). Movements of yellow perch tend to be random over short time periods, but on a larger time scale follow the water circulation pattern of the lake (Whiteside et al. 1985; Imbrock et al. 1996). In Lake Erie, yellow perch form the basis of important commercial and recreational fisheries (Jiao et al. 2006). Lake Erie is the shallowest, warmest, and biologically most productive of the Laurentian Great Lakes (Hartman 1972). Water levels in Lake Erie change on short-term (daily and seasonal) and long-term (annual and decadal) scales, varying over a range of two meters (Lenters 2001; Quinn 2002; Lofgren et al. 2002). Changing water levels can result in shifts in shoreline location, impacting the aquatic system (Chubb and Liston 1985) and affecting the abundance of fish communities (Casselman et al. 2002). Water transparency, water temperature, and dissolved oxygen also influence the abundance and distribution of fish populations in the lake (Hartman 1972; Ryder 1977).

Stock assessment for yellow perch in Lake Erie is carried out by virtual population analysis (VPA) and statistical catch-at-age modeling (YPTG 2006). Catch rate from the fishery-independent survey is used to calibrate population dynamics in the models as an indicator of population size. Currently, the estimation of catch rate does not consider the influences of yellow perch's distribution and environmental factors in the lake. A catch rate standardization that includes these factors has the potential to improve significantly the stock assessment. In this study, I provide a recommendation on the most suitable approach to catch rate standardization for yellow perch in Lake Erie.

Methods

Study site.-Yellow perch gillnet survey data were obtained from the cooperative partnership fisheries-independent survey between the Ontario Commercial Fisheries' Association (OCFA) and the Ontario Ministry of Natural Resources (OMNR) Lake Erie Fisheries Management Unit. These survey data were taken from 1990 to 2003 within the Canadian side of Lake Erie, which corresponds to approximately half the area of the lake (YPTG 2006; see Figure1). The data set included, for each survey sample: catch weight of yellow perch, and measurements of longitude, latitude, set duration, bottom depth, gear depth, transparency (Secchi depth), water temperature at surface, water temperature at gear depth, and dissolved oxygen (DO) (Table 1.1). Gillnet catch is not linearly correlated to set duration, because catchability reduces as the fish accumulate on it (Olin et al. 2004). So in this study, I used catch instead of catch per hour as the response variable. Considering the effect of possible set saturation, I regarded set duration as one of the explanatory variables. Transparency, temperature, and DO were measured at the beginning of each sample. The survey used bottom gillnets and canned (mid-water) gillnets. Canned gillnets accounted for only 6.6% by weight of the total yellow perch catch. Therefore only bottom gillnet data were analyzed in this study.

Spatial autocorrelation.-Moran's I (Moran 1950) was used to measure spatial autocorrelation of the log-transformed catch data. Moran's I can be expressed as:

$$MI = \frac{n}{(n-1)S^2 w_{\cdot\cdot}} \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (Y(s_i) - \bar{Y})(Y(s_j) - \bar{Y}) \qquad (1)$$

where n is the number of data sample, $Y(s_i)$ and $Y(s_j)$ are two catch data at spatial locations i and j, $\overline{Y}$ is the mean value of all data, S^2 is the variance, and $w_{..}$ is the sum of inverse distance weights w_{ij}. If spatial autocorrelation is absent, the expected value of *MI* is -1/(*n*-1), which tends towards zero as n increases. Significance of spatial autocorrelation was tested by transforming Moran's I to Z-scores:

$$Z = \frac{|MI - E(MI)|}{\sqrt{Var(MI)}} \tag{2}$$

I calculated Moran's I using the ArcGIS software package (version 9.2, 2007, ESRI Inc., USA). To calculate distances *ij*, latitude and longitude were converted to the NAD 1983 UTM 17N projected coordinate system, and the Euclidean distance was used.

Moran's I was also used to test spatial autocorrelation among the residuals of GLM, s-GLM and GAM. An appropriate selection of variables should result in models without strong spatial autocorrelation among their residuals (Zhang et al. 2005).

Explanatory variables selection.- Multi-collinearity was first tested by calculating the pair-wise correlations among all continuous variables available to the catch model (Figure 1.3). Explanatory variables were selected by plotting the ridge regression coefficients of the variables as ridge traces. Those coefficients that stabilized near zero in the ridge trace, or did not stabilize at all, were removed from the equation (Thompson 1978). Year and month were added as categorical data to the remaining variables. Year must always be included, regardless of whether it is shown to be statistically significant, because the purpose of the catch rate standardization is to determine a yearly time series of abundance (Maunder and Punt 2004). In this study I also treated month as a required variable because the surveys progressed in a regular pattern across the lake over several months in each year. Interaction terms often create additional multicollinearity problems and difficulty with extracting year effects (Maunder and Punt 2004; Damalas et al. 2007). Our preliminary analysis with interaction terms supported that these terms increased multicollinearity after I diagnosed the ridge plots and goodness-of-fit. Therefore interaction terms were not included. A linear regression was then calculated and all variables with p-values >0.05 were further removed. The remaining variables were retained in the final model. For consistent comparison, the same variables were applied to the GLM, s-GLM and GAM.

Generalized linear model (GLM).- The basic GLM can be written as:

$$g(\mu) = X^T \beta \tag{3}$$

where g is the link function, μ is the expectation of the observation, X is the vector of explanatory variables, and β is the vector of regression coefficients. When the link function is identity, and the error term is normal, generalized linear model is also called general linear model. Therefore, a general linear model is a special case of generalized linear model. In this study, I consistently used the term Generalized Linear Model (GLM) instead of separating them into generalized linear model and general linear model. Log transformation has been widely used in fisheries and was found to be appropriate in many situations (Quinn and Deriso 1999). However I did diagnose the residual pattern to make sure that this assumption was valid. After a log transformation equation (1) in this study can be expressed as:

$$\ln(I+1) = \beta_0 + \beta_1 year + \beta_2 month + \sum_i \beta_i \, continuous\, survey\, variables + \varepsilon \tag{4}$$

for *i* continuous survey variables, where *I* is the catch of yellow perch; expressed in weight (g) per gillnet lift, and ε is a normal, independent and identically distributed error with expectation zero and variance σ^2. The constant value 1 was added to the catch rate data to prevent computational errors of the natural logarithm when zero catches occurred. The GLM catch rate standardization was calculated using the GENMOD procedure in the SAS software package (Version 9.1, 2007, SAS Inc., USA).

Spatial generalized linear model (s-GLM).-The spatial generalized linear model is a version of the standard GLM (e.g., Equation 3) in which the error terms (ε) are not independent and identically distributed, but correlated by the location of the data points. Thus, Equation 3 can be extended as

$$\begin{aligned}\ln(I+1) &= \beta_0 + \beta_1 year + \beta_2 month + \beta_3 set\ duration + \beta_4 Latitude + \beta_5 Gear\ depth \\ &+ \beta_6 Gear\ temperature + \beta_7 DO + \beta_8 transparency + \varepsilon\end{aligned} \tag{5}$$

where ε is different from that in Equation 4 but distributed as $\varepsilon \sim N(0, V)$, rather than $\varepsilon \sim N(0, \sigma^2)$, where V is the variance-covariance matrix. The covariance $Cov(\varepsilon_i, \varepsilon_j)$ between ε_i and ε_j is a function of the distance d_{ij} between sample locations i and j, and of the range θ (i.e., the maximum distance over which any significant autocorrelation occurs), as specified by the longitude and latitude coordinates of the samples (Nishida and Chen 2004):

$$Cov(\varepsilon_i, \varepsilon_j) = \sigma^2 f(d_{ij}, \theta)$$

Three covariance models were examined in this study:

Exponential model, $$f(d_{ij}, \theta) = \exp(-d_{ij} / \theta) \tag{6}$$

Spherical model, $$f(d_{ij}, \theta) = 1 - 3d_{ij} / (2\theta) + d_{ij}^3 / (2\theta^3) \tag{7}$$

Gaussian model, $$f(d_{ij}, \theta) = \exp(-d_{ij}^2 / \theta^2) \tag{8}$$

The best-fitting of the three covariance models for use in the s-GLM was selected by comparison of their Akaike information criterion (AIC) values.

Calculation of the s-GLM can be derived from the procedure of estimation in the generalized linear mixed model (GLMM); a generalized linear model of which some predictors are random variables (Venables and Dichmont 2004). In this study, after a log transformation, the s-GLM equation was similar to Equation 4 except the error term. The basic GLMM equation:

$$g(\mu) = X^T\beta + Z^T\gamma \tag{9}$$

is reduced to the s-GLM by setting Z, the vector of random effect explanatory variables, to zero (Zhang and Gove 2005). For this study, s-GLM was fitted using the PROC MIXED procedure in the SAS software package (Version 9.1, 2007, SAS Inc., USA).

Generalized additive model (GAM).-Generalized additive models (GAMs) are nonparametric generalizations of GLMs in which linear predictors are replaced by additive predictors (Venables and Dichmont 2004). The basic GAM can be written as:

$$g(\mu) = \overline{\mu} + \sum_{i=1}^{n} s_i(X_i) \tag{10}$$

where *g* is the link function, μ is the expectation of observations, $\overline{\mu}$ is the intercept, X_i is the i*th* explanatory variable, and s_i is a smooth function for the i*th* explanatory variable**.** Lognormal error structure was again assumed, so the catch standardization GAM could be written as:

$$\ln(I+1) = \beta_0 + \beta_1 year + \beta_2 month + \sum_i \beta_i \times s(continuous\, survey\, \mathrm{var}iables) + \varepsilon \tag{11}$$

A fixed smoothness of 3 degrees of freedom was used for each of the *i* explanatory variables, to avoid over-fitting (Liu and Cela 2007). GAM was calculated using the GAM procedure in the SAS software package (Version 9.1, 2007, SAS Inc., USA).

Model Comparison.-GLM, s-GLM and GAM were compared by model fit (measured as AIC), model residuals (to detect whether the assumption of error distribution is appropriate and whether autocorrelation exists), and model prediction ability (measured as MSE of cross-validation). The model residuals were defined as the difference between the observed and appropriately predicted values. The Empirical Best Linear Unbiased Predictions (EBLUP) were used to take spatial autocorrelations into account for predicting the response variable in s-GLM (Zhang and Gove 2005). Residual diagnostics need to be combined with model goodness-of-fit to select the best model (Augustin et al. 2009). The cross-validations were calculated to test the prediction errors of the models (Damalas et al. 2007). The autocorrelations were calculated with Moran's I (equation 1).

Cross-validation tests were applied using the leave-one-out-cross-validation (LOOCV) and *K*-fold methods. For *K*-fold cross-validation, the data are randomly split into *K* equal-sized parts, the model is calculated on the *k*th part, and fitted to the other *K*-1 parts of the data. The prediction error is then calculated using the *k*th part of the data, for $k = 1, 2, \ldots, K$ (Hastie et al. 2001). This process is repeated *m* times to determine the *K*-fold cross-validation MSE according to the formula:

$$MSE = \frac{1}{mkn} \sum_{i=1}^{m} \sum_{j=1}^{k} \sum_{l=1}^{n} \left(Y_{ijl} - \hat{Y}_{ijl} \right)^2 \tag{12}$$

where Y is the observed value, $\hat{Y}$ is the estimated value, *n* is the number of observations in one split part of data, *k* is the number of split parts, and *m* is the number of repetitions. For LOOCV, *n* and $m = 1$, and *k* equals the total number of observations. For *K*-fold CV, I used $m = 100$ and $k = 5$ or 10. A larger k decreases bias but increases variance and computation time. Either $k = 5$ or $k = 10$ is commonly used for cross-validation testing (Breiman and Spector 1992; Hastie et al.

2001). I used both in order to examine potential differences in sensitivity to the level of K-fold among the GLM, s-GLM, and GAM.

Nominal (arithmetic mean) yearly survey catch rates and the estimates of each model were plotted against total biomass estimates of the YPTG (2009) stock assessment to compare the fit of the standardizations. The survey catch rates and model estimates (I_m) can be considered indices of the total biomass estimates (B) with lognormal error structure:

$$I_m = q \times B \times e^{\varepsilon} \tag{13}$$

$$\log I_m = \log q + \log B + \varepsilon$$

which, in log-log conversion, give regressions with slope = 1 and intercept = log of catchability coefficient q. For the three models GLM, GAM, and s-GLM, q is a relative value because catch rate estimates were scaled to the average of the nominal catch rates. The three models were compared by the MSEs of the regression of the log survey catch rates.

Results

Log-transformed catch rates of yellow perch were significantly clustered (positive spatial autocorrelation) at $p < 0.01$ in every year of the 1990-2003 survey period. Moran's I for clustering was notably lowest in 1996 and 1997, the two years with the least numbers of survey samples (Figure 1.2). Greater differences between Moran's I and the Z-scores in some years indicate that clustering was more variable.

Correlations were high between some pairs of continuous variables, notably longitude and latitude of the sampling locations, and bottom depth and gear depth (Figure 1.3). The longitude and latitude correlation is due to the geography of Lake Erie itself being primarily on a southwest-northeast axis (Figure 1.1). The high correlation between bottom depth and (bottom) gear depth is self-evident, but showed variation due to unevenness of the lake bed, which resulted in contact of the gillnet at some locations being well above the average of the bottom depth.

The ridge regression analysis retained six of the independent continuous variables as explanatory variables for yellow perch catch rate: set duration, gear depth, temperature at gear depth, DO, water transparency, and latitude. Each of these variables was significant at $p < 0.05$ in the linear models (GLM and s-GLM) and in the linear component of the GAM, except DO which was marginally significant at $p < 0.075$ (Table 1.2). The significant linear relationships with log catch rate were positive for set duration and gear temperature; negative for gear depth, DO, water transparency and latitude (Figure 1.4). Three of the variables were significant in the non-linear component of the GAM: gear depth, dissolved oxygen, and latitude (Table 1.2). Log catch rate was low in shallow areas (< 10 m), increased with gear depth to approximately 30 m, then decreased to 40 m and increased slightly again below 40 m. Log catch rate increased with DO up to a concentration of approximately 8 mg/L, then leveled off. Log catch rate was lowest in the western part of Lake Erie, increased towards the center, and then decreased slightly in the eastern part of the lake (Figure 1.4).

The exponential covariance model was found to give the best fit for s-GLM: AIC = 4245.9, versus AIC = 4248.9 for the spherical model and AIC = 4275.2 for the Gaussian model. Catch rate standardizations of GLM, s-GLM, and GAM are compared to the un-standardized (nominal) log catch rates per year in Figure 1.5, and per month in Figure 1.6. In general, catches decreased from 1990 to 1993 and increased from 1993 to 2000, with a dip in 1998. Standardized catch rates of the three models were more similar to one another than to the unstandardized catch rates. In particular, the unstandardized yearly catch rates in 1995, 1996, and 1997 were exceptionally higher than in the years before and after, whereas the three standardized catch rates showed more gradual inter-annual changes (Figure 1.5). Inter-annual changes in log catch rate averaged 1.23 for the nominal, un-standardized data, 0.59 for GLM, 0.55 for s-GLM, and 0.46 for GAM. GAM was the lowest of the three catch rate standardizations in each year while GLM and s-GLM were sometimes relatively higher and sometimes lower. Unstandardized monthly catch rates showed a peak in October and a decline towards November whereas the standardized catch rates generally leveled off from October to November (Figure 1.6).

Measures of the GLM, s-GLM, and GAM are compared in Table 1.3. S-GLM had the lowest spatial autocorrelation among residuals, and the second-lowest AIC and average of cross-validation MSEs ($\bar{x}(3.50,3.57,3.53) = 3.53$). GAM had the lowest AIC and average of cross-validation MSEs (3.11) and second-lowest spatial autocorrelation among residuals. GLM had the poorest measures in each category (Table 1.3). Mean square errors of the one hundred 5-fold and 10-fold cross-validations are shown as histograms in Figure 1.7. GAM had the narrowest MSE distributions with 95% of MSE values from the 5-fold cross-validation within 3.013 ± 0.003, and 95% of MSE values from the 10-fold cross-validation within 3.010 ± 0.003. For GLM the 95% confidence intervals of 5-fold and 10-fold cross-validation were respectively 4.084 ± 0.008 and 4.063 ± 0.006, and for s-GLM the 95% confidence intervals were respectively 3.571 ± 0.008 and 3.534 ± 0.006.

Plots between the log YPTG stock assessment biomass and log survey catch rate estimates are shown in Figure 1.8. The estimated biomass was cited from YPTG annual reports (YPTG 2009). All three standardization models correlated significantly with the YPTG stock assessment, and s-GLM had the lowest regression MSE.

Residuals of the catch standardization models were mapped by ordinary kriging interpolation, across the Canadian side of Lake Erie (Figure 1.9). Darker shading on the plots indicates higher absolute values of the residuals, i.e., greater absolute difference between the modeled log catch rates and the actual sampled catch rates. Residual values were normally distributed, as shown by the plot insets. The patterns of residuals were similar for the three models, with highest absolute residual values found in the easternmost part of the Canadian side of Lake Erie, and south of Long Point peninsula. However, with GAM and s-GLM, the lowest absolute residual values (0 - 1) occurred uniformly from the western basin to approximately 80.6 °W longitude, where the central basin and eastern basin are separated by an underwater ridge. With GLM, the lowest absolute residual values occurred consistently only as far east as approximately 81.5 °W longitude. S-GLM had the smallest range of absolute residual values, with all values ≤ 2.5.

Discussion

Model selection requires the inclusion of significant explanatory variables, and the choice of an appropriate model function and error structure. For yellow perch in Lake Erie, significant explanatory variables were the duration of gillnet set, gear depth, temperature at gear depth, DO, water transparency, and latitude. While set duration, depth, and latitude can (usually) be controlled by the operator of a survey; temperature, DO, and water transparency fluctuate naturally in an aquatic environment. The response of yellow perch to these factors underscores the importance of standardizing catch rates in a multi-year survey. With these explanatory variables, s-GLM showed the best absence of significant residual autocorrelation. Best results with s-GLM may be expected, as yellow perch catch rates were highly autocorrelated in space but only three of six variables had statistically significant non-linear components. GAM did have a lower mean squared error than s-GLM in all three cross-validations. Due to the autocorrelation of s-GLM, 'leaving out' any part of the data may change the results of the model more strongly than equivalently for a GAM. However, s-GLM showed the lowest average difference in cross-validation MSE between leave-one-out, 5-fold, and 10-fold, suggesting that a model with autocorrelation function is less sensitive to the scale of cross-validation.

In the Lake Erie survey, temperatures at gear depth ranged from 5 to 24 °C (Figure 1.4), varying by an average of 10 °C within months. Adult yellow perch have been found to prefer temperatures from 17.6 to 20.1 °C, and juveniles from 20.0 to 23.3 °C (McCauley and Read 1973). Behavioral observations have indicated that yellow perch will respond quickly to non-optimal temperatures (Neill and Magnuson 1974; Kelso 1976). There was thus a high potential for yellow perch to seek more favorable thermal conditions throughout this survey.

Water transparency ranged from 0.25 to 11 m Secchi depth (Figure 1.4). Yellow perch are visual foragers requiring clear water (Ali et al. 1977). In this study Secchi depth correlated negatively with log catch rate (Figure 1.4), suggesting that yellow perch selected habitat for reasons other than forage profitability. Yellow perch log catch increased between 3.6 and approximately 25 m gear depth (Figure 1.4), which may represent a clarity threshold: 57% of gillnet sets shallower than 25 m had ≤3 m Secchi depth, while only 7.5% of gillnet sets deeper than 25 m had ≤3 m Secchi depth. The second increase of log catch rate below 40 m (Figure 1.4) likely relates to habitat partitioning between different size classes of yellow perch (Brandt et al. 1980; Sandheinrich and Hubert 1984).

Dissolved oxygen at gear depth ranged from 0.4 to 19.1 mg/L in the Lake Erie survey, and log catch rate showed a significant non-linear increase with DO up to 5 mg/L (Figure 1.4). Rudstam and Magnuson (1985) and Suthers and Gee (1986) reported 5 mg/L and 3 mg/L respectively as hypoxia avoidance thresholds for yellow perch. The overall linear relationship between DO and log catch rate was slightly negative (Figure 1.4), which could be due to avoidance of predators that have comparably high oxygen requirements.

I used the correlation analysis between estimated population biomass and the standardized catch rate from different models. I realized that the population biomass are estimated values and not the "true" values. However, I used population biomass estimates from a stock assessment with data up to 2008 and the time series that I used to analyze catch rate standardization are only up to 2004. Many studies have found that the population trend stabilized a few years back when an age-structured model is used (NRC 1998; Quinn and Deriso 1999). And the population biomass is estimated based on multiple data sources, such as gillnet fishing, trap net fishing, and sport fishing (YPTG 2009). The catch rate of gillnet survey is not a determining factor in this population biomass estimation. Here I do not suggest that it ought to be used as a major criterion to select models of catch rate standardization. However, it may be used an auxiliary criterion to compare models. Models such as measurement error model approach may be done in the future (Jiao et al. 2006).

The choice of which model to use for standardization can potentially influence the abundance estimates of a stock assessment. Statistical methods currently used for Lake Erie stock assessments weight the inclusions of catch, effort, and survey data as a function of their variability (STC 2007). Since standardization can decrease the variability of catch rate data, I recommend that the weight of survey catch rate data should be more heavily in stock assessment models. Current management of yellow perch in Lake Erie also divides the lake into four management units (YPTG 2006). These management units have not been found to correspond to any population structure based on genetic analysis (Billington 1993; Strittholt et al. 1988;

Sepulveda-Villet et al. 2009). As an alternative, population structure may be inferred from life history parameters or the responses to environmental conditions (Begg et al. 1999). In this study, the residuals of log catch rate from GLM, s-GLM, and GAM suggest that one uniform stock extends throughout most of Lake Erie, as far as the central basin (Figure 1.9). But the residuals showed patterns of higher absolute values in the east basin, which suggests different distribution and density characteristics of yellow perch in the eastern basin.

Spatial-GLM has previously been reported to give better goodness-of-fit and abundance estimates than GLM for tuna longline catches in the Indian Ocean (Nishida and Chen 2004). This study has shown that s-GLM can also outperform GLM based on the yellow perch fishery-independent survey data in Lake Erie. It suggests that s-GLM is suitable not only for large ocean-scale commercial data, but also for smaller-scale surveys, such as in a lake. This study has further demonstrated the importance of including within-year (monthly) temporal changes, which are often neglected in catch rate analyses. Un-standardized catch rates appeared to peak in October and then decrease to November, while all three standardization models showed a leveling-off from October to November (Figure 1.6). Ideally, the best model and best selection of variables should be evaluated separately for any given fishery or survey. For yellow perch in Lake Erie, s-GLM and GAM provided better catch rate standardization than GLM based on goodness-of-fit, reduction of spatial autocorrelation, and prediction ability.

References

Akaike, H. 1973. Information theory and an extension of the maximum likelihood principle. In: Petrov, B.N., Csaki, F. (Eds.), Proceedings of the 2nd International Symposium on Information Theory. Publishing House of the Hungarian Academy of Sciences, Budapest 268-281.

Ali, M.A., R.A. Ryder, and M. Anctil. 1977. Photoreceptors and visual pigments related to behavioral responses and preferred habitats of perches (*Perca* spp.) and pike perches (*Stizostedion* spp.). Journal of the Fisheries Research Board of Canada 34:1475-1480.

Augustin, N.H., M., Musio, K., Von Wilpert, E., Kublin, S.N.,Wood, and M., Schumacher. 2009. Modeling spatiotemporal forest health monitoring data. Journal of American Statistics Association Vol.104. No.487: 899-911.

Begg, G.A., J.A, Hare, and D.D., Sheehan. 1999. The role of life history parameters as indicators of stock structure. Fisheries Resources 43:141-163.

Billington, N. 1993. Genetic variation in Lake Erie yellow perch (*Perca flavescens*) demonstrated by mitochondrial DNA analysis. Journal of Fish Biology 43:941-943.

Bishop, J., W.N., Venables, and Y., Wang. 2004. Analysing commercial catch and effort data from a Panaeid trawl fishery - A comparison of linear models, mixed models, and generalised estimating equations approaches. Fisheries Research 70:179-193.

Brandt, S.B., J.J., Magnuson, and L.B., Crowder. 1980. Thermal habitat partitioning by fishes in Lake Michigan. Canadian Journal of Fisheries and Aquatic Sciences 37:1557-1564.

Breiman, L., and P., Spector. 1992. Submodel selection and evaluation in regression. The X-random case. International Statistical Review 60:291-319.

Carlson, J.K., J., Osborne, and T.W., Schmidt. 2007. Monitoring the recovery of smalltooth sawfish, *Pristis pectinata*, using standardized relative indices of abundance. Biological Conservation 136:195-202.

Casselman, J.M. 2002. Effects of temperatures, global extremes, and climate change on year class production of warmwater, coolwater and coldwater fishes in the Great Lakes basin. McGinn, N.A., editors. Fisheries in a Changing Climate. American Fisheries Society Symposium 32. Bethesda, Maryland.

Cheng, Y.W., and M.P., Gallinat. 2004. Statistical analysis of the relationship among environmental variables, inter-annual variability and smolt trap efficiency of salmonids in the Tucannon River. Fisheries Research 70:229-238.

Chubb, S., and C.R. Liston.1985. Relationships of water level fluctuations and fish. Prince, H.H., and D'Itri, F.M., editors. Coastal Wetlands. Lewis Publishers, Inc., Chelsea, Michigan.

Craig, J.F.1987. The Biology of Perch and Related Fish. Timber Press, Portland, Oregon.

Damalas, D., P., Megalofonou, and M., Apostolopoulou. 2007. Environmental, spatial, temporal and operational effects on swordfish (*Xiphias gladius*) catch rates of eastern Mediterranean Sea longline fisheries. Fisheries Research 84:233-246.

Dorugade, A.V., and Kashid, D.N. 2009. Variable selection in linear regression based on ridge estimator. Journal of Statistical Computation and Simulation 00(0): 1-14.

Efroymson, M.A.1960. Multiple regression analysis. In: Ralston, A., Wilf, H.S. (Eds.), Mathematical Methods for Digital Computers. Wiley, New York.

Gavaris, S. 1980. Use of a multiplicative model to estimate catch rate and effort from commercial data. Canadian Journal of Fisheries and Aquatic Sciences 37:2272-2275.

Graham, M.H. 2003. Confronting multicolinearity in ecological multiple regression. Ecology 84:2809-2815.

Guisan, A., T.C., Edwards, and T., Hastie. 2002. Generalized linear and generalized additive models in studies of species distributions: setting the scene. Ecological Modelling 157: 89-100.

Harley, S. J., R.A., Myers, and A., Dunn. 2001. Is catch-per-unit-effort proportional to abundance? Canadian Journal of Fisheries and Aquatic Sciences 58:1760–1772.

Hartman, W.L. 1972. Lake Erie: effects of exploitation, environmental changes, and new species on the fishery resources. Journal of the Fisheries Research Board of Canada. 29:931-936.

Hastie, T.J., R.J., Tibshirani, and J., Friedman. 2001. Elements of statistical learning: data mining. In: Inference and Prediction. Springer, New York.

Hinton, M.G., and M.N., Maunder. 2004. Methods for standardizing CPUE and how to select among them. Collective Volume of Scientific Papers. The International Commission for the Conservation of Atlantic Tunas 56(1):169-177.

Hoerl, A.E. 1962. Applications of ridge analysis to regression problems. Chemical Engineering Progress 58:54-59.

Hoerl, A.E., and R.W., Kennard. 1970. Ridge regression: biased estimation for nonorthogonal problems. Technometrics 12:55-67.

Imbrock, F., A., Appenzeller, and R., Eckmann. 1996. Diel and seasonal distribution of perch in Lake Constance: a hydroacoustic study and in situ observations. Journal of Fish Biology 49:1-13.

Jiao, Y., K., Reid, and T., Nudds. 2006. Variation in the catchability of yellow perch (*Perca flavescens*) in the fisheries of Lake Erie using a Bayesian error-in-variable approach. ICES Journal of Marine Science 63:1695-1704.

Kelso, J.R.M.1976. Movement of yellow perch (*Perca flavescens*) and white sucker (*Catostomus commersoni*) in a nearshore Great Lakes habitat subject to a thermal discharge. Journal of the Fisheries Research Board of Canada 33:42-53.

Legendre, P. 1993. Spatial autocorrelation: trouble or new paradigm? Ecology 74:1659–1673.

Lenters, J.D. 2001.Long-term trends in the seasonal cycles of Great Lakes water levels. Journal of Great Lakes Research 27(3):342-353.

Liu, W., and J., Cela. 2007. Improving credit scoring by generalized additive model. SAS Global Forum.

Lofgren, B.M., F.H., Quinn, A.H., Clites, R.A., Assel, A.J., Eberhardt, and C.L., Luukkonen. 2002. Evaluation of potential impacts on Great Lakes water resources based on climate scenarios of two GCM's. Journal of Great Lakes Research 28:537-554.

Marquardt, D.W. 1970. Generalized inverses, ridge regression, biased linear estimation, and nonlinear estimation. Technometrics 12:591-612.

Maunder, M.N., and A.E., Punt. 2004. Standardizing catch and effort data: a review of recent approaches. Fisheries Research 70:141-159.

Maunder, M.N., J.R., Sibert, A., Fonteneau, J., Hampton, P., Kleiber, and S.J., Harley. 2006. Interpreting catch per unit effort data to assess the status of individual stocks and communities. ICES Journal of Marine Science 63(8):1373-1385.

McCauley, R.W., and L.A.A., Read. 1973. Temperature selection by juvenile and adult yellow perch (*Perca flavescens*) acclimated to 24 C. Journal of the Fisheries Research Board of Canada 30:1253-1255.

Montgomery, D.C., E.A., Peck, and G.G., Vining. 2006. Introdution to linear regression analysis. John Wiley & Sons, Inc., Hoboken, New Jersey.

Moran, P.A.P. 1950. Notes on continuous stochastic phenomena. Biometrika 37: 17-23.

Neill, W.H., and J.J., Magnuson. 1974. Distributional ecology and behavioral thermoregulation of fishes in relation to heated effluent from a power plant at Lake Monona, Wisconsin. Transactions of the American Fisheries Society 103:663-710.

Nishida, T., and D. Chen. 2004. Incorporating spatial autocorrelation into the general linear model with an application to the yellowfin tuna (*Thunnus albacares*) longline CPUE data. Fisheries Research 70:265-274.

NRC (National Research Council). 1998. Improving fish stock assessments. National Academy Press, Washington, D.C.

O'Brien, L., and R.K., Mayo. 1988. Sources of variation in catch per unit effort of yellowtail flounder, *Limanda ferruginea* (Storer), harvested off the coast of New England. Fishery Bulletin 86:91-108.

Olin, M., M. Kurkilahti, P. Peitola, and J. Ruuhijärvi. 2004. The effects of fish accumulation on the catchability of multimesh gillnet. Fisheries Research 68:135-147.

Quinn, F.H. 2002. Secular changes in Great Lakes water level seasonal cycles. Journal of Great Lakes Research 28:451-465.

Quinn II, T.J., and R.B., Deriso. 1999. Quantitative fish dynamics. Oxford University Press, New York.

Rudstam, L.G., and J.J., Magnuson. 1985. Predicting the vertical distribution of fish populations: analysis of cisco, *Coregonus artedii*, and yellow perch, *Perca flavescens*. Canadian Journal of Fisheries and Aquatic Sciences 42:1178-1188.

Ryan, T.P. 1997. Modern Regression Methods. John Wiley & Sons, Inc., New York.

Ryder, R.A. 1977. Effects of ambient light variations on behavior of yearling, subadult, and adult walleye (*Stizostedion vitreum vitreum*). Canadian Journal of Fisheries and Aquatic Sciences 34:1481-1491.

Sandheinrich, M.B., and W.A., Hubert. 1984. Intraspecific resource partitioning by yellow perch (*Perca flavescens*) in a stratified lake. Canadian Journal of Fisheries and Aquatic Sciences 41:1745-1752.

Sepulveda-Villet, O.J., A.M., Ford, J.D., Williams, and C.A., Stepien. 2009. Population genetic diversity and phylogeographic divergence patterns of the yellow perch (*Perca flavescens*). Journal of Great Lakes Research 35:107-119.

Shono, H. 2008. Application of the Tweedie distribution to zero-catch data in CPUE analysis. Fisheries Research 93:154-162.

Standing Technical Committee (STC). 2007. Lambda Review Workshop Completion Report to the Lake Erie Committee of the Great Lakes Fishery Commission. 8pp.

Strittholt, J.R., S.J., Guttman, and T.E., Wissing. 1988. Low levels of genetic variability of yellow perch (*Perca flavescens*) in Lake Erie and selected impoundments. In: Downlhower, J.E. (Ed.), The Biogeography of the island Region of Western Lake Erie. Ohio State University Press, Columbus, Ohio, pp. 246-257.

Suthers, I.M., and J.H., Gee. 1986. Role of hypoxia in limiting diel spring and summer distribution of juvenile yellow perch (*Perca flavescens*) in a prairie marsh. Canadian Journal of Fisheries and Aquatic Sciences 43:1562-1570.

Swartzman, G., C., Huang, and S., Kaluzny. 1992. Spatial analysis of Bering Sea groundfish survey data using generalized additive models. Canadian Journal of Fisheries and Aquatic Sciences 49:1366-1378.

Thompson, M.L. 1978. Selection of variables in multiple regression: Part I. A review and evaluation. International Statistical Institute 46:1-19.

Venables, W.N., and C.M., Dichmont. 2004. GLMs, GAMs and GLMMs: an overview of theory for applications in fisheries research. Fisheries Research 70:319-337.

Whiteside, M.C., C.M., Swindoll, and W.L., Doolittle. 1985. Factors affecting the early life history of yellow perch, *Perca flavescens*. Environmental Biology of Fishes Vol 12 No 1:47–56.

Whittingham, M.J., P.A., Stephens, R.B., Bradbury, and R.P., Freckleton. 2006. Why do we still use stepwise modelling in ecology and behaviour? Journal of Animal Ecology 75:1192-1189.

Ye, Y., M., Al-Husaini, and A., Al-Baz. 2001. Use of generalized linear models to analyze catch rates having zero values: the Kuwait driftnet fishery. Fisheries Research 53:151-168.

Yellow Perch Task Group (YPTG). 2006. Report of the Lake Erie yellow perch task group. Yellow perch task group. Wheatley, Ontario.

Yellow Perch Task Group (YPTG). 2009. Report of the Lake Erie yellow perch task group. Yellow perch task group. Wheatley, Ontario.

Zhang, L., and J.H., Gove. 2005. Spatial assessment of model errors from four regression techniques. Forest Science 51:334-346.

Zhang, L., J.H., Gove, and L.S., Heath. 2005. Spatial residual analysis of six modeling techniques. Ecological Modelling 186:154-177.

TABLE 1.1.- Summary of data collected in the 1990-2003 yellow perch fisheries-independent survey in Lake Erie.

Variables	**Unit**	**Remarks**
Catch weight	g	Per species
Longitude	degree	Converted to NAD 1983 UTM 17N
Latitude	degree	Converted to NAD 1983 UTM 17N
Set duration	hour	Standing time of gillnet in water
Bottom Depth	m	Per sampling site
Gear Depth	m	Depth to bottom of the gillnet
Transparency	m	Secchi depth
Water Temperature	℃	At surface
Gear Temperature	℃	At gear depth
Dissolved Oxygen (DO)	mg/L	At gear depth

TABLE 1.2.- Comparison of test statistics and significance of the continuous variables used in the GLM, s-GLM, and GAM catch rate standardizations.

Variables	GLM		s-GLM		GAM			
					Non-linear		Linear	
	χ^2	*p*-value	*t*-value	*p*-value	χ^2	*p*-value	*t*-value	*p*-value
Set duration	9.43	0.002	2.27	0.023	5.26	0.154	2.94	0.003
Gear Temp.	144.95	<0.001	9.65	<0.001	2.23	0.525	8.65	<0.001
Gear Depth	90.90	<0.001	-7.40	<0.001	154.07	<0.001	-15.29	<0.001
DO	24.06	<0.001	-4.08	<0.001	13.44	0.004	-1.80	0.072
Transparency	8.71	0.003	-2.52	0.012	5.44	0.142	-4.07	<0.001
Latitude	23.32	<0.001	-4.4	<0.001	16.19	0.001	-6.83	<0.001

TABLE 1.3.- Comparative measures of the GLM, s-GLM, and GAM catch rate standardizations for yellow perch in Lake Erie. MSE values of the 5-fold and 10-fold cross-validations are the means of the $m = 100$ repetitions.

Analysis	Measure	Model		
		GLM	s-GLM	GAM
Goodness-of-fit	AIC	4346.47	4288.16	4123.51
	R^2	0.64	0.90	0.72
	MSE	3913.38	1095.18	3035.72
Prediction (Cross-validation)	LOOCV MSE	3.98	3.50	3.30
	5-fold MSE	4.08	3.57	3.01
	10-fold MSE	4.06	3.53	3.01
Residual autocorrelation	Moran's I	0.05	0.01	0.02
	Z score	5.58**	1.39	2.25*

* $p < 0.05$

** $p < 0.01$

Figure Captions:

FIGURE 1.1.- Distribution of sampling locations of the cooperative partnership fisheries-independent survey in Lake Erie in one typical year (1993). The solid line indicates the Canada / US border through the lake.

FIGURE 1.2.- Moran's I and Z values of yearly log-transformed catch rates.

FIGURE 1.3.- Pair-wise scatter plots of nine continuous variables sampled in the Lake Erie gillnet survey. A 95% bivariate normal density ellipse is imposed on each scatter plot.

FIGURE 1.4.- Linear and non-linear effects of continuous explanatory variables on log catch rate, calculated over all years of the survey (1990 – 2003).

FIGURE 1.5.- Yearly log arithmetic mean (nominal) catch rates and catch rate standardizations by GLM, s-GLM, and GAM.

FIGURE 1.6.- Monthly log arithmetic mean (nominal) catch rates and catch rate standardizations by GLM, s-GLM, and GAM.

FIGURE 1.7.- Mean square errors from the one hundred 5-fold and 10-fold cross-validations of catch rate standardization with the GLM, s-GLM and GAM. The mean of each plot corresponds to Table 1.3.

FIGURE 1.8.- Nominal yearly log catch rate and GLM, s-GLM, and GAM catch rate standardizations plotted against the log of annual biomass estimates from the YPTG statistical catch-at-age model. Regression slopes are fixed = 1.

FIGURE 1.9.- Interpolation maps of the absolute residual values of each catch rate standardization model. Interpolations were calculated by ordinary kriging.

FIGURE 1.1.

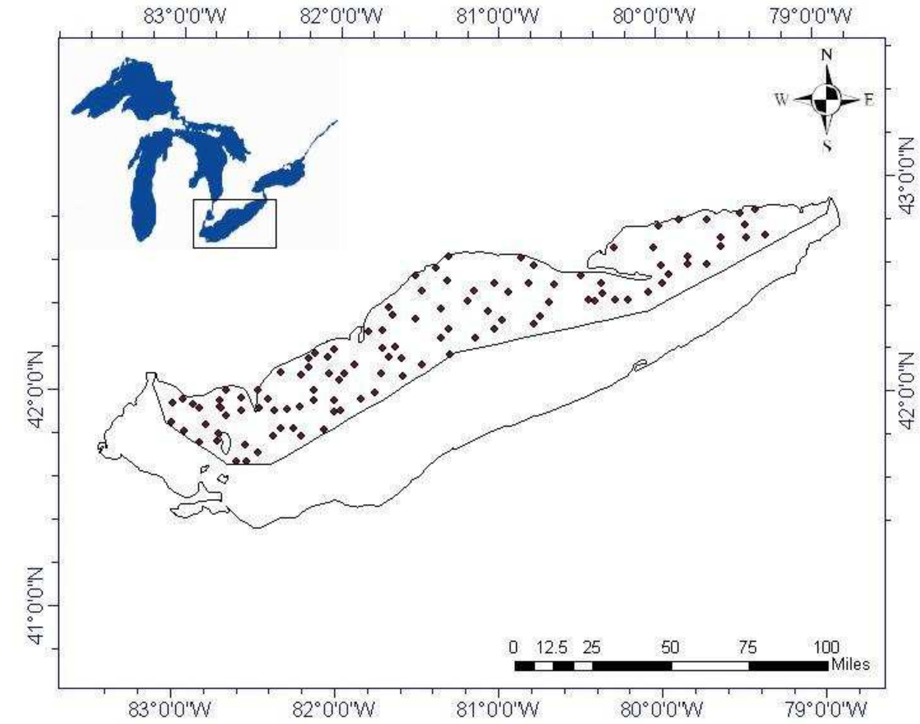
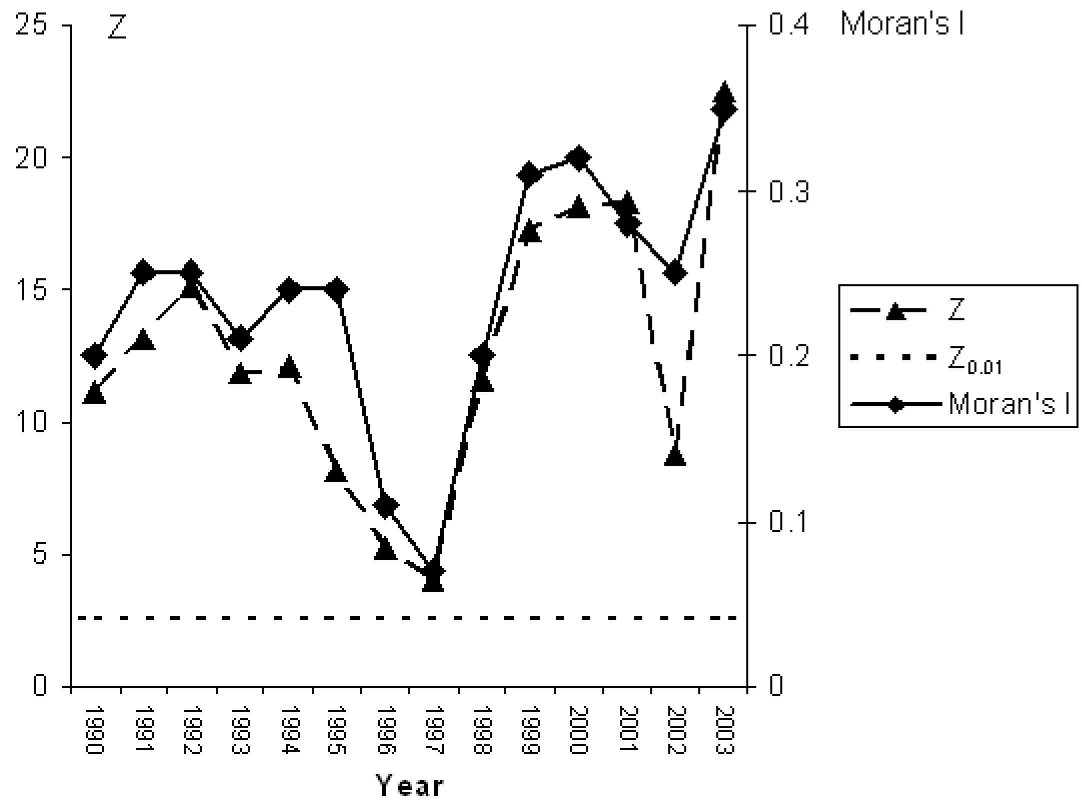

83°0'0"W
82°0'0"W
81°0'0"W
80°0'0"W
79°0'0"W
N
W
E
S
43°0'0"N
42°0'0"N
41°0'0"N
0
12.5
25
50
75
100
Miles

FIGURE 1.2.



25
20
15
10
5
0
Z
0.4
0.3
0.2
0.1
0
Moran's I
Z
$Z_{0.01}$
Moran's I
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
Year

FIGURE 1.3

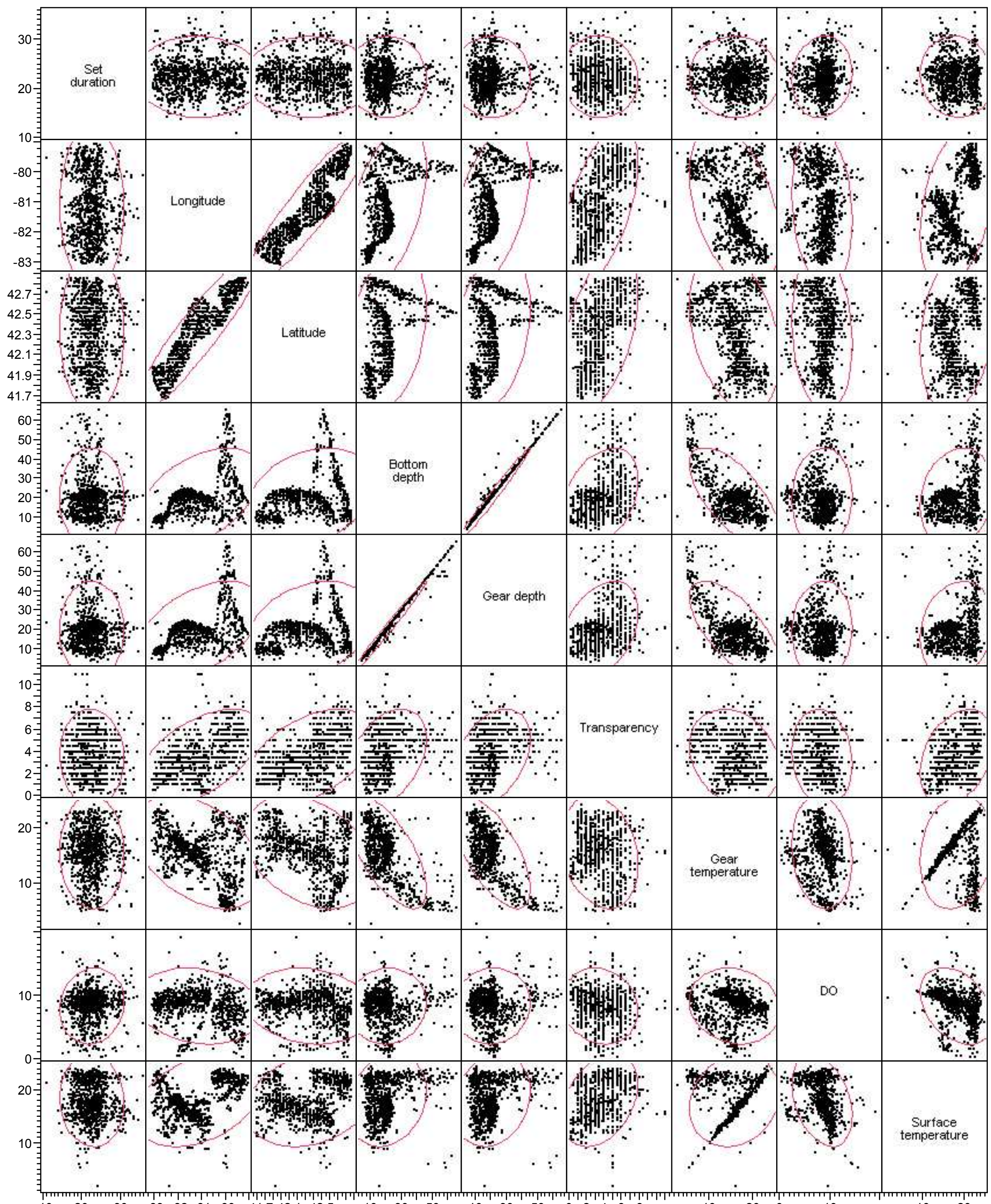

Set duration
Longitude
Latitude
Bottom depth
Gear depth
Transparency
Gear temperature
DO
Surface temperature

FIGURE 1.4.

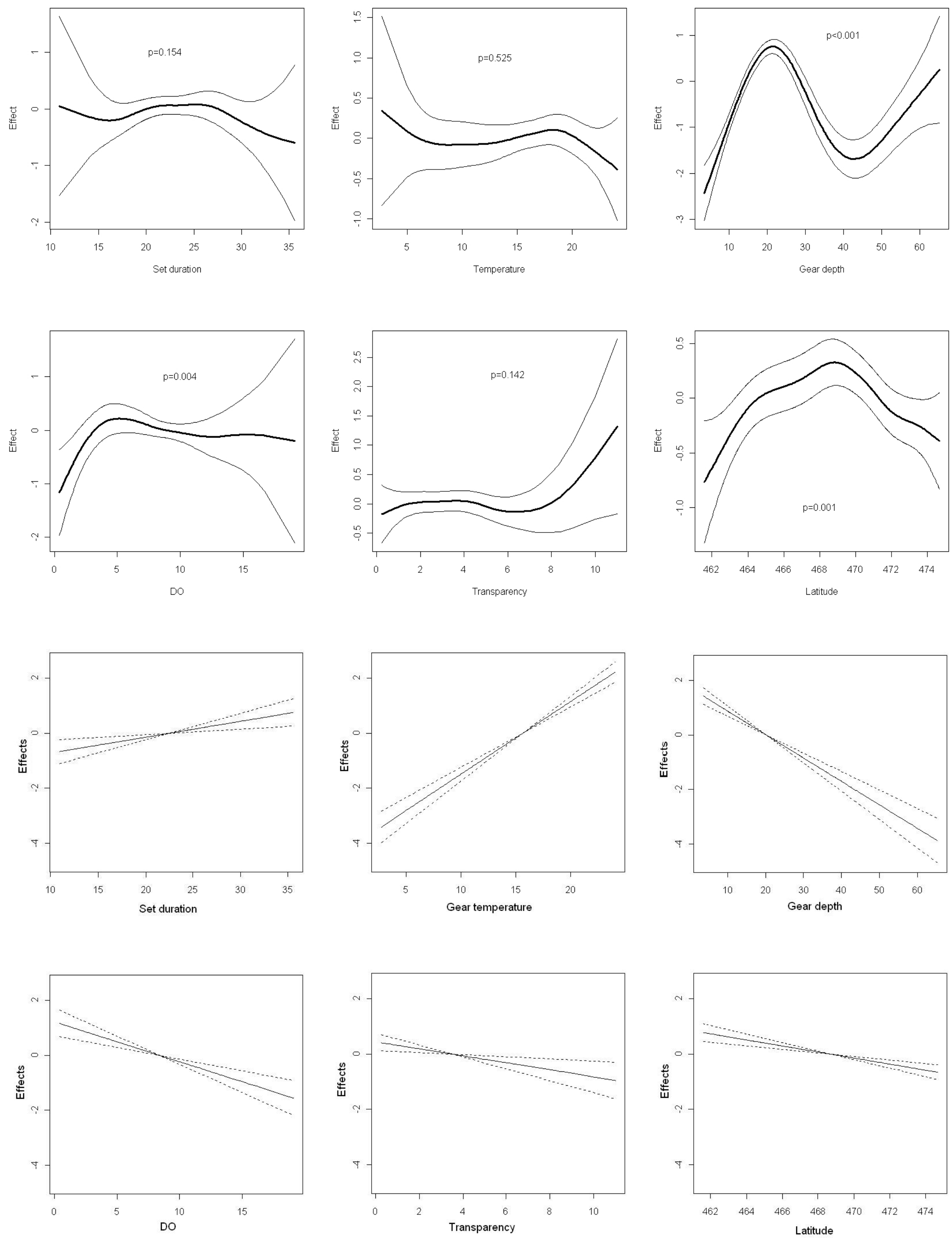
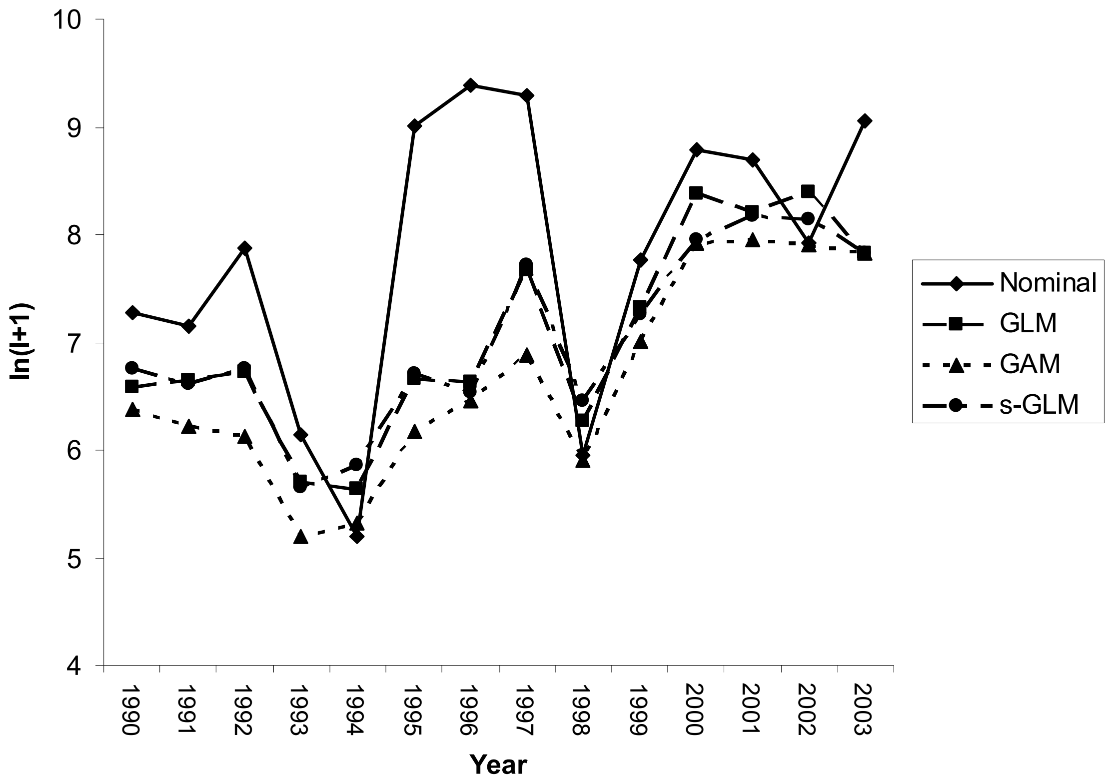

p=0.154
Effect
Set duration
p=0.525
Effect
Temperature
p<0.001
Effect
Gear depth
p=0.004
Effect
DO
p=0.142
Effect
Transparency
p=0.001
Effect
Latitude
Effects
Set duration
Effects
Gear temperature
Effects
Gear depth
Effects
DO
Effects
Transparency
Effects
Latitude

FIGURE 1.5.



10
9
8
7
6
5
4
ln(I+1)
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
Year
Nominal
GLM
GAM
s-GLM

FIGURE 1.6.

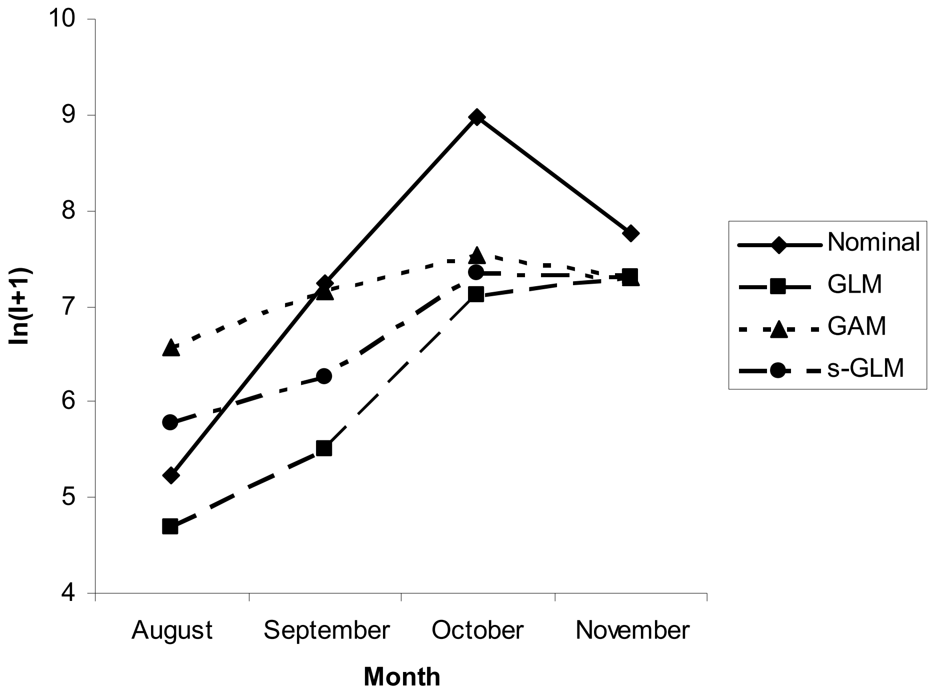

10
9
8
7
6
5
4
ln(I+1)
August
September
October
November
Month
Nominal
GLM
GAM
s-GLM

FIGURE 1.7.

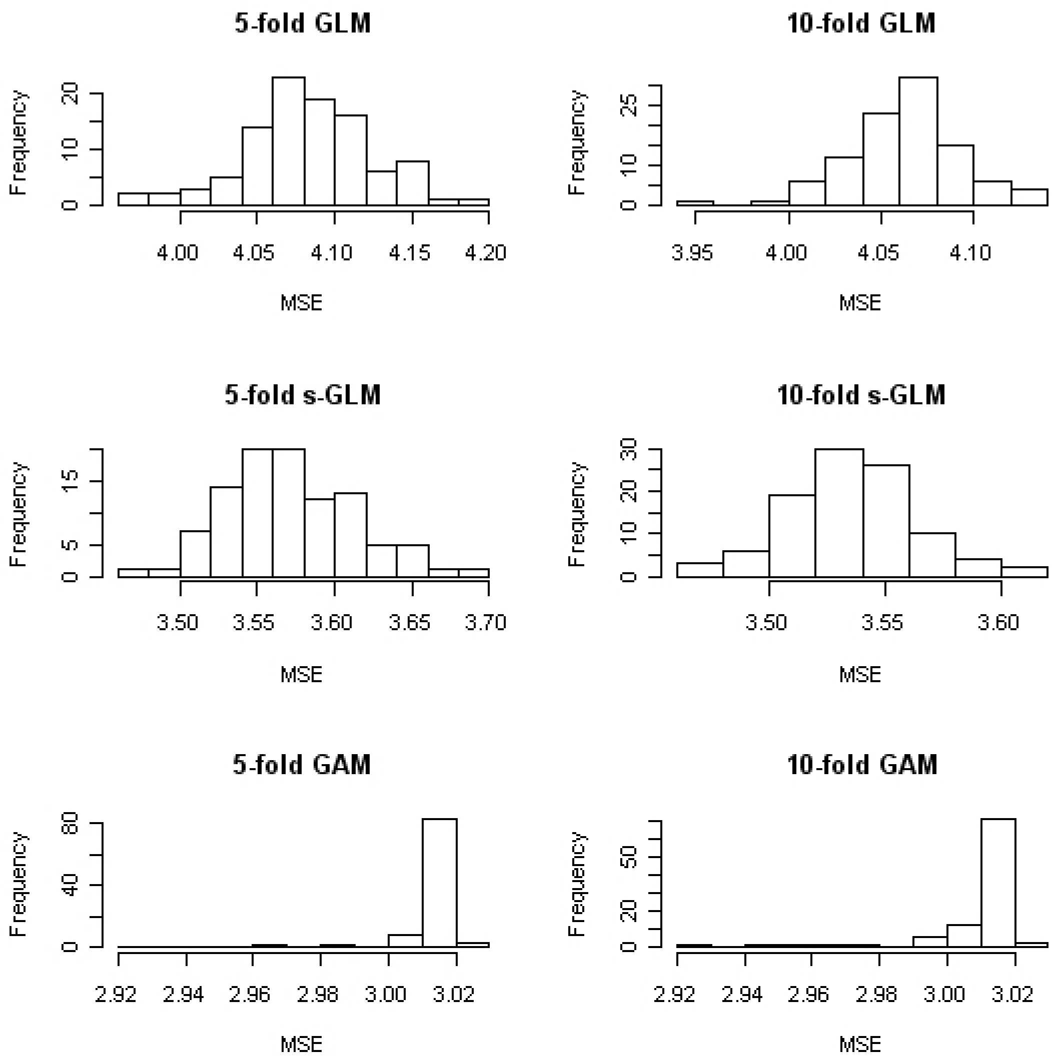

5-fold GLM
Frequency
0 10 20
4.00 4.05 4.10 4.15 4.20
MSE
10-fold GLM
Frequency
0 10 25
3.95 4.00 4.05 4.10
MSE
5-fold s-GLM
Frequency
0 5 15
3.50 3.55 3.60 3.65 3.70
MSE
10-fold s-GLM
Frequency
0 10 20 30
3.50 3.55 3.60
MSE
5-fold GAM
Frequency
0 40 80
2.92 2.94 2.96 2.98 3.00 3.02
MSE
10-fold GAM
Frequency
0 20 50
2.92 2.94 2.96 2.98 3.00 3.02
MSE

FIGURE 1.8.

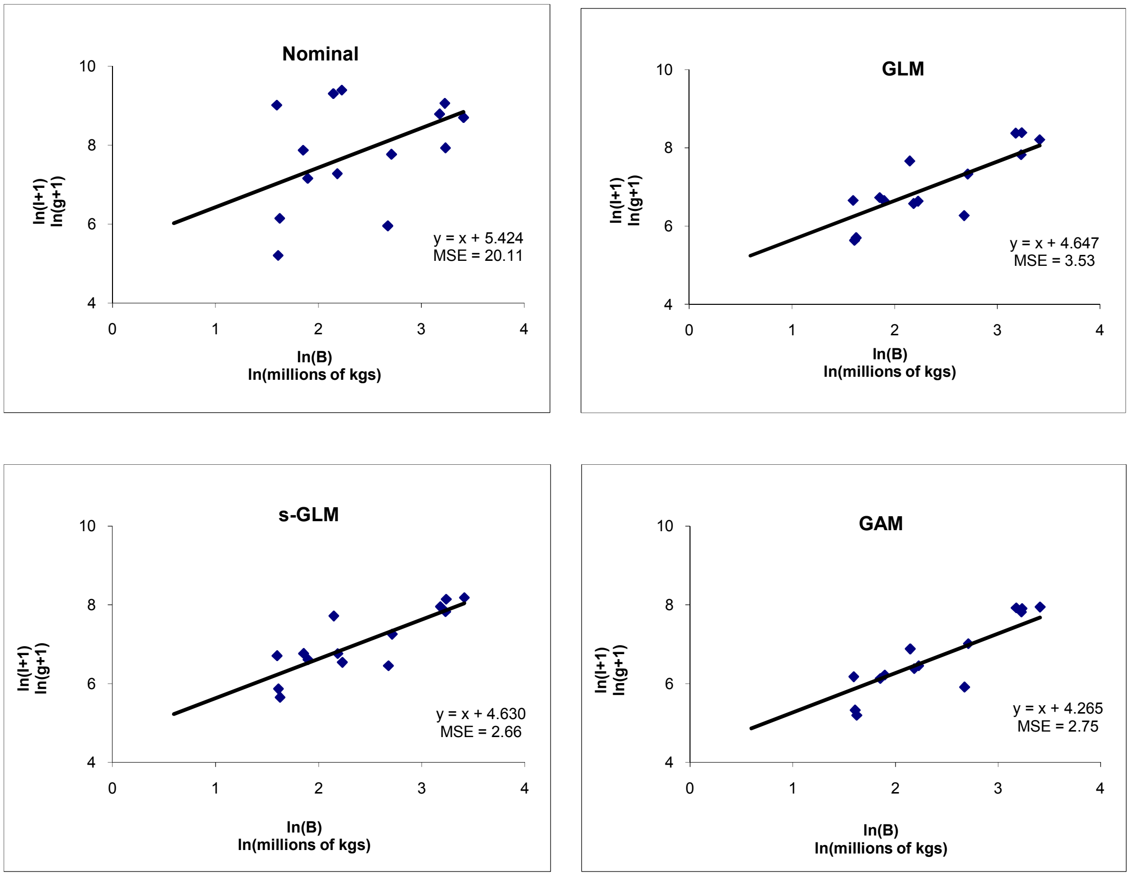
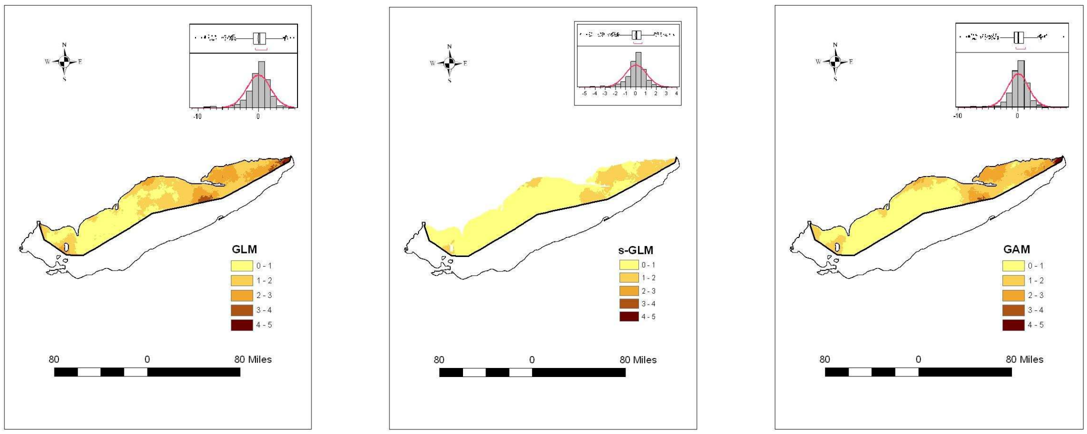

Nominal
y = x + 5.424
MSE = 20.11
GLM
y = x + 4.647
MSE = 3.53
s-GLM
y = x + 4.630
MSE = 2.66
GAM
y = x + 4.265
MSE = 2.75
ln(I+1)
ln(g+1)
ln(B)
ln(millions of kgs)
0
1
2
3
4
10
8
6
4

FIGURE 1.9.


GLM
0 - 1
1 - 2
2 - 3
3 - 4
4 - 5
80 0 80 Miles
s-GLM
0 - 1
1 - 2
2 - 3
3 - 4
4 - 5
80 0 80 Miles
GAM
0 - 1
1 - 2
2 - 3
3 - 4
4 - 5
80 0 80 Miles

Chapter 2

[1]Performance comparison of traditional sampling designs and adaptive sampling designs for fishery-independent surveys: a simulation study

Abstract: Fishery-independent surveys play important roles in fisheries stock assessment. An efficient sampling design is the key to a successful fishery-independent survey. In this study, I compared the performance of two traditional sampling designs with three adaptive sampling designs using fishery-independent survey data for yellow perch in Lake Erie as an example. Based on the existing survey data (1990 – 2003), yellow perch were observed to be heterogeneously distributed, and this heterogeneity varies over time. Traditionally, the Lake Erie fishery-independent survey has been conducted with a stratified random sampling design based on depth strata; however, adaptive sampling designs are thought to be more suitable for surveying heterogeneous populations. A simulation study was conducted to compare these designs by examining the accuracy and precision of the estimators. Initially in the simulation study, I used bias, mean absolute error (MAE), and mean squared error (MSE) of the estimators to compare simple random sampling, stratified random sampling and adaptive two-phase sampling (ATS). ATS was the best design according to these measurements. I then compared ATS, adaptive cluster sampling (ACS), adaptive two-stage sequential sampling (ATSS), and the currently used stratified random sampling design. ATS performed better than the other two approaches and the current stratified random sampling design. This is the first study that compared three adaptive sampling designs through a simulation study. I concluded that

[1]Formatted for submission to the Canadian Journals of Fisheries Aquatic Sciences

ATS is preferable to the current stratified random sampling design for yellow perch fishery independent survey in Lake Erie.

Introduction

Fishery independent surveys provide valuable information on fish population characteristics and play important roles in fisheries stock assessment (Rago 2005). The importance of fishery independent surveys has been well recognized, but the important role of sampling design for these surveys is rarely appreciated. People usually use traditional survey methods without doing background information analysis on how to improve the accuracy and precision of the estimators (Mier and Picquelle 2008). Fishery independent surveys are expensive and time-consuming, and an efficient sampling design is key to the success of these surveys. Recently, investigators are beginning to pay more attention to the importance of survey sampling and are exploring a variety of aspects of designs (Jolly and Hampton 1990; Bez 2002; Brown 2003; Kimura and Somerton 2006; Jardim and Ribeiro Jr. 2007; Poulard and Trenkel 2007; Link et al. 2008; Morrison et al. 2008). Based on the previous studies, I compared the performance of traditional and adaptive sampling designs with emphasis on simulation application for performance comparison.

Simple random sampling (SRS) and stratified random sampling (StRS) are the most commonly used sampling methods for fishery independent surveys. SRS is the simplest sampling method and is often used in more complex sampling methods (Cadima et al. 2005). StRS is used for heterogeneously distributed populations to increase the precision of estimates (Cadima et al. 2005). In StRS, the survey area is divided into strata that are internally more homogeneous based on habitat characteristics, such as basins and bathymetry etc. Stratum construction and sample allocation are critical for a successful StRS (Rago 2005). The best allocation of the sample in each stratum is usually determined by three factors: (1) the total number of elements in each stratum; (2) the variability of observations within each stratum; and (3) the cost of obtaining an observation from each stratum (Scheaffer et al. 2006). If variance and cost information is not available, proportional allocation can be used to allocate the total sample size among the strata (Scheaffer et al. 2006).

For patchy or rare populations, these traditional sampling designs can be inefficient. In the current study, adaptive sampling designs have been used to improve the precision of the estimates (Francis 1984; Thompson 1990; Thompson and Seber 1996; Hanselman et al. 2003; Su and Quinn 2003; Brown et al. 2008). A sampling design is defined as "adaptive" when the sample selection procedure depends on previous observations in the sample (Salehi and Smith 2005). Such "adaptive" sampling designs appearing in the literature include adaptive two-phase sampling design (ATS) (Francis 1984), adaptive cluster sampling design (ACS) (Thompson and Seber 1996), and adaptive two-stage sequential sampling design (ATSS) (Brown et al. 2008).

ACS has been reported to be more efficient than SRS for aggregated or rare populations (Thompson 1990; Thompson and Seber 1996). Several researchers have applied this method to fishery surveys and obtained satisfactory results (Hanselman et al. 2003; Sullivan et al. 2008). In ACS, if the density of a sampled unit is larger than a pre-defined critical value, such as number of fishes per square meter, then its neighborhood will be sampled in the next round. This sampling process will not stop until all units that satisfy the critical value are sampled (Thompson and Seber 1996). The outermost units are called "edge" units. However, there are difficulties for applying ACS in practice, such as how to determine appropriate critical values, the indefinite sampling problem due to a low critical value, and the costly "edge" unit issue

(Hanselman et al. 2003; Su and Quinn 2003). ATSS may solve some of these issues (Salehi and Smith 2005; Brown et al. 2008). However just like ACS, we still need to predetermine a critical value for ATSS. Compared to ACS and ATSS, ATS is more practical and flexible because the critical value is not needed for ATS, there is no "edge" unit issue, and adding or deleting a small number of sites does not influence the estimates statistically (Francis 1984; Brown 2008).

Yellow perch is one of the most important commercial and sport fish species in Lake Erie (Baldwin and Saalfeld 1962; Regier and Hartman 1973; Jiao et al. 2006). Previous studies (YPTG 2008) found that the distribution of yellow perch in the lake is heterogeneous that the western area has higher density than the eastern area. Based on our preliminary study, there are a few small areas that have much higher density than their neighborhoods in the lake. Therefore I wanted to evaluate if adaptive sampling designs would provide more efficient estimates than the design currently used in Lake Erie fishery independent survey, which is a partnership survey between the Ontario Commercial Fisheries' Association (OCFA) and the Ontario Ministry of Natural Resources (OMNR) Lake Erie Fisheries Management Unit (LEMU). Additionally, there are some problems associated with the current stratified survey design. For instance, fish density in each stratum is not homogeneous and the heterogeneity varies among years, which may adversely affect the efficiency of the stratified design relative to SRS. This allocation of the sample into each stratum only based on the size of each area could yield a less precise estimate. To deal with these problems, I developed a simulation study to compare SRS, StRS, ACS, ATSS, and ATS based on the example data of yellow perch fishery independent survey. My objectives were to explore the efficiency of the current method (StRS) and to find out the most efficient sampling designs in order to improve the fishery independent survey in the Great Lakes. This is the first study that compares the efficiencies of ACS, ATSS and ATS together through a simulation study. It should also be helpful for other field survey designs and fishery-independent surveys.

Materials and Methods

Study area and current survey design

Lake Erie is nearly evenly divided by Canada and the United States, and the current fishery independent survey is only conducted within the Canadian side of the lake. The Canadian side is partitioned into five basins for this survey; the Western basin, West-Central basin, East-Central basin, Pennsylvania ridge, and the Eastern basin. The Lake Erie fishery independent survey has been conducted within the Canadian side of Lake Erie annually since 1989. In this survey, standard gangs of gillnet consisting of fourteen different mesh sizes are fished in two distinct manners: canned and bottomed sets. The bottomed sets are mainly used for collecting yellow perch, so in this study only the bottomed sets design were analyzed. In this design, each basin was divided into 2 or 3 strata based on water depth, and each stratum contains many cells, each of which is 2.5 x 2.5 minutes (Fig.2.1). Some of these cells are not included in the sampling frame (un-sampled) because they are located on shipping routes or other obstacles. The number of cells (population size) varies from stratum to stratum. In total there are 14 strata, and a total sample size of 119 (cells) was used (Table 2.1).

In the simulations, in order to compare the efficiency of StRS and ATS, I divided the study area into 2, 3 and 4 strata respectively based on water depth, and the cell size was set to 2 X 2 minutes (Fig.2.2).

"True" population used in the simulation study

Ordinary kriging was used to interpolate the survey data. I used the interpolated survey data in 1993 and 2003, respectively, as our "true" population. The number of fish caught (fish/lift) at each site was interpolated to a density surface using ArcGIS software package (version 9.2, 2007, ESRI Inc., USA) (Fig.2.3). The cell size of the interpolated density maps was 2×2 minutes. The lake was divided into 1, 2, 3, and 4 strata based on the water depth. For each stratum, I calculated the mean, standard deviation (SD) and coefficient of variation (CV) of the survey data in 1993 and 2003 respectively (Table 2.2). The density of yellow perch in 1993 had higher SD and CV but lower mean value than those in 2003.

Sampling Design

Stratified random sampling (StRS)

The current Lake Erie fishery independent survey is based on a stratified random sampling design. The surface of the water was divided into 2-3 strata for each basin based on the water depth (Table 2.2). The formula for the estimator of the mean for StRS is

$$(1)\ \hat{\mu} = \frac{1}{N}\sum_{i=1}^{L} N_i \bar{y}_i \ ,$$

where N is the total number of the population units, L is the number of strata, N_i is the number of population units in the ith stratum, $\bar{y}_i$ is the mean of the samples from the ith stratum.

Adaptive cluster sampling (ACS)

Thompson and Seber (1996) described ACS in detail and provided two unbiased estimators of the mean: Hansen-Hurwitz estimator (HH) and Horvitz-Thompson estimator (HT). An ACS design usually includes the following two steps: (i) *n* units are first randomly selected from the study area; and (ii) the neighborhoods of each initial sampling unit are sampled if their values are larger than a predefined critical value, and the neighborhoods of the newly sampled units are also selected based on the same rule until all the desirable neighborhoods are sampled. The adjacent units that have been sampled form many networks. The formula for the Hansen-Hurwitz (HH) estimator is,

$$(2)\quad \hat{\mu}_{HH} = \frac{1}{n_1}\sum_{i=1}^{n_1}\frac{1}{m_i}\sum_{j\in K_i} y_j = \frac{1}{n_1}\sum_{i=1}^{n_1} w_i \quad ,$$

where y_j is the density of unit *j*, K_i is the *i*th network, m_i is the number of units in K_i, n_1 is the number of networks, w_i is the mean of the m_i observations in K_i.

The formula for the Horvitz-Thompson (HT) estimator is

$$(3)\quad \hat{\mu}_{HT} = \frac{1}{N}\sum_{k=1}^{K}\frac{y_k}{\alpha_k} \quad ,$$

$$(4)\quad \alpha_k = 1 - \left[\binom{N - x_k}{n_1}\Big/\binom{N}{n_1}\right],$$

where y_k is the sum of the y-values for the *k*th network, *K* is the total number of distinct networks in the population, *N* is the number of population units, α_k is the probability that a unit in network *k*, which contains x_k units.

To evaluate the properties of the HH and HT estimators, I sampled repeatedly from the interpolated survey data (the "true" population) for 1993 or 2003 with n_1 set as 30 units and the critical value set as the sample mean of these 30 units. A stopping rule of level 2 (Su and Quinn 2003) was used to limit the total sampling effort. When a stopping rule is used, both HH and HT estimators are biased (Su and Quinn 2003).

Adaptive two-stage sequential sampling (ATSS)

Brown et al. (2008) described the procedure for ATSS and the formula to calculate an unbiased estimate of the mean. ATSS is performed in two stages. Suppose a total population of *N* units were divided into *M* primary areas based on the preliminary knowledge of the population distribution, which can be uniformly selected or selected based on geographical characteristics or management convenience. In the first stage, *m* areas from the *M* primary areas are selected randomly without replacement. In the second stage, an initial n_{i1} units were selected from each area m_i using simple random sampling. If the mean value of the random sample is larger than a pre-defined critical value, e.g., 5 fishes per square meter, and g_i is the number of samples whose values are larger than the critical value in the m_i area, then $g_i \times \lambda$ number of additional units would be selected at random from the remaining units in the m_i area. Here, λ is a predetermined value to quantify the extra sampling intensity. In the present study, n_{i1} = 15 units were randomly sampled in each stratum at stage 2, and the mean value of the initial samples across the *m* area was used as the critical value. In the present study, I let $m = M = 5$ and $\lambda = 2$. The formula to calculate ATSS estimator of the mean density is

$$(5)\ \hat{\mu} = \frac{1}{m}\sum_{i=1}^{m}\left(\frac{g_i}{n_{i1}}\overline{y}_{ic} + \frac{n_{i1} - g_i}{n_{i1}}\overline{y}_{i\bar{c}}\right) \ ,$$

where $\overline{y}_{ic}$ and $\overline{y}_{i\bar{c}}$ are the mean of units satisfying and not satisfying the condition C in the final sample set from area m_i. Here, condition C is true when the sample value is larger than the critical value.

Adaptive two-phase sampling

Francis (1984) described the procedure of ATS and discussed its advantages. An ATS survey is carried out in two phases. The first phase is designed in the same way as a traditional stratified random sampling. Based on catches obtained from the first phase, more stations are allocated to some strata for the second phase of the survey. Let A_i be the area of the stratum i , n_i be the sample sizes for stratum i in Phase 1, and V_i be the variance of the samples from the Phase 1 survey in stratum i. Let n be the total sample size allocated for sampling for the survey and $\mathrm{n}_1 = \sum_{\mathrm{h}=1}^{\mathrm{L}} \mathrm{n}_\mathrm{i}$ be the initial (phase 1) station allocation. Here n_1 is set as a fraction of n. Phase 2 stations should be allocated according to the following procedure:

Step 1. calculate the estimated relative gain (reduction in variance) G_i from adding 1 station to stratum i by

$$(6)\ G_i = \frac{A_i^2 V_i}{n_i(n_i+1)} \quad .$$

Step 2. allocate 1 station to the stratum with the highest value of G_i.

Step 3. add 1 to n_i and recalculate G_i for the stratum just chosen.

Step 4. repeat steps 2 and 3 as many times as necessary until $n_1 = n$.

In this study, I set $n_1 = 0.8n$ in phase 1. In estimating fish density and its variance, 2-phase data are treated as if they came from a traditional stratified sampling design. Thus, the estimator of the mean in ATS is

$$(7)\ \hat{\mu} = \frac{1}{N}\sum_{i=1}^{L} N_i \bar{y}_i \ ,$$

where $\bar{y}_i$ is the mean of the samples from the ith stratum calculated based on the final sample units allocated to stratum i in phase 2. The ATS tends to give biased estimates because in phase 2 surveys more stations are more likely to be added in high density strata (Francis 1984).

Simulation study

It is difficult to compare the five sampling designs directly because the final sample size of the two adaptive sampling designs is unknown during the design stage and is hard to control. Therefore I divided these designs into two groups where they can be easily compared: (1) SRS, StRS, and ATS; and (2) ACS, ATS and ATS. I first compared the performance of the sampling designs in each group and found that ATS performed the best in both groups. Therefore, in the third comparison, I examined the performance of ATS and the currently used StRS design based on the current survey settings.

In the first simulation situation, I compared two traditional sampling designs, SRS and StRS with one adaptive sampling design, ATS. I stratified each of the 1993 and 2003 populations into 2, 3 or 4 strata, and varied the total sample sizes (defined as *n*, which is the total number of element units drawn from the surveyed population) from 50 to 150 with step size of 50. For StRS, stratum sample size n_i was allocated based on proportional allocation (Fig. 2.4a).

Secondly, I compared the adaptive sampling designs ACS with ATS, and ATS with ATSS. When comparing ATS and ATSS, I used 5 strata because the lake was divided into 5 basins when doing the fishery-independent survey. I did not consider stratification in ACS because Brown (1999) found the stratified ACS was not more efficient than ACS. For ACS, I first randomly sampled n_1 =30 sites in the lake and then used the mean catch of these 30 samples as the critical value. For ATSS, I first randomly sampled n_{1i} = 15 sites at each stratum respectively and then used the mean catch of these 75 samples as the critical value. When comparing ATS with ACS or ATS with ATSS, it is not possible to know the exact final total sample size *n* for ACS and ATSS before the survey. To overcome this difficulty, I used the average final sample sizes ($\overline{n} = \sum_{r=1}^{R} n_r$) from R = 1000 simulation replications of ACS or ATSS as the total sample size *n* used in ATS in the comparisons of ATS with ACS and ATS with ATSS, respectively (Fig.2.4b).

Finally I compared the best adaptive sampling design with the currently used sampling method. Here, it was ATS that was found to perform the best from the previous 2 simulation scenarios. In this scenario, 14 strata and n= 119 were used, which is the current sampling approach (Fig.2.4c).

Performance measurements

I used four performance measures to compare the statistical properties and relative performance of the different designs. They are bias (*B*), variance of the mean (V), mean of absolute error (*MAE*), the mean squared error (*MSE*), and the relative efficiency (*RE*) of each estimator. The formulas are shown as follows:

$$(7)\ B = \frac{1}{R}\sum_{i=1}^{R}(\hat{\mu}_i - \mu) \quad ,$$

$$(8)\ V = \frac{1}{R}\sum_{i=1}^{R}(\hat{\mu}_i - \overline{\mu})^2 \ ,$$

$$(9)\ MAE = \frac{1}{R}\sum_{i=1}^{R}\left|\hat{\mu}_i - \mu\right|,$$

$$(10)\ MSE = B^2 + V \ ,$$

$$(11)\ RE = \frac{MSE_1}{MSE_2},$$

where $\hat{\mu}_i$ is the estimated mean value, μ is the "true" mean, $\overline{\mu}$ is the mean of $\hat{\mu}_i$, *R* is the number of runs of simulation for each scenario. For SRS, StRS, and ATSS, the estimates are unbiased, so *MSE* = *V* theoretically. In this study because the stopping rule is applied, the estimators from ACS and ATS are biased, so for ACS and ATS, I used $MSE = B^2 + V$. Sampling design 1 is more efficient when *RE* is less than 1.

Results

Comparison of SRS, StRS and ATS

Since the estimators of μ from SRS and StRS are unbiased, only the bias of $\hat{\mu}_{ATS}$ is shown for the interpolated survey data in 1993 and 2003 respectively (Table 2.3). The biases from all these sampling designs were very small compared with the mean values (Table 2.1).

For the 1993 data, *MAE* decreased with increasing number of strata (L) and sample size (n) for all the three sampling designs (Fig. 2.5): ATS always resulted in the smallest *MAE* at each combination of L and n for all the designs, and SRS resulted in the largest *MAE*. For the 2003 data, the ranking of the designs based on *MAE* is not as uniform as in 1993, especially at $L = 2$ (Fig. 2.5). At $n = 50$, SRS resulted in the largest *MAE*, and *MAE* from StRS are the smallest among the three designs. When $n \geq 100$ and $L \geq 3$, StRS and ATS perform very close (Fig. 2.5). I also compared SRS, StRS and ATS with *MSE* for 1993 and 2003 (Table 2.4) and obtained similar results as *MAE*. The relative efficiency (*RE*) between StRS and ATS was compared (Fig. 2.6). In 1993, REs were larger than 1 for all sampling designs, and in 2003, 6 out of 9 REs were larger than 1. It indicated that in most situations, ATS was more efficient than StRS.

Comparison of ATS with ACS and ATS with ATSS

In simulation situation 2, first I compared ACS with ATS with the 1993 and 2003 data. The final average sample sizes $\overline{n}_{acs}$ obtained from ACS were 99.1 and 139.9 for 1993 and 2003 respectively. Then I ran simulations for ATS with $L = 5$ strata, and $n = 100$ or 140 for 1993 and 2003 separately. Bias, *MAE*, variance of the mean, and *MSE* were compared in Table 2.5. For ACS, both HH and HT estimators were calculated; the HT estimator had lower bias, lower *MAE* and lower *MSE* than the HH estimator. ATS performed better than ACS in terms of bias, *MAE* and *MSE* (Table 2.5).

Similarly, to compare ATSS with ATS, I first ran simulations for ATSS for 1993 and 2003. The final average sample sizes $\bar{n}_{atss}$ were 109.2 and 140.7 for 1993 and 2003 respectively. Then I ran simulation for ATS with sample sizes set to 110 and 140 for 1993 and 2003 respectively. ATS resulted in smaller *MAE* and *MSE* than those from ATSS whereas their bias was negligible (Table 2.5).

Comparison of ATS with the current survey design

In the third simulation situation, I compared the best adaptive sampling approach (ATS) with the design currently used (StRS). Bias, *MAE*, variance of the mean and *MSE* were compared in Table 2.6. StRS can provide unbiased estimators if all units in each stratum have the same probability to be chosen. Since some locations can not be sampled (Fig. 2.1), the estimators from both StRS and ATS are biased. ATS resulted in smaller *MAE* and *MSE* than those from the current sampling design in 1993 and 2003. Current sampling design resulted in larger biases than ATS in both 1993 and 2003 but these bias values are negligible (Table 2.5).

Discussion

This study showed that ATS performed better than the traditional SRS and StRS, and the adaptive sampling designs of ACS and ATSS for yellow perch fishery independent survey data in Lake Erie. The reason that ATS had better precision than StRS is that samples allocation in each stratum is based on not only the size of each stratum but also the variance of samples in the first phase. The premise that StRS has better precision than SRS is that the variable of interest in each stratum is almost homogeneous (Scheaffer et al. 2006). In Lake Erie, yellow perch density varies temporally and spatially, it is difficult to find an appropriate strata division for each year. When the density in each stratum is heterogeneous and sample size is small, StRS performed even worse than SRS (Fig.2.5). ACS and ATSS in this case are not as good as they were described in other cases (Hanselman et al. 2003; Brown et al. 2008). Brown (1999) mentioned that the reasons may include 1) the studied population is not sufficiently clustered, 2) the critical value is too small, and 3) the neighborhood definition is too large. In this study, the reason is very likely to be the first one. For ACS, I calculated both HH and HT estimators. The HT estimator is preferable in a stopping rule case (Su and Quinn 2003). In this study, HT was less biased and had smaller *MAE* but larger variance of the mean (Table 2.5).

Besides efficiency, ATS is more flexible and practical in reality as well than StRS. The formula used to calculate variance reduction (Eq.6) could include a cost factor that is of interest. A subjective weighting factor derived from prior knowledge may be added to it. For example, if we know the cost for each trip before the second phase, we can include this information into this formula, which can be revised as $G_i = \dfrac{A_i^2 V_i}{n_i(n_i+1)\sqrt{c_i}}$, where c_i is the cost for each trip in stratum *i*. This is one of the tradeoffs that fisheries managers often face, i.e., better estimation or lower cost? It also gives them alternative options when they make decisions on survey plans.

In a conventional sampling, it is possible that some strata will be under-sampled or not sampled due to bad weather and vessel or gear problems (Francis 1984). This happened for the yellow perch fishery independent survey in some years (1989, 1995, 1996 and 1997). Traditional sampling designs lack the ability to deal with this situation because the sample plan is determined before sampling. In contrast, ATS is able to decrease the negative effect of under sampling. This is because once the first phase sampling is finished, theoretically there is no problem if the samples in phase 2 are not totally allocated (Francis 1984).

ATS performed better for the data with a larger range of relative variation among strata. I used Coefficient of variation (CV) to measure the relative variation in each stratum, $CV = \frac{s}{m}$, where s and m are the standard deviation and mean of the samples respectively. When 1993 was treated as the true population, the CVs were 0.40, 0.51 and 0.49 for 2, 3 and 4 strata respectively. When 2003 was treated as the true population, the ranges were only 0.17, 0.11 and 0.13. ATS resulted in much smaller MAE and MSE than SRS and StRS when 1993 year data were used in the simulation. But MAE and MSE from SRS, StRS and ATS were close to each other when 2003 year data were used in the simulation (Table 2.4). The reason for large range of CVs is that the strata division is not totally consistent with the density distribution. In some strata, density distribution is more heterogeneous than the others. Traditional sampling methods often lead to low accuracy and precision, but ATS is more suitable for this situation. When each stratum shows similar relative variation, the efficiency of ATS will be decreasing. In general, ATS is preferable to ACS ant ATSS for yellow perch fishery-independent survey in Lake Erie.

Adaptive sampling designs have showed advantages compared with traditional methods in some cases, but they also have their practical limitations. For ACS, if prior knowledge about the population distribution before survey is limited, selecting an appropriate critical value can be difficult (Su and Quinn 2003). Hanselman et al. (2003) recommended three methods that can be used to determine a fixed critical value, and they are 80^{th} quantile of the past survey data, the mean of the past survey data, and the mean of initial samples. In this study, the mean of initial samples was used as a critical value. Because yellow perch density changed a lot over time, past survey data would not be representative for the current data. High critical value may lead to smaller sample size, and low critical value may make sampling continue indefinitely. Su and Quinn (2003) suggested using order statistics in ACS to replace an arbitrary critical value, but this method still has its limitations (Hanselman et al. 2003). Furthermore, “edge units” do not involve later statistical estimation, but require much effort. To avoid these problems, I used a relatively large initial sample size (30) and a stopping rule to terminate the sampling process (Lo et al. 1997). I applied ACS instead of stratified ACS (SACS) in this study because Brown (1999) found the differences between ACS and SACS are small and statistically insignificant based on sample sizes and variances. ATSS avoided “edge units” and neighborhood sampling, but it still has to face problems of critical value and initial sample size as in ACS. Both ACS and ATSS cannot give the exact total sample size before sampling. The problems mentioned above do not exist in ATS. So ATS makes calculation easier and plausible. The only difficulty of using ATS may be the sample size in Phase 1. Francis (1984) recommended allocating about 75% of total sample size into Phase 1, and 80% of total sample size was used in this study. The results showed that it was a reasonable proportion to apply.

Our simulation study also suggested that in different fisheries, the best sampling design can be different. Previous simulation studies have found that ACS (Hanselman et al. 2003; Sullivan et al. 2008) and ATSS (Salehi and Smith 2005; Brown et al. 2008) performed better in Pacific ocean perch, sea lampreys, freshwater mussels, and blue-winged teal populations. Simulation studies are suggested to search for most appropriate fisheries survey designs in general.

References

Baldwin, N.S., and Saalfeld, R.W. 1962. Commercial fish population in the Great Lakes, 1867-190. Great Lakes Fishery Commission Technical Report No.3.

Bez, N. 2002. Global fish abundance estimation from regular sampling: the geostatistical transitive method. Can. J. Fish. Aquat. Sci. 59:1921-1931.

Brown, J.A. 1999. A comparison of two adaptive sampling designs. Austral. & New Zealand J. Statist. 41(4): 395-403.

Brown, J.A. 2003. Designing an efficient adaptive cluster sample. Environ. Ecol. Stat. 10: 95-105.

Brown, J.A., Salehi, M.M., Moradi, M., Bell, G., and Smith, D.R. 2008. An adaptive two-sequential design for sampling rare and clustered populations. Popul. Ecol. 50: 239-245.

Cadima, E.L., Caramelo, A.M., Afonso-Dias, M., Tandstad, M.O., and Leiva-Moreno, J.I. 2005. Sampling methods applied to fisheries science: a manual. Volume 434 of FAO fisheries technical paper, 2005. Food & Agriculture Org. Publ. Rome.

Francis, R.I.C.C. 1984. An adaptive strategy for stratified random trawl surveys. New Zeal. J. Mar. Fresh. 18: 59-71.

Hanselman, D.H., Quinn, T.J., Lunsford, C., Heifetz, J., and Clausen, D. 2003. Applications in adaptive cluster sampling of Gulf of Alaska rockfish. Fish. Bull. 101: 501-513.

Jardim, E., and Ribeiro Jr, P.J. 2007. Geostatistical assessment of ampling designs for Portuguese bottom trawl surveys. Fish. Res. 85:239-247.

Jiao, Y., Reid, K., and Nudds, T. 2006. Variation in the catchability of yellow perch (*Perca flavescens*) in the fisheries of Lake Erie using a Bayesian error-in-variable approach. ICES J. Mar. Sci. 63: 1695-1704.

Jolly, G.M., and Hampton, I. 1990. A stratified random transect design for acoustic surveys of fish stocks. Can. J. Fish. Aquat. Sci. 47:1282-1291.

Kimura, D.K., and Somerton, D.A. 2006. Review of statistical aspects of survey sampling for marine fisheries. Res. Fish. Sci. 14:3245-3283.

Link, J., Burnett, J., Kostovick, P., and Galbraith, J. 2008. Value-added sampling for fishery independent surveys: Don't stop after you're done counting and measuring. Fish. Res. 93:229-233.

Lo, N.C.H., Griffith, D., and Hunter, J.R. 1997. Using restricted adaptive cluster sampling to estimate Pacific hake larval abundance. CalCOFI Report. 38: 103-113.

Mier, K.L., and Picquelle, S.J. 2008. Estimating abundance of spatially aggregated populations: comparing adaptive sampling with other survey designs. Can. J. Fish. Aquat. Sci. 65:176-197.

Morrison, L.W., Smith, D.R., Young, C.C., and Nichols, D.W. 2008. Evaluating sampling designs by computer simulation: a case study with the Missouri bladderpod. Popul. Ecol. 50:417-425.

Poulard, J., and Trenkel, V.M. 2007. Do survey design and wind conditions influence survey indices? Can. J. Fish. Aquat. Sci. 64:1551-1562.

Rago, P.J. 2005. Fishery independent sampling: survey techniques and data analyses. In: Musick, J.A. (Ed.), Management techniques for elasmobranch fisheries. Volume 474 of FAO fisheries technical paper, 2005. Food & Agriculture Org. Publ., pp. 201-215.

Regier, H.A., and Harman, W.L. 1973. Lake Erie's fish community: 150 years of cultural stresses. Sci. 180 (4092): 1248-1255.

Salehi, M.M., and Smith, D.R. 2005. Two-stage sequential sampling: a neighborhood-free adaptive sampling procedure. J. Agric. Biol. Envir. S. 10(1): 84-103.

Schaeffer, R.L., Mendenhall, W., and Ott, R.L. 2006. Elementary survey sampling, 6th ed. Duxbury Press. Australia.

Su, Z., and Quinn, T. 2003. Estimator bias and efficiency for adaptive cluster sampling with order statistics and a stopping rule. Environ. Ecol. Stat. 10: 17-41.

Sullivan, W.P., Morrison, B.J., and Beamish, F.W.H. 2008. Adaptive cluster sampling: estimating density of spatially autocorrelation larvae of the sea lamprey with improved precision. J. Great Lakes Res. 34: 86-97.

Thompson, S.K. 1990. Adaptive cluster sampling. J. Am. Stat. Assoc. 85: 1050-1059.

Thompson, S.K., and Seber, G.A. 1996. Adaptive sampling. John Wiley & Sons, Inc. New York.

Table 2.1. Current spatial stratification of fishery-independent survey for each basin in the Canadian side of Lake Erie. The strata stratification is based on water depth. West Basin was divided into two strata, and each of the other 4 basins was divided into 3 strata.

Basin	Stratification by surface area	Sample size
West Basin (WB)	Water depth from 0-10m	16
	Water depth >10m	6
West-Central (WC) &	Water depth from 0-15m	11(WC)/8(EC)
East-Central Basin (EC)	Water depth from 15-20m	15(WC)/11(EC)
	Water depth >20m	10(WC)/17(EC)
Pennsylvania Ridge (PR)	Water depth from 0-15m	1(PR)/6(EB)
& Eastern Basin (EB)	Water depth from 15-30m	1(PR)/8(EB)
	Water depth >30m	2(PR)/7(EB)

Table 2.2. Mean, standard deviation (SD) and coefficient variation (CV) of the survey data in 1993 and 2003. The unit for the mean value is individuals/lift.

Number of	Stratum	Mean		SD		CV	
strata	index	1993	2003	1993	2003	1993	2003
1	1	43.61	275.51	47.50	168.26	1.09	0.61
2	1	58.13	282.07	55.98	153.51	0.96	0.54
	2	21.77	265.64	12.10	188.06	0.56	0.71
3	1	73.85	291.97	67.27	150.60	0.91	0.52
	2	29.93	302.82	12.09	164.28	0.40	0.54
	3	7.27	47.14	5.92	29.59	0.81	0.63
4	1	85.43	291.76	74.55	145.10	0.87	0.50
	2	39.03	275.29	23.65	159.00	0.61	0.58
	3	26.09	330.65	9.91	164.85	0.38	0.50

Table 2.3. Biases from ATS based on the "true" data after 1000 times simulation when the 1993 and 2003 year were treated as true populations.

Strata	Sample sizes					
	1993			2003		
	50	100	150	50	100	150
2	0.101	0.008	0.100	-1.365	0.397	-0.035
3	0.013	0.200	0.028	-0.391	0.472	-0.395
4	-0.204	-0.196	-0.089	-0.254	-0.224	0.301

Table 2.4. Estimated MSEs in the simulation when scenarios 1 was used, i.e., comparison among SRS, StRS and ATS. The 1993 and 2003 years' densities were treated as the true population.

Strata		SRS			StRS			ATS	
1993	50	100	150	50	100	150	50	100	150
2	43.54	20.99	12.57	37.09	18.2	12.24	31.55	15.88	9.8
3				35.36	16.12	9.44	25.55	11.54	7.1
4				31.05	14.65	8.52	21.4	10.96	6.34
2003	50	100	150	50	100	150	50	100	150
2	536.95	234.09	160.85	579.79	237.71	161.49	559.56	262.6	166.22
3				489.04	218.89	127.41	448.53	216.85	126.19
4				451.43	203.33	126.73	441.83	205.54	138.81

Table 2.5. Estimated bias, MAE, variance of the mean and MSEs when scenario 2 was used, i.e., comparison between ATS and ACS; ATS and ATSS. The 1993 and 2003 data were treated as true.

Performance measures	1993			2003		
	ATS	ACS		ATS	ACS	
		HH	HT		HH	HT
Bias	**-0.05**	-4.14	-0.43	**0.29**	-23.18	5.97
MAE	**1.23**	6.39	5.56	**4.53**	28.61	24.31
Variance of the mean	**2.33**	43.96	48.96	**31.77**	688.28	862.18
MSE	**2.33**	61.10	49.14	**31.86**	1225.59	897.82
	ATS	ATSS		ATS	ATSS	
Bias	**0.03**	0		**0.29**	0	
MAE	**1.11**	1.17		**4.53**	6.13	
Variance of the mean	**1.92**	2.13		**31.77**	60.05	
MSE	**1.92**	2.13		**31.86**	60.05	

Table 2.6. Comparison of bias, MAE and variance of the mean from ATS and current sampling design (i.e., scenario 3) based on the “true” data in 1993 and 2003

Year	1993		2003	
	Current	ATS	Current	ATS
Bias	-0.49	0.01	-2.16	0.93
MAE	1.20	1.06	4.72	4.21
Variance of the mean	1.42	1.32	5.54	5.24
MSE	1.66	1.32	10.21	6.10

Fig.2.1. Basins and strata partitions of the study area of current fishery-independent sampling survey in Lake Erie. Number1, 2, 3, 4 and 5 represent Western Basin, West-Central Basin, East-Central Basin, Pennsylvania Ridge and Eastern Basin respectively. The cell size is 2.5X2.5 minutes and the number of strata in each basin is 2 or 3 based on water depth. The darker color means shallow water and light color means deep water.

Fig.2.2. Strata partitions of the study area used in the simulation study: comparison among simple random sampling (SRS), stratified random sampling (StRS) and adaptive two-phase sampling (ATS). The study area was divided into 2, 3 and 4 strata respectively.

Fig.2.3. Density interpolation maps of yellow perch based on survey data of 1993 and 2003. (a) 1993, with mean density 43.6 individuals/lift, and standard deviation of 47.5; (b) 2003 with mean density 275.5 individuals/lift, and standard deviation of 168.3.

Fig.2.4. The simulation procedure used to compare the different sampling designs. (a) scenario 1: comparison among SRS, StRS and ATS; (b) scenario 2: comparison among ACS, ATSS and ATS; (c) scenario 3: comparison between the current sampling design and ATS. The same procedure was used for simulations when the 1993 and 2003 were assumed as the "true" population.

Fig.2.5. Estimated mean absolute error (MAE) based on the "true" data after 1000 times simulation in 1993 and 2003. The sample sizes were 50, 100, and 150; the strata were 2, 3, and 4.

Fig.2.6. Relative efficiencies (*RE*) of the estimator between StRS and ATS when the 1993 and 2003 were assumed as the "true" population. The sample sizes were 50, 100, and 150; the strata were 2, 3, and 4.

Fig.2.1

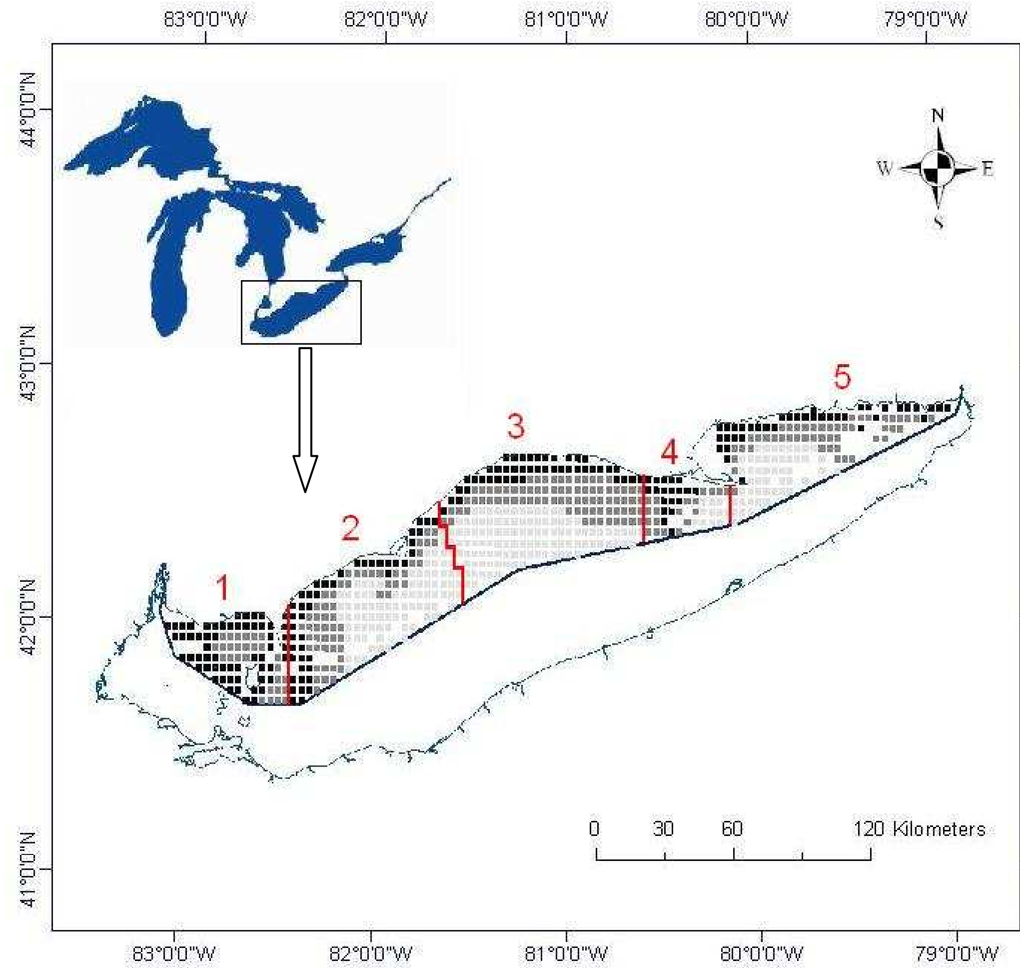
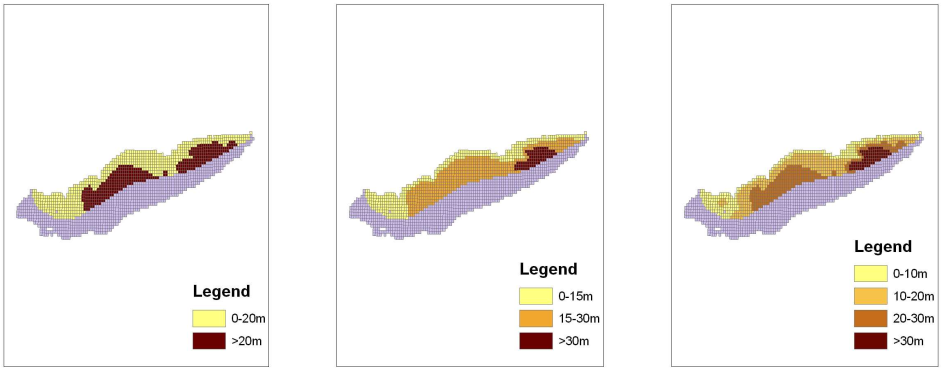
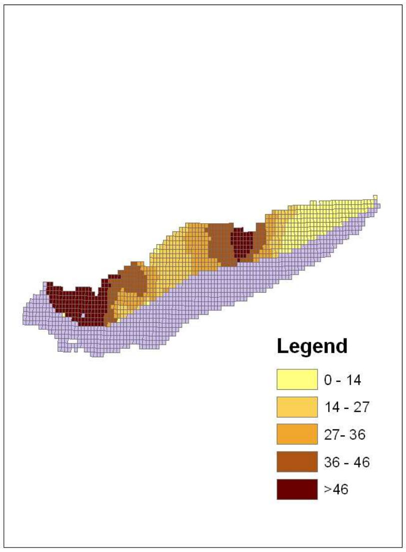

83°0'0"W
82°0'0"W
81°0'0"W
80°0'0"W
79°0'0"W
44°0'0"N
43°0'0"N
42°0'0"N
41°0'0"N
N
W
E
S
1
2
3
4
5
0 30 60 120 Kilometers

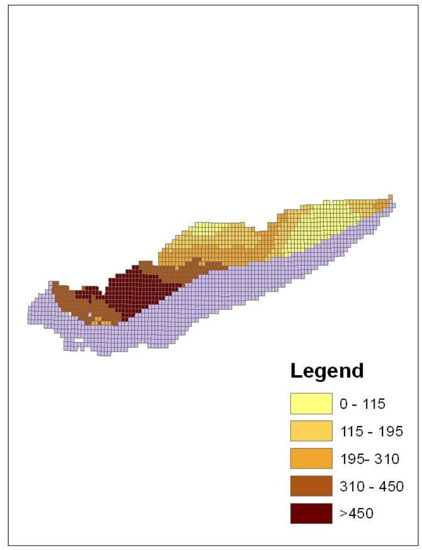
Fig.2.2



2 strata 3 strata 4 strata

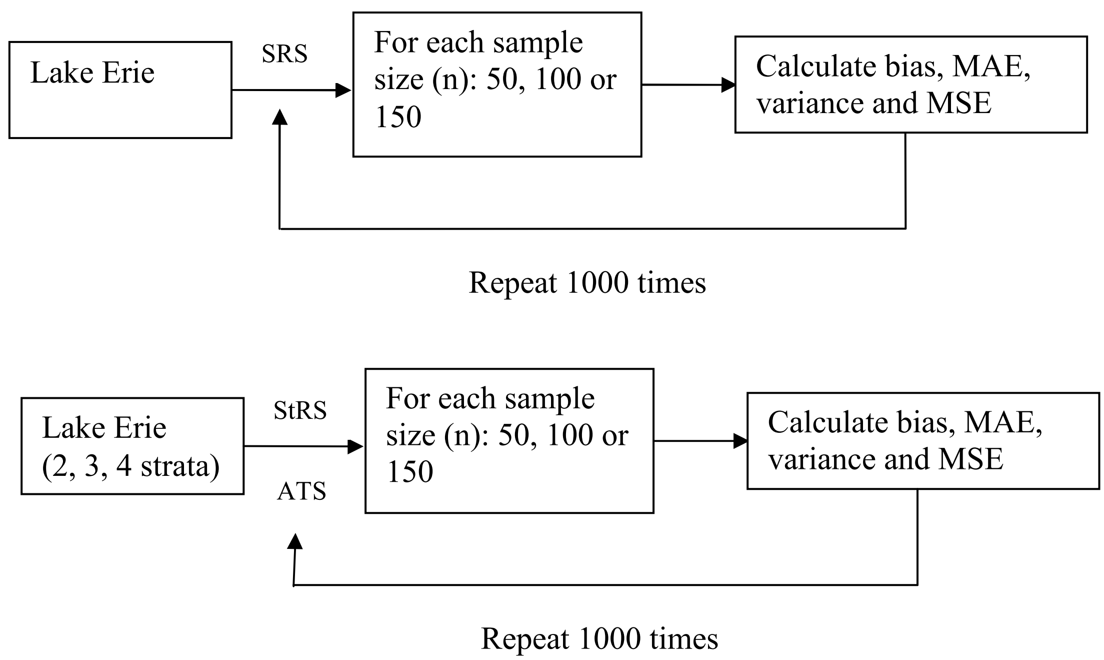
Fig.2.3


Legend
0 - 14
14 - 27
27- 36
36 - 46
>46

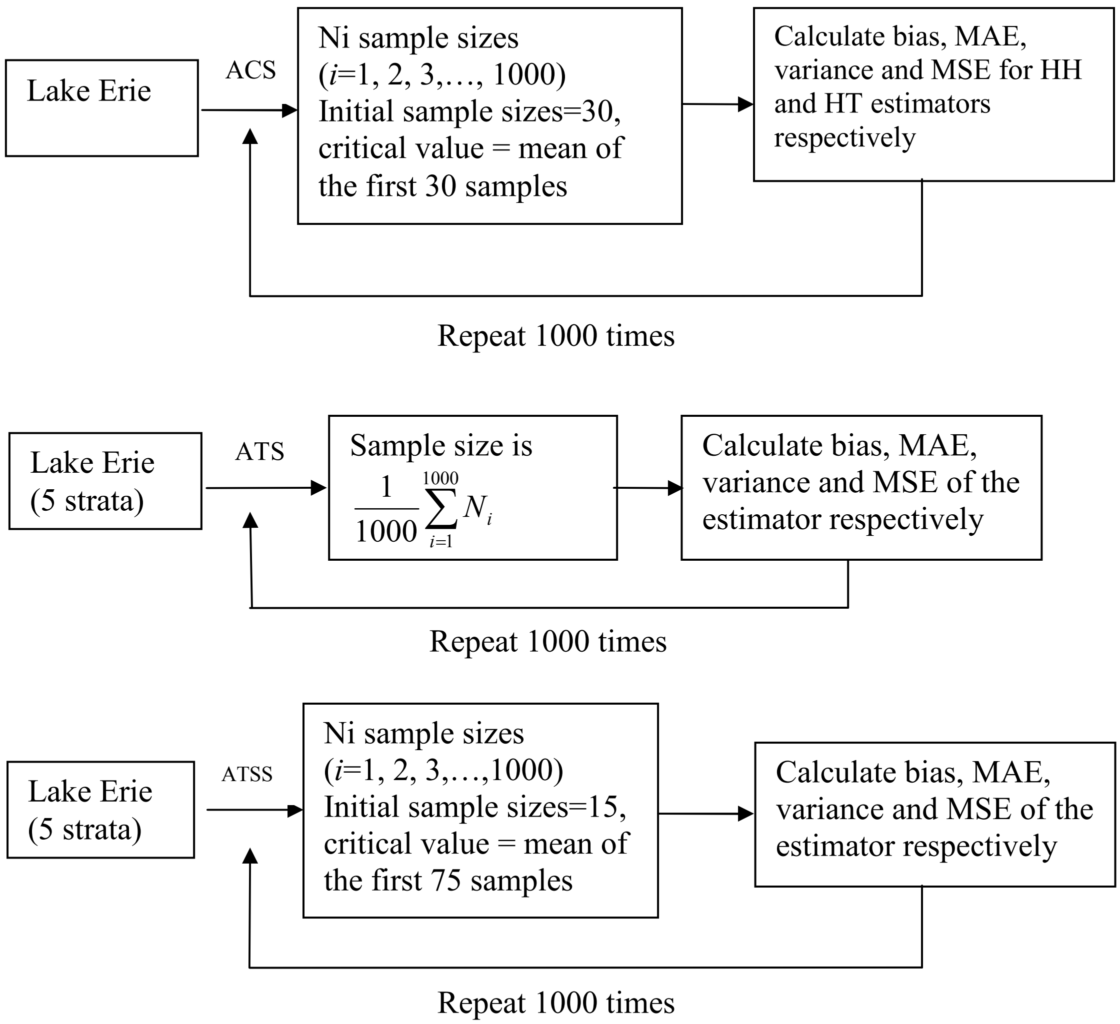

Legend
0 - 115
115 - 195
195- 310
310 - 450
>450

(a) (b)

Fig.2.4 (a)

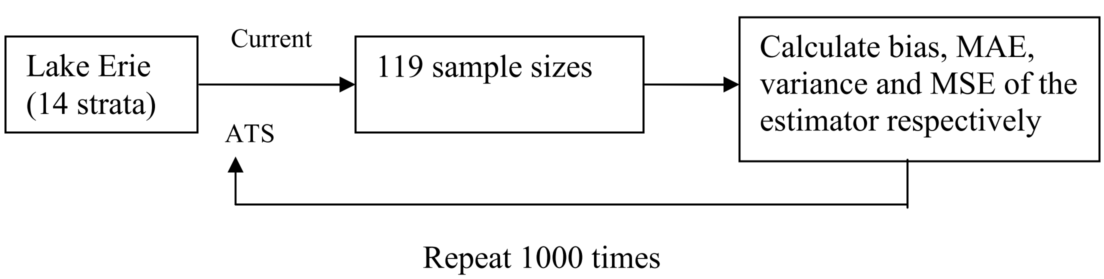

Lake Erie
SRS
For each sample size (n): 50, 100 or 150
Calculate bias, MAE, variance and MSE
Repeat 1000 times
Lake Erie (2, 3, 4 strata)
StRS
ATS
For each sample size (n): 50, 100 or 150
Calculate bias, MAE, variance and MSE
Repeat 1000 times

(b)



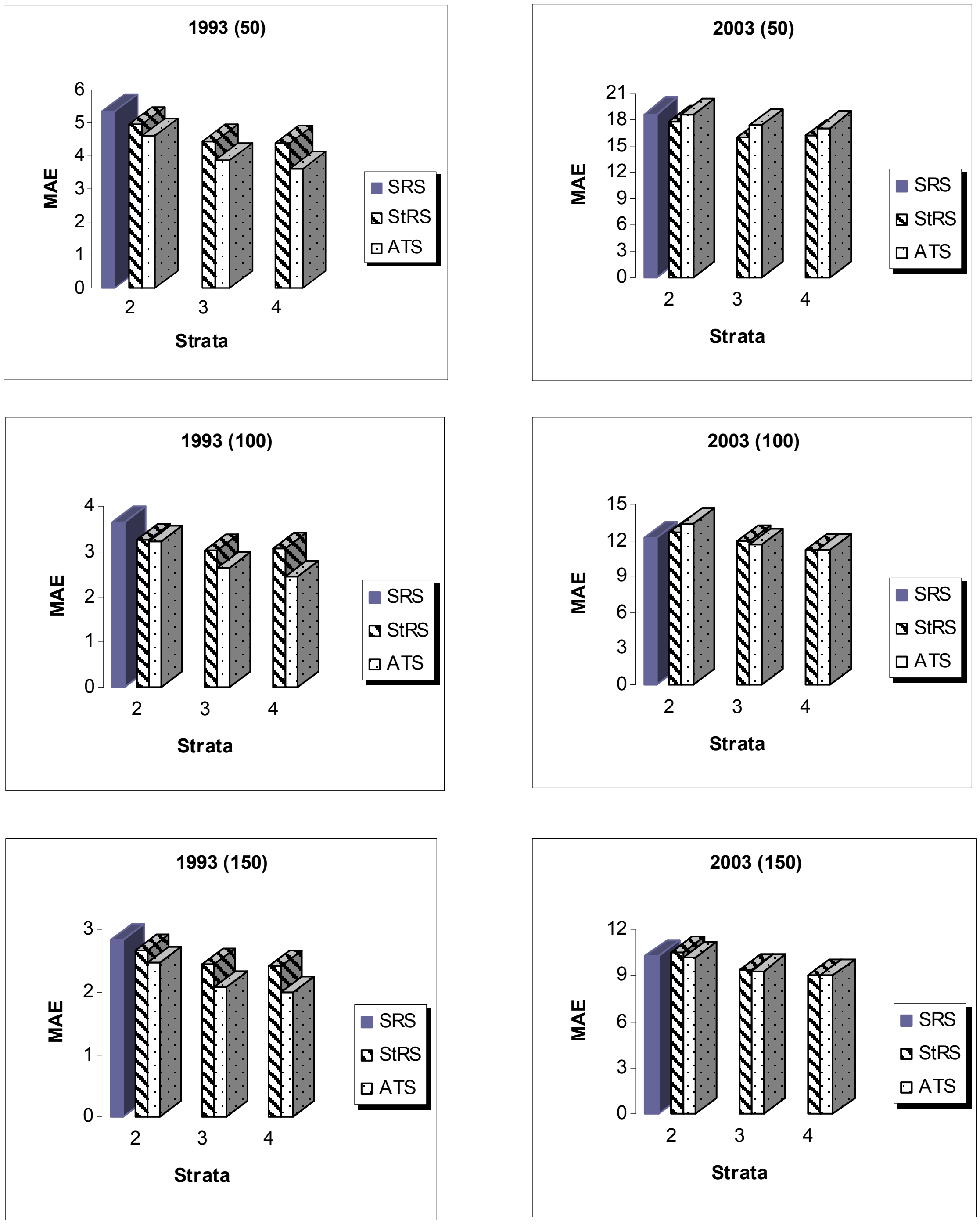
Lake Erie
ACS
Ni sample sizes
(i=1, 2, 3,…, 1000)
Initial sample sizes=30,
critical value = mean of
the first 30 samples
Calculate bias, MAE,
variance and MSE for HH
and HT estimators
respectively
Repeat 1000 times
Lake Erie
(5 strata)
ATS
Sample size is
$\frac{1}{1000}\sum_{i=1}^{1000} N_i$
Calculate bias, MAE,
variance and MSE of the
estimator respectively
Repeat 1000 times
Lake Erie
(5 strata)
ATSS
Ni sample sizes
(i=1, 2, 3,…,1000)
Initial sample sizes=15,
critical value = mean of
the first 75 samples
Calculate bias, MAE,
variance and MSE of the
estimator respectively
Repeat 1000 times

(c)



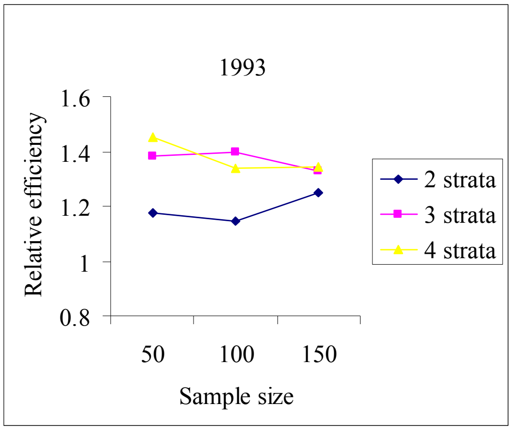
Lake Erie
(14 strata)
Current
ATS
119 sample sizes
Calculate bias, MAE,
variance and MSE of the
estimator respectively
Repeat 1000 times

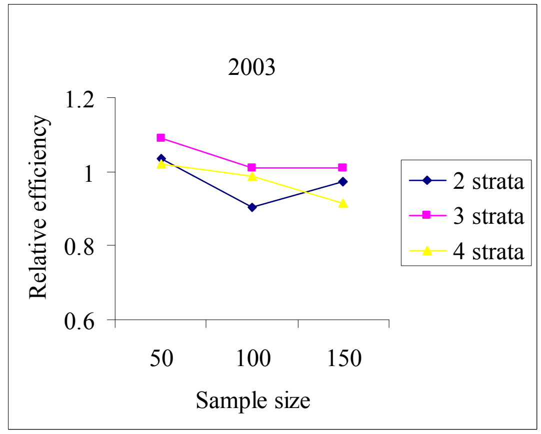
Fig.2.5



1993 (50)
MAE
6
5
4
3
2
1
0
2
3
4
Strata
SRS
StRS
ATS
2003 (50)
MAE
21
18
15
12
9
6
3
0
2
3
4
Strata
SRS
StRS
ATS
1993 (100)
MAE
4
3
2
1
0
2
3
4
Strata
SRS
StRS
ATS
2003 (100)
MAE
15
12
9
6
3
0
2
3
4
Strata
SRS
StRS
ATS
1993 (150)
MAE
3
2
1
0
2
3
4
Strata
SRS
StRS
ATS
2003 (150)
MAE
12
9
6
3
0
2
3
4
Strata
SRS
StRS
ATS

Fig.2.6


1993
Relative efficiency
1.6
1.4
1.2
1
0.8
50
100
150
Sample size
2 strata
3 strata
4 strata


2003
Relative efficiency
1.2
1
0.8
0.6
50
100
150
Sample size
2 strata
3 strata
4 strata

Chapter 3

[1]Performance comparison of generalized linear model, generalized additive model and spatial interpolation for relative abundance index estimation through a simulation study

Abstract: The relative abundance index (RAI) as an indicator of population abundance is important in fisheries stock assessment, and the standardized catch rate is usually used as relative abundance index in stock assessment models. Generalized linear models (GLM) and generalized additive models (GAM) are commonly used to standardize catch rates. However, there are many practical limitations when using the GLM and GAM such as lack of data of needed explanatory variables, model selection uncertainty, error structure assumption, high percentage of zero catches and methods in dealing with interaction terms. Because in most situations, data on catch rate are spatially correlated, spatial interpolation (SI) is applied as an alternative way to analyze catch rate as a relative abundance index. In this study, I compared the performance of GLM, GAM and SI through a simulation study which is based on fishery independent survey of yellow perch in Lake Erie. The sample sizes used in this study were 60, 120 and 180 respectively, and the simulated random errors were 0.5, 1 and 2 times the "true" estimated random errors respectively. For each combination of sample size and error magnitude, 100 simulations were conducted to estimate correlation coefficients between the "true" abundance and the standardized catch rate from GLM, GAM and SI. I found that performance of all three methods was improved when the sample sizes increased, but became worse when the magnitude of simulated errors increased. In general the GLM performed consistently better than GAM. SI performed

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better than GLM and GAM only when the simulated errors were low, and SI was more sensitive than GLM and GAM to the magnitude of the simulated random errors. When the sampling only covered part of the survey area, GLM and GAM performed better than SI. I recommend that SI is preferable than AM when environmental factors information is not available; GLM and GAM are preferred for incomplete survey.

Introduction

The fundamental goal of fisheries stock assessment is to estimate the abundance of target species, and standardized catch rate is commonly used as an index of relative abundance in fisheries studies. Numerous research efforts have proven that catch rates need to be standardized before using them in population dynamics models (Gavaris 1980; Lo et al. 1992; Harley et al. 2001; Walsh and Kleiber 2001; Bishop et al. 2004; Maunder and Punt 2004; Shono 2008). The reason to use standardized catch rate as an index of relative abundance is that I assume catch rates can be used to calibrate population abundance in stock assessment models (Quinn and Deriso 1999; Maunder and Punt 2004). Unstandardized catch rate usually can not correctly reflect abundance change and induces biased estimates in stock assessment. Catch rate standardization serves to keep the impact from abundance change and removes the effects from all the other factors (Maunder and Punt 2004). Therefore, a variety of models have been put forward to standardize catch rates. Within them, generalized linear models (GLMs) and generalized additive models (GAMs) are commonly used in this standardization process (O'Brien and Mayo 1988; Ye et al. 2001; Campbell 2004; Nishida and Chen 2006; Damalas et al. 2007).

GLMs were first introduced in the 1970s (Nelder and Wedderburn 1972) and have been used to standardize catch rates since the 1980s (Gavaris 1980). They assume a linear relationship between a link function (e.g., identity, logistic, and log) of the expected value of the response variable and the explanatory variables (Maunder and Punt 2004). GLMs are very useful to deal with the stochastic response variable in catch rate standardization. GAMs are extensions of GLMs by replacing the explanatory variables with smooth functions, and they are often used to deal with nonlinear relationships between the response variable and explanatory variables (Hastie and Tibshirani 1990). Nonlinear relationships are common between fish densities and environmental factors, so GAMs are also widely used in catch rate standardization (Borchers et al. 1997; Denis et al. 2002; Walsh and Kleiber 2001). However, both GLMs and GAMs have disadvantages when standardizing catch rates, which includes 1) lack of data of needed explanatory variables, 2) error structure assumption, 3) model selection uncertainties, 4) high percentage of zero catches, and 5) methods in dealing with intersection terms (Maunder and Punt 2004).

Geographic information systems (GIS) are widely used to display and analyze spatial characteristics in fisheries data (Rahel 2004). Spatial interpolation (SI) is one of the applications of GIS, and it has been applied in estimating aquatic biological resources density since the 1990s (Simard et al. 1992; Maynou et al. 1996; Rivoirard et al. 2000; Wyatt 2003). However this is the first time to apply SI for relative abundance indices estimation I fisheries. The densities of most fishery species within their distribution areas are spatially correlated with one another because the environmental factors are more similar when the distances are closer, so spatial interpolation should apply for estimating abundance indices. GLMs and GAMs are used to eliminate the other factors' effects (e.g., environmental factors and spatial autocorrelation) on population abundances, but SI is using spatial autocorrelation to generate a smooth surface of the abundance index. They both estimate an index of population abundance, but they are based on contrary ideas.

Kriging is one of the most commonly used SI methods (Schabenberger and Gotway 2005). The fundamental idea of kriging is to estimate the value at an unknown point by using the combination of weights and the values at known local points, which only requires survey data and coordinates of spatial locations. For relative abundance index estimation, catch rate data with spatial location information are enough for kriging interpolation. However the disadvantages of kriging are also apparent: 1) tremendous effect of measurement errors; 2) need for records of survey locations. According to different assumptions, kriging can be divided into many types (e.g., simple kriging, ordinary kriging, universal kriging, etc.). In this study, ordinary kriging is used because it assumes the mean value is constant and unknown (Schabenberger and Gotway 2005). This is an appropriate assumption in analyzing fish population distribution and abundances.

Yellow perch is one of the most important commercial and recreational fish species in Lake Erie (Baldwin and Saalfeld 1962; Regier and Hartman 1973). Yellow perch stock assessment is key information needed for fisheries management departments to make relevant policies. Yellow perch population varies dramatically over time and the catch rate data are spatially autocorrelated (YPTG 2008). There is not a generally accepted method to standardize yellow perch catch rate in Lake Erie, and the arithmetic mean (AM) of catch rate is currently used to estimate the relative abundance index. In this study, I used yellow perch catch rate as an example to compare the performance of AM, GLM, GAM, and SI for relative abundance index estimation in order to find the most appropriate method. This is the first study that compares the performance of AM, GLM, GAM, and SI together through a simulation study. I expect that this study will also be helpful for other species stock assessments.

Material and Methods

Example study area and survey

The study area is within the Canadian side of Lake Erie (Fig. 3.1). I used data from the partnership fishery-independent surveys (1991, 1992, 1993, 2000, 2001, and 2003) between the Ontario Commercial Fisheries' Association (OCFA) and the Ministry of Natural Resources (OMNR) Lake Erie Fisheries Management Unit (LEMU). This independent survey has been conducted annually since 1989, and includes catch data as well as the information on gear and environmental factors (Table 3.1). The study area was divided into 2X2 minute cells using the ArcGIS software package (version 9.2, 2007, ESRI Inc., USA). The catch rate and environmental factors were interpolated within the Canadian side using ordinary kriging function in each year respectively.

Simulation study

I used three simulation scenarios to test the performances of AM, GLM, GAM and SI with complete survey, which covers the whole area where the fish distributed (Fig. 3.2). In the first scenario, GLM was applied to the survey data to estimate the coefficient of each explanatory variable, the predicted catch rate and the regression residuals. Then I interpolated the number of fish caught at each survey site using ordinary kriging to get a catch rate distribution surface in the study area. In the same way, I interpolated environmental factors in the study area. Then I conducted simple random sampling without replacement in the interpolated surface, with the sample sizes of 60, 120 and 180. I obtained new "true" catch rates and environmental factors after this sampling procedure. The combination of newly sampled "true" catch rates and randomly sampled residuals (0.5, 1, and 2 times of the real error) was the newly "surveyed" catch rates. I fitted the new "surveyed" data to AM, GLM, GAM and SI respectively and obtained newly estimated catch rates. I assumed that 1% of the total fish was caught during the survey period. The sum of interpolated catch at each location times 100 is the "true" abundance of yellow perch in the study area. Lastly I calculated the correlation coefficients between estimated relative abundance indices and the "true" abundance. In the second scenario, I used the same procedure except the coefficients of explanatory variables, the predicted catch rate, and residuals Ire from GAM. In the third scenario, SI was used to predict catch rates and environmental factors at each location. The other steps were the same as the first two scenarios.

One special scenario was added to test the performance of the models when the sampling only covered part of the survey area (i.e., incomplete survey). In this scenario, the study area (Canadian side of Lake Erie, cell size is 2X2 minute) was divided into three sub-areas which are the western area, central area, and eastern area. In the western area, no units were sampled; in the central area, only half of the total units had the opportunity to be chosen; in the eastern area, every unit had the same probability to be sampled (Fig. 3.6a). The data were generated based on the GLM (same as in the scenario 1), sample size was 60, and the magnitude of the error term was the same as the real error. I used this combination of sample size and random variation of the catch rate because it was closest to the real sampling in the example fishery used in this study. One hundred simulations (the procedure was same to scenario 1) were conducted for this scenario.

Generalized linear model

The basic GLM can be written as

(1) $g(\mu) = X^T \beta$

where g is the link function, μ is the expectation of the observation, X is the vector of explanatory variables, and β is the vector of the regression coefficients. When the link function is identity, and the error term is normal, a generalized linear model is also called a general linear model. Therefore, the general linear model is a special case of generalized linear model. In this study, I consistently used the term Generalized Linear Model (GLM) instead of separating them into generalized linear model and general linear model. Here I treated μ as the expectation of the log transformed observation of catch rate, and a normal error distribution is used when using the GLM. Log transformation has been widely used in fisheries and was found to be appropriate in many situations (Quinn and Deriso 1999). However I did diagnose the residual pattern to make sure that this assumption was valid in the yellow perch survey data analysis before it was used as an example fishery in the simulation study. I also did preliminary analysis of explanatory variable selection. Lastly gear depth, gear temperature and transparency were chosen as explanatory variables in GLM. After a log transformation, equation (1) in this study can be expressed as:

(2) $\ln(I+1) = \beta_0 + \beta_1 year + \beta_2 gear\ depth + \beta_3 gear\ temperature + \beta_4 transparency + \varepsilon$,

where I is the catch rate of yellow perch expressed in number of fish per gillnet lift, and ε is a normal, independent and identically distributed error with expectation zero and variance σ^2. In this study , the percentage of zero catches for yellow perch survey data was about 11%. The constant value 1 was added to the catch rate data to prevent computational errors of the natural logarithm when zero catches occurred. The GLM catch rate standardization was conducted using the “glm” function in the R software package (Version 2.9.1, 2009, USA). Year effect was generated and regarded as the relative abundance index after exponential transformation.

Generalized additive model

Generalized additive models (GAMs) are nonparametric generalizations of GLMs in which linear predictors are replaced by additive predictors (Venables and Dichmont 2004). The basic GAM can be written as

$$(3)\ \ g(\mu) = \overline{\mu} + \sum_{i=1}^{n} s_i(X_i) \quad ,$$

where g is the link function, μ is the expectation of observations, $\overline{\mu}$ is the intercept, X_i is the i*th* explanatory variable, and s_i is a smooth function for the i*th* explanatory variable**.** To compare the efficiency of GLM and GAM directly, I used the same explanatory variables in GAM as GLM. Lognormal error structure was again assumed, so the catch standardization GAM could be written as

$$(4)\ \ \ln(I+1) = \beta_0 + \beta_1 year + \beta_2 s(gear\ depth) + \beta_3 s(gear\ temperature) + \beta_4 s(transparency) + \varepsilon \ .$$

GAM was calculated using the “gam” function in the R software package (Version 2.9.1, 2009, USA). The relative abundance index was estimated in the same way as GLM.

Ordinary kriging

Ordinary kriging is the most commonly used type of spatial interpolation (Cressie 1993). It assumes that the constant mean is unknown, which is especially reasonable for fish relative abundance index estimation. The prediction of an unknown point is based on the statistical relationship among the surrounding measured points (Johnson 2001). The general formula for prediction is

(5) $\hat{Z}(s_0) = \sum_{i=1}^{N} \lambda_i Z(s_i)$,

where s_0 is the prediction location, $\hat{Z}(s_0)$ is the predicted value, $Z(s_i)$ is the measured value at the *i*th location, λ_i is an unknown weight for the measured value at the *i*th location, and *N* is the total number of measured values. The formula to estimate λ_i is

(6) $\Gamma \times \lambda = g$

or,

(7) $$\begin{pmatrix} \gamma_{11} & \cdots & \gamma_{1n} & 1 \\ \vdots & \ddots & \vdots & \vdots \\ \gamma_{n1} & \cdots & \gamma_{nn} & 1 \\ 1 & \cdots & 1 & 0 \end{pmatrix} * \begin{pmatrix} \lambda_1 \\ \vdots \\ \lambda_n \\ m \end{pmatrix} = \begin{pmatrix} \gamma_{10} \\ \vdots \\ \gamma_{n0} \\ 1 \end{pmatrix},$$

where matrix Γ contains the semivariogram values between all pairs of sample locations. The vector *g* contains the modeled semivariogram values between each measured location and the prediction location. $\gamma(h)$ is the semi-variogram function, and it can be estimated by

(8) $\gamma(h) = \frac{1}{2*|N(h)|} \sum_{N(h)} (z_i - z_j)^2$,

where $N(h)$ is the set of all pairwise Euclidean distances, $h = i - j$. $|N(h)|$ is the number of distinct pairs in $N(h)$, and z_i and z_j are data values at spatial locations *i* and *j*, respectively.

Performance comparison

The Pearson correlation coefficient (*r*) between estimated relative abundance index and the “true” abundance was used to compare the performance of the models. The model with the highest correlation coefficient is preferable. For GLM and GAM, I also compared their Akaike's information criterion (AIC) (Akaike 1973), and the smaller AIC is preferable. Given N pairs of observations (x_i, y_i), the formula to calculate correlation coefficient is

$$(9)\ \ r = \frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2 \sum_{i=1}^{N}(y_i - \bar{y})^2}},$$

where r is correlation coefficient, x_i and y_i are the ith element in vector X and Y respectively, N is the number of elements in vector X and Y, $\bar{x}$ and $\bar{y}$ are the mean values of x_i and y_i, respectively.

The formula for AIC is

$$(10)\ \ AIC = -2\ln(L) + 2k,$$

where k is the number of parameters in the statistical model, and L is the maximum likelihood of the model.

Results

According to the interpolated catch rate data for six years, yellow perch density distribution varied spatially and temporally in Lake Erie (Fig. 3.3). In 1991, the highest density area was between the central basin and eastern basin, and a few areas with high density were patchily distributed in the western basin and central basin. The fish density distribution was similar in 1992, 1993 and 2001; the western basin had the highest value, and the west-central basin had higher value than the east-central basin and eastern basin. In 2000 and 2003, the highest density area was the west-central area, and the western basin and east-central basin had higher density than the eastern basin. The abundance in the lake is also variable over time. The abundances of 2000, 2001, and 2003 are higher than those of 1991, 1992, and 1993.

Three environmental factors used in the GLM and GAM were also interpolated using ordinary kriging (Fig. 3.4). The eastern basin had the highest gear depth, and the central basin had higher gear depth than the western basin. The gear temperature distribution varied over time. In 1991, the high value area was between the central basin and eastern basin. In 1992, the eastern basin, western basin, and east-central basin were high value areas. In 1993, 2000, 2001, and 2003, the western basin and part of the eastern basin had highest gear temperature. The transparency distribution was more uniform over time than the other two environmental factors. The eastern basin had highest value and the central basin had a higher value than the western basin except for year 2001. In 2001, the western basin had a higher value than the central basin.

The mean values of AIC from GLM and GAM after 100 simulations were calculated (Table 3.2). AIC values increased when the error term was amplified or sample size increased. When the "true" data came from the prediction of GLM, AIC values from GLM and GAM were close; when the "true" data came from the prediction of GAM or SI, AIC values from GAM were smaller than those from GLM. The mean values of correlation coefficients (r) from GLM and GAM after 100 simulations were calculated (Table 3.2). The r values increased when the error term was amplified; r values decreased when the sample size increased. Comparing with Table 3.2, the pattern of AIC and r did not completely match: GLM resulted in higher r values in most situations, but GAM always resulted in smaller AICs than GLM did.

The correlation coefficients (r) between the "true" abundance and the estimated relative abundance indices were calculated. In the first scenario, the "true" abundance was generated from the prediction of GLM (Fig. 3.5a). When the magnitude of the error was half of the real error, the median of *r* values was larger than 0.97 for every model, and the median of *r* when SI was used was the highest and had the narrowest range than when the other three models were used. GLM and GAM resulted in similar median of *r* values, but *r* from GAM had wider range when the sample sizes were 120 and 180. When the magnitude of the error term was equivalent to the real error, SI still resulted in the highest median of *r* values, but the ranges of *r* were larger than when GLM or GAM with sample sizes of 60 and 120 were used. AM resulted in the second high median of *r* values, but the ranges of *r* were the widest. When the magnitude of the error term was two times the real error, *r* median values when GLM and GAM were used was higher and the ranges of r were narrower than when SI and GAM were used. SI had higher median of *r* values and smaller ranges than AM. The median of *r* values decreased when I amplified the error term or reduced the sample size.

In the second scenario, the "true" data were generated from the prediction of GAM (Fig. 3.5b). When the magnitude of the error was half of the real error, the ranges of *r* values when SI and AM were used were narrower than when GLM and GAM were used. The ranges of *r* values when GAM was used were narrower than when GLM was used, and the narrowest ranges were when SI was used as Scenario 1. When the magnitude of the error term was equivalent to the real error and when sample size of 60 was used, the medians of *r* values were very close to each other. SI resulted in narrowest range of *r* values, and AM resulted in the widest range. When the magnitude of the error term was equivalent to the real error and when a sample size of 120 was used, GAM resulted in the smallest median and widest range of *r* values, but SI resulted in the largest median and narrowest range. When the error term was the real error and the sample size was 180, GLM had the largest range, and SI had the largest median and smallest range when sample size was 120. When the magnitude of the error term was equivalent to two times of the real error, both SI and AM resulted in smaller medians and wider ranges than when GLM and GAM were used. In terms of medians and ranges of *r* values, GLM and GAM performed nearly the same, and SI performed better than AM.

In the third scenario, the "true" data were generated based on the prediction of SI (Fig. 3.5c). When the magnitude of the error was equivalent to half of the real error, GLM and SI performed similarly, and they resulted in larger medians and narrower ranges than when GAM and AM were used. The medians of *r* values were very close when GAM and AM were used, but AM had wider ranges than GAM especially when the sample size was 180. When I amplified the error term, the medians from each model decreased and the ranges increased. When the error term was equivalent to the real error, GLM resulted in the narrowest ranges and largest medians. GAM resulted in larger medians and narrower ranges than when SI and AM were used. SI and AM were very close. When the error term was equivalent to two times the real error, GLM was still the best model in terms of the medians of the *r* values. GAM resulted in smaller medians of *r* values than when GLM was used but medians were larger than those from SI and AM. When the sample size was 60, SI and AM resulted in narrower ranges of *r* values than when GLM and GAM were used. When I increased the number of samples from 60 to 120, the estimation of relative abundance indices from GLM and GAM improved, but it did not improve when SI and AM were used. However when the sample size was increased from 120 to 180, the estimation from GLM or GAM was not improved but did result in a little improvement for SI and AM.

The performance of the models was compared when the sampling area only covered part of the survey area (i.e., incomplete survey) with that from a complete survey (Fig. 3.6). The performance of GLM and GAM was not affected by the incomplete sampling. However the performance of SI decreased with the median of *r* values decreased, and the range of *r* increased significantly. When AM was used in this situation, the median of *r* values decreased as shown when SI was used, but the range of *r* did not change much.

Discussion

Model selection is an important issue for GLM and GAM model building. AIC is the most commonly used criterion for model selection when GLM/GAM is used to estimate relative abundance indices (Maunder and Punt 2004). However, AIC may overestimate the effect of the number of parameters in the case of small samples, and tends to select the complicated model (Shono 2005). In this study, AIC is also proved not a perfect criterion of model selection. The recommended models based on the correlation coefficients of estimated relative abundance index and "true" abundance from GLM and GAM, did not always match these recommended by their AICs. For example, in all situations, GAM always resulted in smaller AIC values (Table 3.2). That means GAM should be preferable to GLM if AIC is the model selection criterion. However, 74.1% of the correlation coefficients from GLM had higher values than GAM (Table 3.3). That means the relative abundance index estimated from GLM could represent the abundances better. . Therefore, model selection should consider more criteria such as model predictions rather than only the goodness-of-fit to the data.

In addition, dealing with zero catches in GLMs and GAMs is also a common difficulty (Maunder and Punt 2004). The zero catches can cause computational problems when natural logarithm of catch rates is used in the models. Zero-inflated models and delta models are often applied for survey data with many zeros. Both zero-inflated models and delta models need to divide the dataset into two components and then fit the two parts of data with different distributions, which increases the complexity of the analysis. In addition, each part will face the problem of selecting appropriate explanatory variables respectively. SI obviously avoids this difficulty in dealing with zeros in relative abundance estimation and is a possible alternative from this point. Ordinary kriging used in this study requires no distributional assumptions of the data (Schabenberger and Gotway 2005). Some zero data will not influence the estimation, and the computation is simple and straightforward.

The magnitude of the random error dramatically influenced the performance of SI (Fig. 3.5). When the error term was small (half of the magnitude of the real error), the performance of SI was better than GLM, GAM, and AM shown as the higher *r* values. When the error term was amplified, the performance of SI and AM as shown by the *r* values decreased dramatically, but SI performed better than AM. The reason was that the estimated relative abundance index from AM was only determined by the surveyed catch rate data. SI also included the spatial relationship among sampling locations. Therefore, it performed better than AM when the error term was amplified. The performances of GLM and GAM were less affected by the magnitude of the error term than the performances of SI and AM. This is because the environment factors as explanatory variables were included in GLM and GAM, which can reduce the influence of measurement errors in the dependent variable; while SI is working on the dependent variable directly and more influenced by the random error of it. The disadvantages of SI include the requirement for high quality sampling design and enough sampling locations. In a good sampling design, the samples can represent the population efficiently. The number of sampling locations will affect the accuracy of ordinary kriging prediction.

In general, GLM, GAM, SI, and AM showed good performance for relative abundance index estimation in this study. However, different models are suitable for different situations and data sources. The AM method is only preferred when neither environment factors nor spatial information of sampling locations are available. When the random error of the survey catch is limited, SI performed better than the other methods shown as high r values. If the survey cannot cover the distribution area of the population due to biased design or lack of sampling locations, the estimated relative abundance index will not reflect the real abundance level when SI is used. In this situation, GLM and GAM are preferable to SI. Simulation was used in this study to compare the performance of these models in analyzing catch rate, and I highly recommend this approach in other fisheries when catch rate data are analyzed.

References

Akaike, H. 1973. Information theory and an extension of the maximum likelihood principle. In: Petrov, B.N., Csaki, F. (Eds.), Proceedings of the 2nd International Symposium on Information Theory. Publishing House of the Hungarian Academy of Sciences, Budapest, pp. 268-281.

Baldwin, N.S., and Saalfeld, R.W. 1962. Commercial fish population in the Great Lakes, 1867-190. Great Lakes Fishery Commission Technical Report No.3.

Bishop, J., Venables, W.N., and Wang, Y. 2004. Analysing commercial catch and effort data from a Panaeid trawl fishery - A comparison of linear models, mixed models, and generalised estimating equations approaches. Fish. Res. 70: 179-193.

Borchers, D.L., Buckland, S.T., Priede, I.G., and Ahmadi, S. 1997. Improving the precision of the daily egg production method using generalized additive model. Can. J. Fish. Aquat. Sci. 54: 2727-2742.

Campbell, R.A. 2004. CPUE standardization and the construction of indices of stock abundance in a spatially varying fishery using general linear models. Fish. Res. 70: 209-227.

Cressie, N.1993. Statistics for spatial data. John Wiley & Sons, New York.

Damalas, D., Megalofonou, P., and Apostolopoulou, M. 2007. Environmental, spatial, temporal and operational effects on swordfish (*Xiphias gladius*) catch rates of eastern Mediterranean Sea longline fisheries. Fish. Res. 84: 233-246.

Denis, V., Lejeune, J., and Robin, J.P. 2002. Spatio-temporal analysis of commercial trawler data using general additive models: patterns of Loliginid squid abundance in the north-east Atlantic. ICES J. Mar. Sci. 59: 633-648.

Gavaris, S. 1980. Use of a multiplicative model to estimate catch rate and effort from commercial data. Can. J. Fish. Aquat. Sci. 37: 2272-2275.

Guisan, A., Edwards, Jr, T.C., amd Hastie, T. 2002. Generalized linear and generalized additive models in studies of species distributions: setting the scene. Ecol. Model. 157: 89-100.

Harley, S. J., Myers, R.A., and Dunn, A. 2001. Is catch-per-unit-effort proportional to abundance? Can. J. Fish. Aquat. Sci. 58: 1760–1772.

Hastie, T., and Tibshirani, R. 1990. Generalized additive modes. Chapman & Hall, London.

Johnston, K., Hoef, J.M.V., Krivoruchko, K., and Lucas, N. 2001. Using ArcGIS Geostatistical Analyst. RSRI, Redlands, CA.

Lo, N. C., Jacobson, L. D., and Squire, J. L. 1992. Indices of relative abundance from fish spotter data based on delta-lognormal models. Can. J. Fish. Aquat. Sci. 49: 2515–2526.

Maunder, M.N., and Langley, A.D. 2004. Integrating the standardization of catch-per-unit-of-effort into stock assessment models: tesing a population dynamics model and using multiple data types. Fish. Res. 70: 389-395.

Maunder, M.N., and Punt, A.E. 2004. Standardizing catch and effort data: a review of recent approaches. Fish. Res. 70: 141-159.

Maynou, F., Conan, G., Cartes, J.E., Company, J.B., and Sarda, F. 1996. Spatial structure and seasonality of crustacean decapod populations in Northwestern Mediterranean slope. Limnol. Oceanogr. 41: 113-125.

Montgomery, D.C., Peck, E.A., and Vining, G.G. 2006. Introdution to linear regression analysis. John Wiley & Sons, Inc., Hoboken, New Jersey.

Nelder, J.A., and Wedderburn, J.M. 1972. Generalized linear models. J. Roy. Stat. Soc. Ser. A 135: 370-384.

Nishida, T., and Chen, D. 2004. Incorporating spatial autocorrelation into the general linear model with an application to the yellowfin tuna (*Thunnus albacares*) longline CPUE data. Fish. Res. 70: 265-274.

O'Brien, L., and Mayo, R.K. 1988. Sources of variation in catch per unit effort of yellowtail flounder, *Limanda ferruginea* (Storer), harvested off the coast of New England. Fish. Bull. 86: 91-108.

Punt, A.E., Walker, T.I., Taylor, B.L., and Pribac, F. 2000. Standardization of catch and effort data in a spatially-structured shark fishery. Fish. Res. 45: 129-145.

Quinn II, T.J., and Deriso, R.B. 1999. Quantitative fish dynamics. Oxford University Press, New York, USA.

Rahel, F.J. 2004. Introduction to geographic information systems in fisheries. *In* Geographic information systems in fisheries. *Edited by* W. L. Fisher and F.J. Rahel. Maryland, USA.

Ryan, T.P. 1997. Modern Regression Methods. John Wiley & Sons, Inc., New York.

Regier, H.A., and Harman, W.L. 1973. Lake Erie's fish community: 150 years of cultural stresses. Science. 180 (4092): 1248-1255.

Rivoirard, J., Simmonds, J., Foote, K.G., Fernandes, P., and Bez, N. 2000. Geostatistics for estimating fish abundance. Blackwell Science, London, England.

Schabenberger, O., and Gotway, C.A. 2005. Statistical methods for spatial data analysis. Chapman & Hall, London, England.

Shono, H. 2005. Is model selection using Akaike's information criterion appropriate for catch per unit effort standardization in large samples? Fish. Sci. 71: 978-986.

Shono, H. 2008. Application of the Tweedie distribution to zero-catch data in CPUE analysis. Fish. Res. 93: 154-162.

Simard, Y., Legendre, P., Lavoie, C., and Marcotte, D. 1992. Mapping, estimating biomass and optimizing sampling programs for spatially autocorrelated data: case study of the northern shrimp (Pandalus borealis). Can. J. Fish. Aquat. Sci. 49: 32-45.

Venables, W.N., and Dichmont, C.M. 2004. GLMs, GAMs and GLMMs: an overview of theory for applications in fisheries research. Fish. Res.70: 319-337.

Walsh, W.A., and Kleiber, P. 2001. Generalized additive model and regression tree analyses of blue shark (*Prionace glauca*) catch rates by the Hawaii-based commercial longline fishery.

Walters, C. 2003. Folly and fantasy in the analysis of spatial catch rate data. Can. J. Fish. Aquat. Sci. 60: 1433-1436.

Wyatt, R.J. 2003. Mapping the abundance of riverine fish populations: integrating hierarchical Bayesian models with a geographic information system (GIS). Can. J. Fish. Aquat. Sci. 60: 997-1006.

Ye, Y., Al-Husaini, M., and Al-Baz, A. 2001. Use of generalized linear models to analyze catch rates having zero values: the Kuwait driftnet fishery. Fish. Res. 53: 151-168.

Yellow Perch Task Group (YPTG). 2008. Report of the Lake Erie to the Standing Technical Committee, Lake Erie Committee of the Great Lakes Fishery Commission.

Table 3.1. Summary of data collected in the 1990-2003 yellow perch fisheries-independent survey in Lake Erie.

Variables	Unit	Remarks
Catch number	individual	Per species
Longitude	degree	Converted to NAD 1983 UTM 17N
Latitude	degree	Converted to NAD 1983 UTM 17N
Set duration	hour	Standing time of gillnet in water
Bottom Depth	m	Per sampling site
Gear Depth	m	Depth to bottom of the gillnet
Transparency	m	Secchi depth
Water Temperature	℃	At surface
Gear Temperature	℃	At gear depth
Dissolved Oxygen (DO)	mg/L	At gear depth

Table 3.2. Mean values of AIC from GLM and GAM after 100 simulations, and the sample sizes were 60, 120, and 180.

"True" data	Sample size	Real error *0.5		Real error *1		Real error *2	
		GLM	GAM	GLM	GAM	GLM	GAM
	60	769.57	767.66	1274.58	1272.77	1771.77	1770.12
GLM	120	1542.76	1540.61	2541.52	2539.91	3531.95	3530.05
	180	2305.46	2303.66	3796.35	3794.60	5298.66	5297.10
	60	916.97	682.95	1241.58	1168.95	1688.58	1667.80
GAM	120	1818.77	1329.21	2483.84	2331.04	3369.29	3329.33
	180	2731.62	1996.56	3718.93	3491.94	5037.37	4977.47
	60	1455.88	1323.69	1665.06	1600.07	2039.95	2018.05
SI	120	2896.70	2627.37	3318.30	3185.84	4059.33	4017.10
	180	4349.94	3951.47	4972.53	4775.23	6074.32	6012.95

Table 3.3. Mean values of Correlation coefficients from GLM and GAM after 100 simulations, and the sample sizes were 60, 120, and 180.

"True" data	Sample size	Real error *0.5		Real error *1		Real error *2	
		GLM	GAM	GLM	GAM	GLM	GAM
	60	0.9702	0.9695	0.9521	0.9531	0.8882	0.8800
GLM	120	0.9731	0.9731	0.9632	0.9605	0.9347	0.9280
	180	0.9764	0.9761	0.9695	0.9688	0.9429	0.9403
	60	0.9729	0.9777	0.9602	0.9583	0.9159	0.9113
GAM	120	0.9792	0.9810	0.9732	0.9701	0.9390	0.9287
	180	0.9816	0.9828	0.9777	0.9747	0.9514	0.9449
	60	0.9362	0.8775	0.8680	0.8101	0.7103	0.6636
SI	120	0.9475	0.8964	0.8982	0.8325	0.7343	0.7668
	180	0.9638	0.9088	0.9111	0.8443	0.6771	0.7105

Figure Captions:

Figure 3.1. The Canadian side and the United States' side of Lake Erie. The lake was divided into 2X2 minute cells. The dark color area is the Canadian side and the light color area belongs to the United States.

Figure 3.2. The flow chart of the procedure of three simulations to estimate the correlation coefficients between the "true" abundance and the relative abundance indices (RAI). (a) The "true" abundance was estimated from GLM. (b) The "true" abundance was estimated from GAM. (c) The "true" abundance was estimated from SI.

Figure 3.3. Interpolated catch rates within the study area in 1991, 1992, 1993, 2000, 2001 and 2003. The dark color areas denote high values and light color areas denote low values.

Figure 3.4. Interpolated environmental factors within the study area in 1991, 1992, 1993, 2000, 2001 and 2003. The dark color areas denote high values and light color areas denote low values.

Figure 3.5. The box-plots of the correlation coefficients between the "true" abundance and the relative abundance indices for all combinations after 100 simulations. The residuals added to the "true" catch rate were 0.5 times, 1 time, and 2 times of the real residuals. The sample sizes were 60, 120, and 180. (a) The "true" data were generated from GLM, (b) the "true" data were generated from GAM , and (c) the "true" data were generated from SI.

Figure 3.6. Performance comparison of correlation coefficients between the "true" abundance and the relative abundance indices from complete sampling and incomplete sampling designs. (a) Map of survey area (the Canadian side of Lake Erie). The dark color denotes possibly sampled units and the light color denotes the units not being sampled.

The units within the eastern part of the lake had the same probability of being sampled; only half of the units in the central area had the same probability to be sampled, and the other half would not be sampled; and no units in the western area could be sampled. (b) Box plots of correlation coefficients estimated from complete sampling, and (c) Box plots of correlation coefficients estimated from incomplete sampling.

Fig. 3.1.

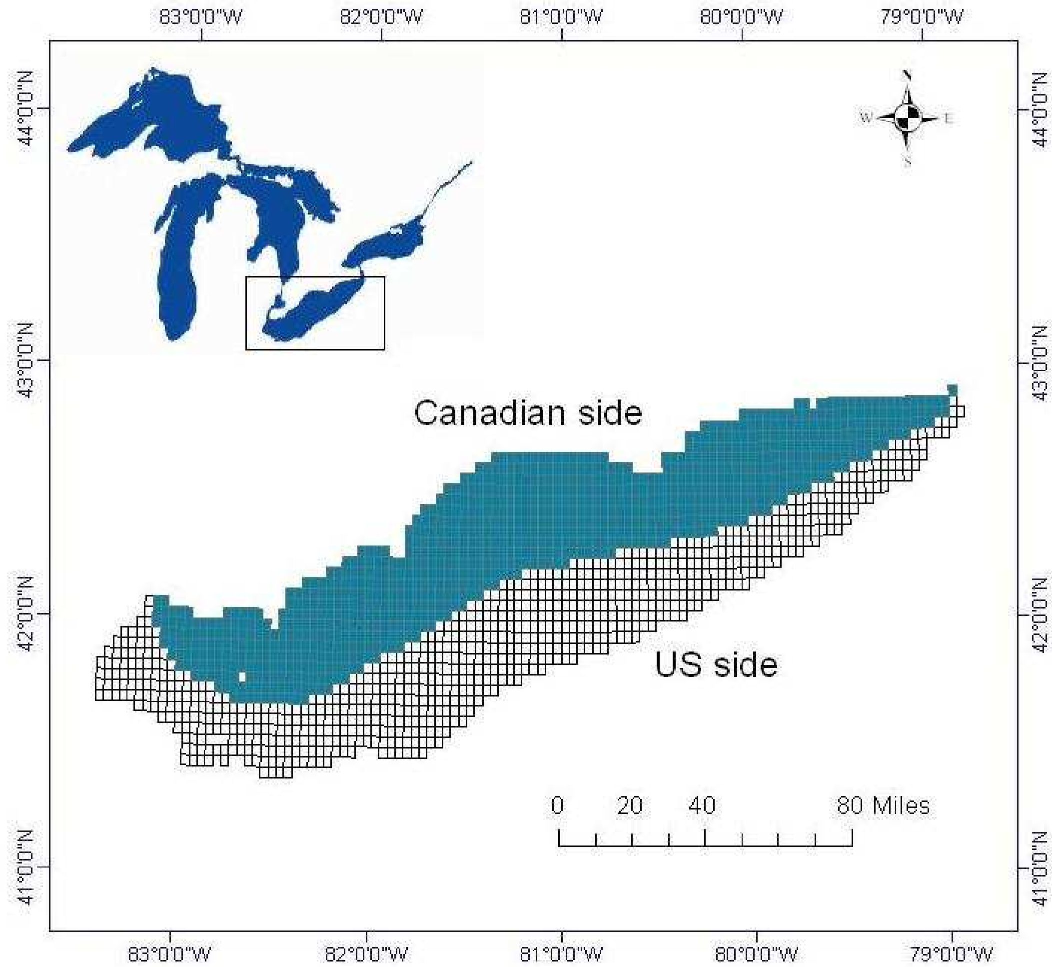
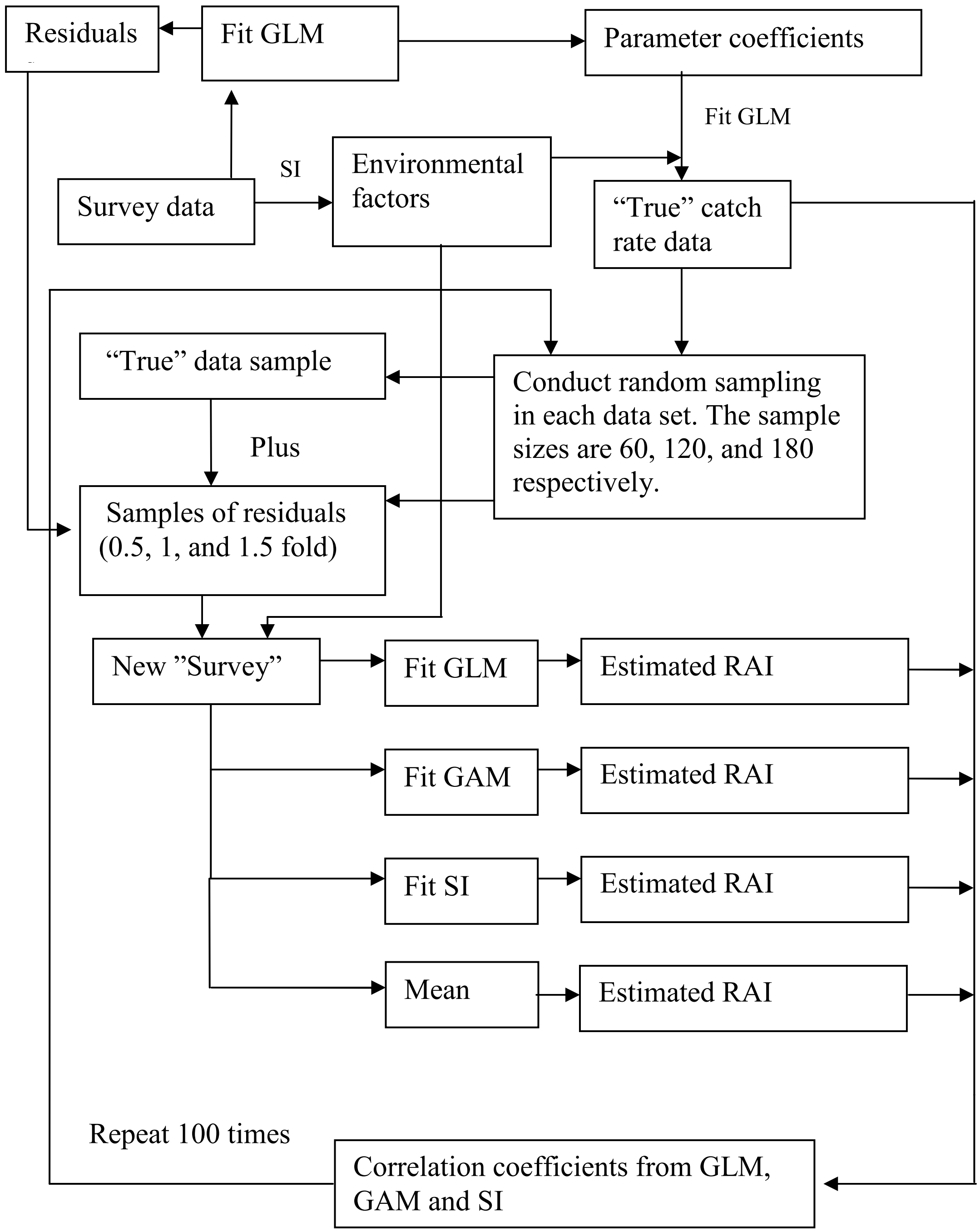

83°0'0"W
82°0'0"W
81°0'0"W
80°0'0"W
79°0'0"W
44°0'0"N
43°0'0"N
42°0'0"N
41°0'0"N
N
W
E
S
Canadian side
US side
0 20 40 80 Miles

Fig. 3.2. (a)



Residuals
Fit GLM
Parameter coefficients
Fit GLM
SI
Environmental factors
Survey data
"True" catch rate data
"True" data sample
Conduct random sampling in each data set. The sample sizes are 60, 120, and 180 respectively.
Plus
Samples of residuals (0.5, 1, and 1.5 fold)
New "Survey"
Fit GLM
Estimated RAI
Fit GAM
Estimated RAI
Fit SI
Estimated RAI
Mean
Estimated RAI
Repeat 100 times
Correlation coefficients from GLM, GAM and SI

Fig. 3.2. (b)

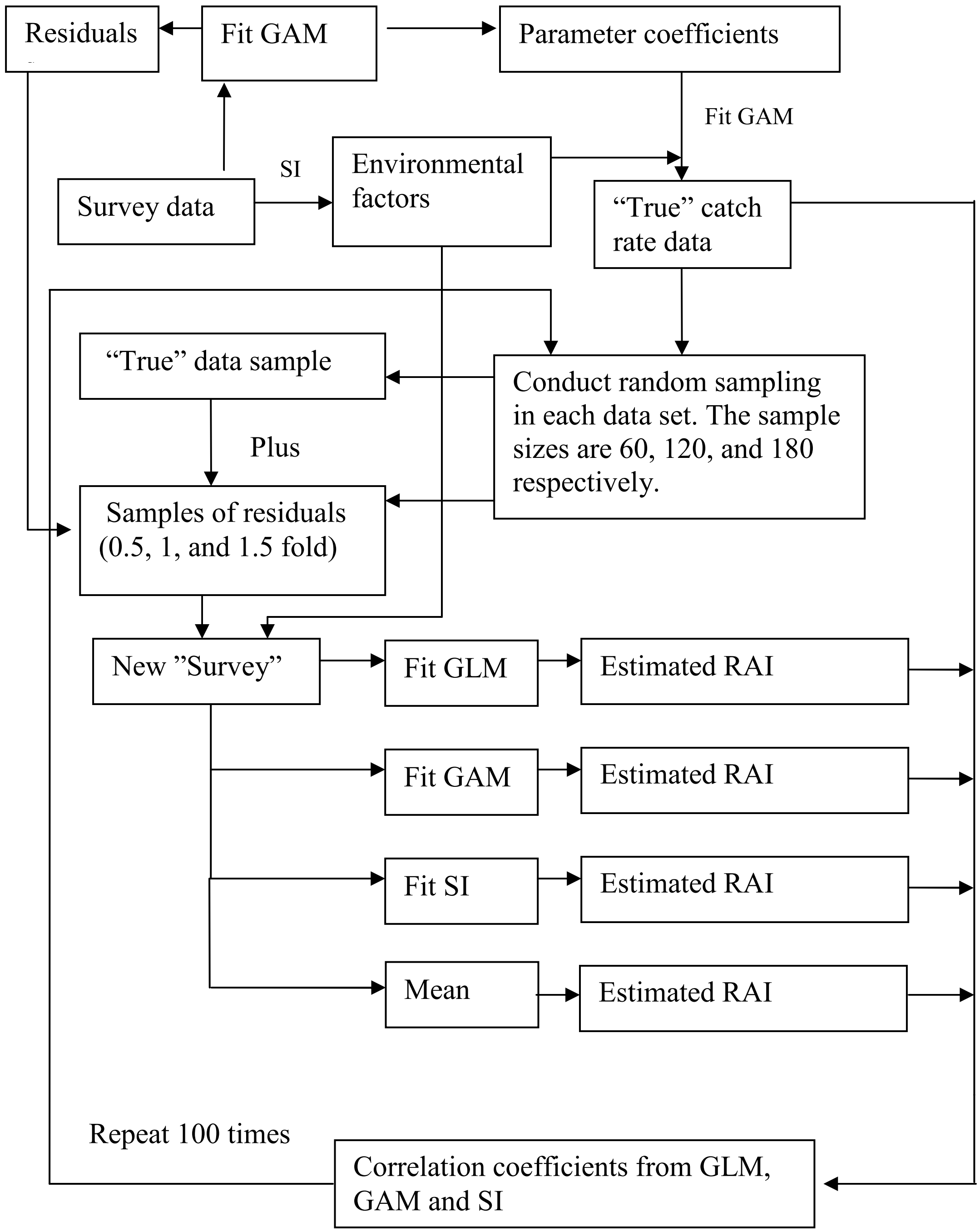

Residuals
Fit GAM
Parameter coefficients
Fit GAM
SI
Environmental factors
Survey data
"True" catch rate data
"True" data sample
Plus
Conduct random sampling in each data set. The sample sizes are 60, 120, and 180 respectively.
Samples of residuals (0.5, 1, and 1.5 fold)
New "Survey"
Fit GLM
Estimated RAI
Fit GAM
Estimated RAI
Fit SI
Estimated RAI
Mean
Estimated RAI
Repeat 100 times
Correlation coefficients from GLM, GAM and SI

Fig. 3.2. (c)

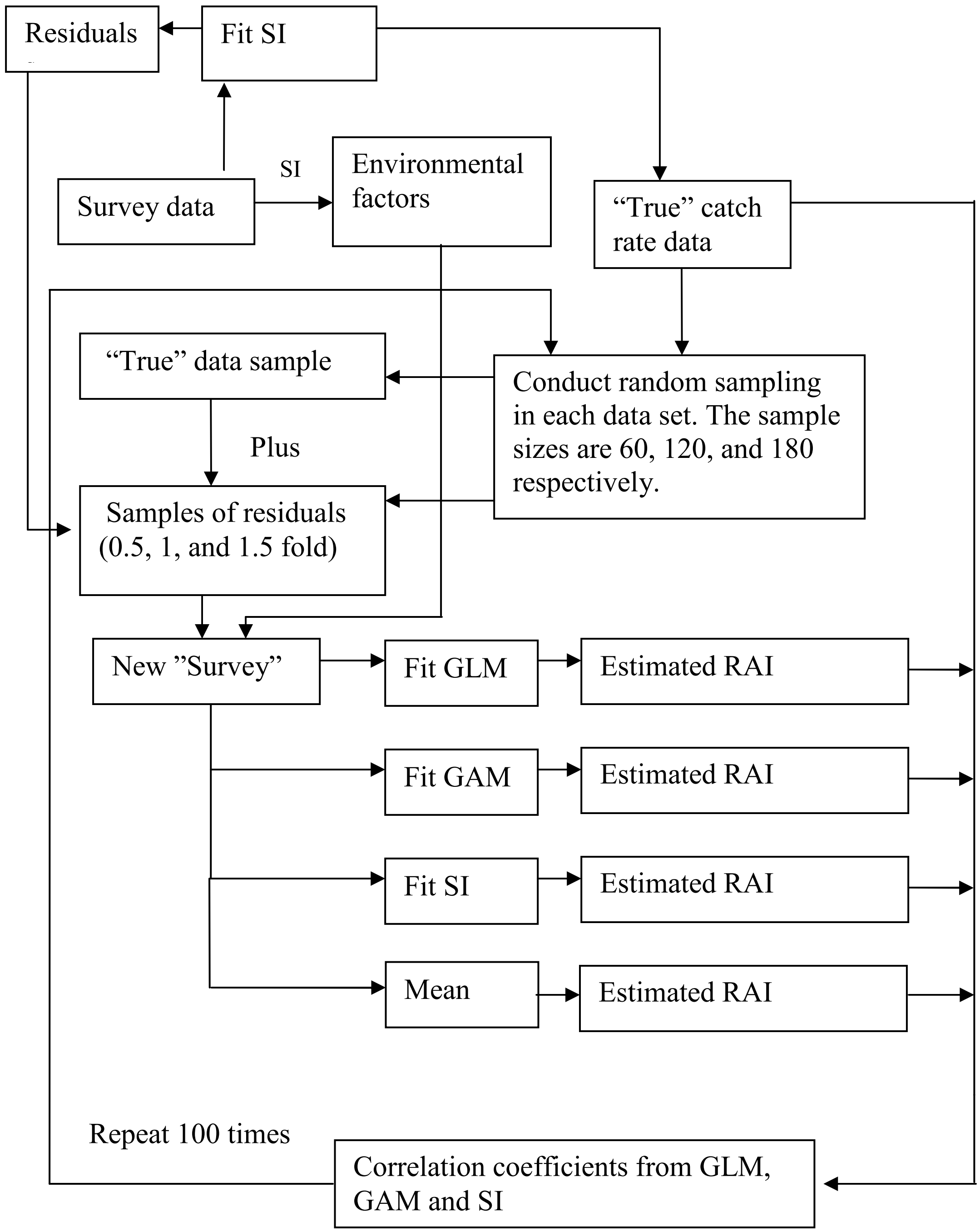

Residuals
Fit SI
SI
Environmental factors
Survey data
"True" catch rate data
"True" data sample
Conduct random sampling in each data set. The sample sizes are 60, 120, and 180 respectively.
Plus
Samples of residuals (0.5, 1, and 1.5 fold)
New "Survey"
Fit GLM
Estimated RAI
Fit GAM
Estimated RAI
Fit SI
Estimated RAI
Mean
Estimated RAI
Repeat 100 times
Correlation coefficients from GLM, GAM and SI

Fig. 3.3.

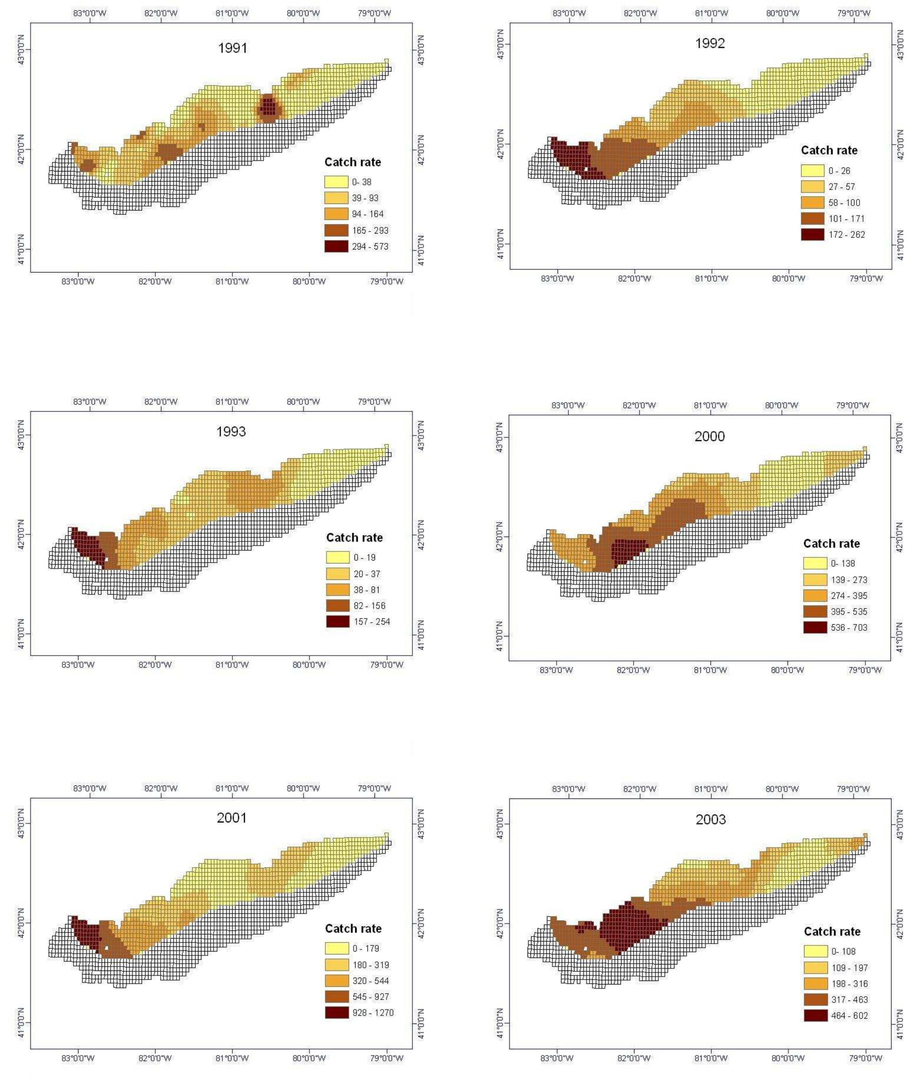

1991
Catch rate
0- 38
39 - 93
94 - 164
165 - 293
294 - 573
1992
Catch rate
0 - 26
27 - 57
58 - 100
101 - 171
172 - 262
1993
Catch rate
0 - 19
20 - 37
38 - 81
82 - 156
157 - 254
2000
Catch rate
0- 138
139 - 273
274 - 395
395 - 535
536 - 703
2001
Catch rate
0 - 179
180 - 319
320 - 544
545 - 927
928 - 1270
2003
Catch rate
0- 108
109 - 197
198 - 316
317 - 463
464 - 602
83°0'0"W
82°0'0"W
81°0'0"W
80°0'0"W
79°0'0"W
43°0'0"N
42°0'0"N
41°0'0"N

Fig. 3.4.

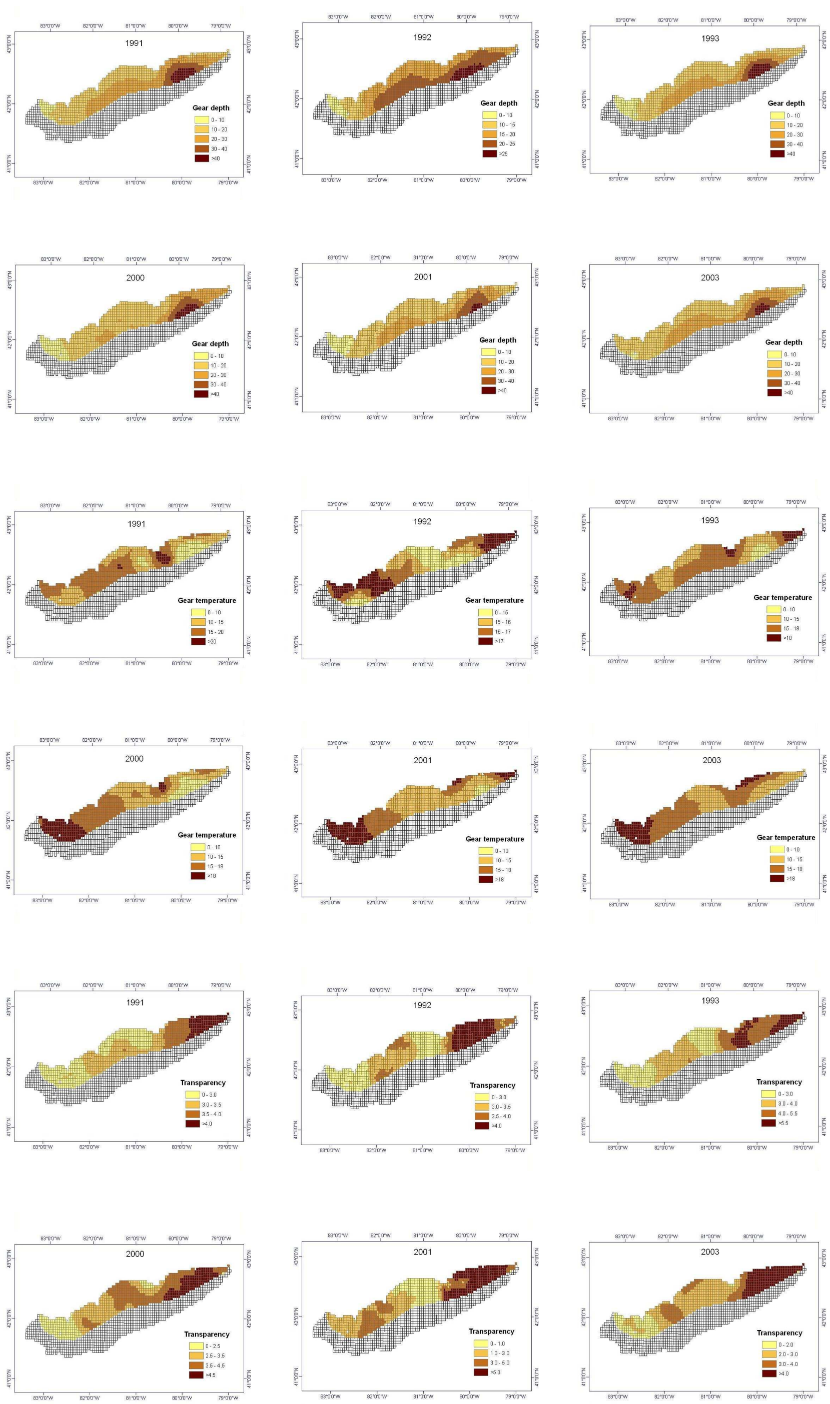
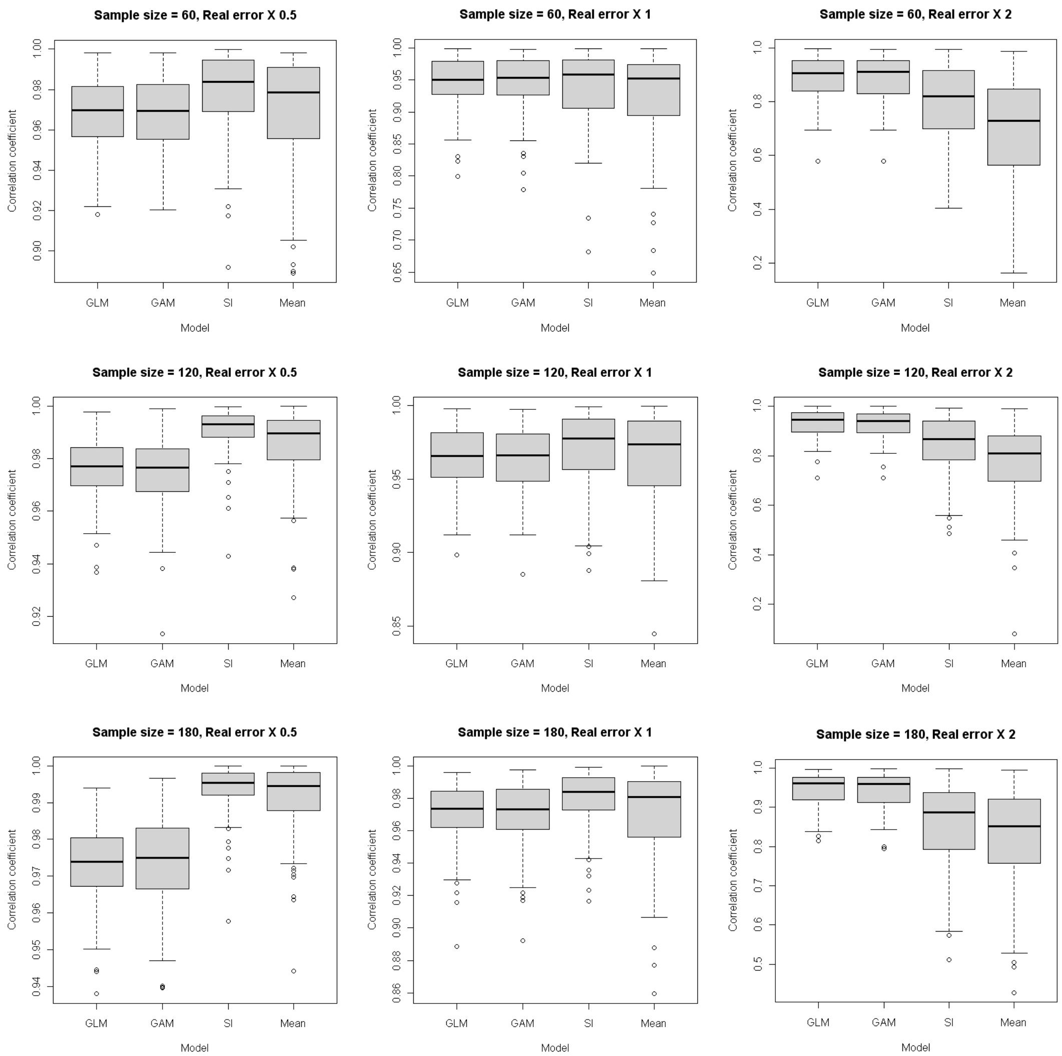

1991
Gear depth
1992
Gear depth
1993
Gear depth
2000
Gear depth
2001
Gear depth
2003
Gear depth
1991
Gear temperature
1992
Gear temperature
1993
Gear temperature
2000
Gear temperature
2001
Gear temperature
2003
Gear temperature
1991
Transparency
1992
Transparency
1993
Transparency
2000
Transparency
2001
Transparency
2003
Transparency

Fig. 3.5. (a)



Sample size = 60, Real error X 0.5
Sample size = 60, Real error X 1
Sample size = 60, Real error X 2
Sample size = 120, Real error X 0.5
Sample size = 120, Real error X 1
Sample size = 120, Real error X 2
Sample size = 180, Real error X 0.5
Sample size = 180, Real error X 1
Sample size = 180, Real error X 2
Correlation coefficient
GLM
GAM
SI
Mean
Model

Fig. 3.5. (b)

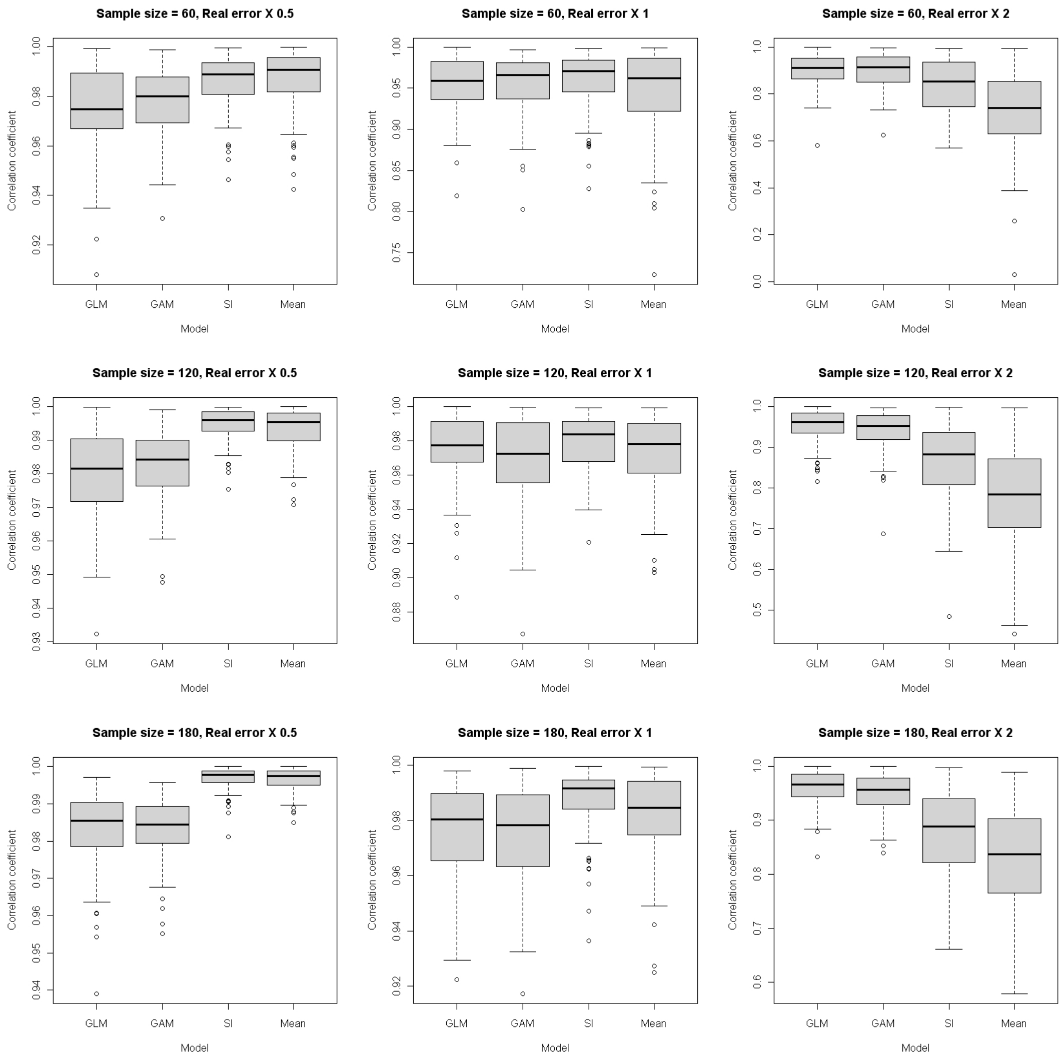
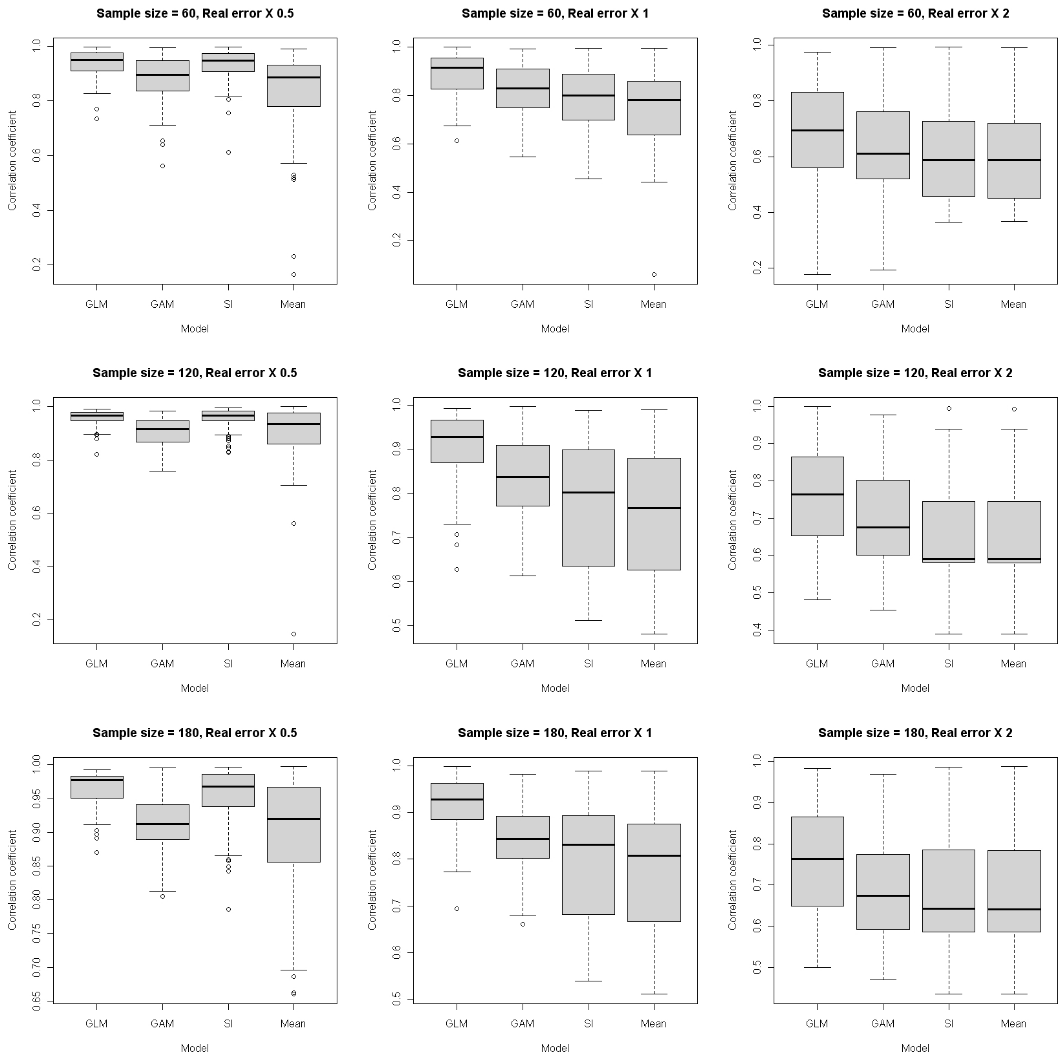
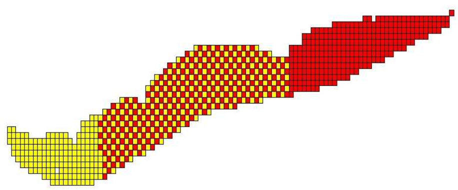

Sample size = 60, Real error X 0.5
Sample size = 60, Real error X 1
Sample size = 60, Real error X 2
Sample size = 120, Real error X 0.5
Sample size = 120, Real error X 1
Sample size = 120, Real error X 2
Sample size = 180, Real error X 0.5
Sample size = 180, Real error X 1
Sample size = 180, Real error X 2
Correlation coefficient
GLM
GAM
SI
Mean
Model

Fig. 3.5. (c)

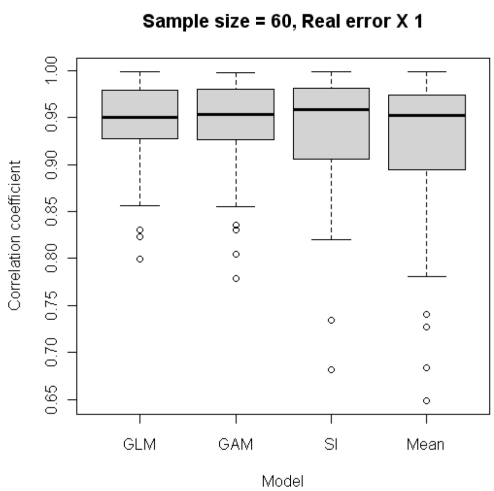


Sample size = 60, Real error X 0.5
Sample size = 60, Real error X 1
Sample size = 60, Real error X 2
Sample size = 120, Real error X 0.5
Sample size = 120, Real error X 1
Sample size = 120, Real error X 2
Sample size = 180, Real error X 0.5
Sample size = 180, Real error X 1
Sample size = 180, Real error X 2
Correlation coefficient
Model
GLM
GAM
SI
Mean

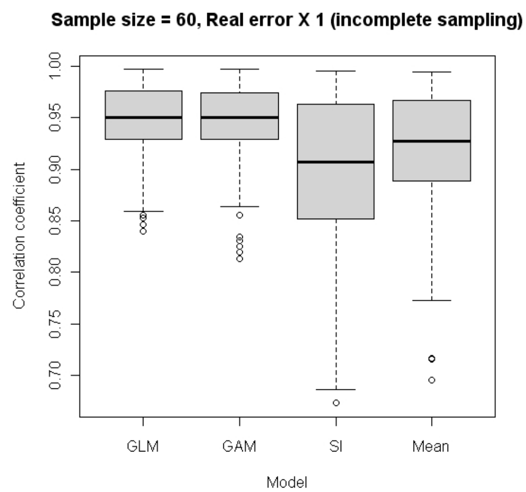
Fig. 3.6.
(a)



(b)


Sample size = 60, Real error X 1
Correlation coefficient
0.65
0.70
0.75
0.80
0.85
0.90
0.95
1.00
GLM
GAM
SI
Mean
Model

(c)


Sample size = 60, Real error X 1 (incomplete sampling)
Correlation coefficient
0.70
0.75
0.80
0.85
0.90
0.95
1.00
GLM
GAM
SI
Mean
Model

CONCLUSION

Yellow perch population varied spatially and temporally in Lake Erie. Understanding its temporal and spatial variation is very important in fisheries population dynamics and stock assessment as well as to manage this important commercial and recreational species. This dissertation focused on analyzing the spatial and temporal variation of yellow perch population through analyzing the fishery-independent surveys on its distribution and abundance. Beyond understanding and modeling temporal and spatial variation of yellow perch in Lake Erie, model-based approaches were developed to estimate the relative abundance index which reflected the temporal variation of the population. I also used the design-based approaches by comparing the performances of two traditional sampling designs and three adaptive sampling designs to deal with the situations that population density varies both spatially and temporally. These studies are very important and greatly needed for yellow perch stock assessment and management but have not been done before this study. This study explored new ideas and models that are either model-based or design-based approaches with a goal of incorporating spatial and temporal variation into fisheries stock assessment. Model comparison was performed throughout the dissertation. The models and methods used in this study can also be helpful for other species, locations and researches on natural resources studies.

In Chapter 1, model-based approaches were applied to explore the temporal variation of yellow perch population by analyzing the relative abundance index. GLM, s-GLM, and GAM were compared by comparing the goodness-of-fit, reduction of spatial autocorrelation, and prediction errors from cross-validation. GAM showed the best goodness-of-fit and lowest prediction errors but s-GLM resulted in the best reduction of spatial autocorrelation. The relationship between yellow perch density distribution and some environmental factors was also studied in this Chapter. The temperatures at gear depth indicated that there was a high potential for yellow perch to quickly seek more favorable thermal conditions. Secchi depth correlated negatively with log catch rate, suggesting that yellow perch selected habitat for reasons other than forage profitability. S-GLM has previously been reported to give better goodness-of-fit and abundance estimates than GLM for tuna longline catches in the Indian Ocean (Nishida and Chen 2004). This study has shown that s-GLM can also outperform GLM based on the yellow perch fishery-independent survey data in Lake Erie. It suggests that s-GLM is suitable not only for large ocean-scale commercial data, but also for smaller-scale surveys, such as in a lake. This study has further demonstrated the importance of including within-year (monthly) temporal changes, which are often neglected in catch rate analyses. For yellow perch in Lake Erie, the evidence indicates that s-GLM and GAM provided better catch rate standardization than GLM.

In Chapter 2, design-based approaches were used to study the spatial and temporal dynamic pattern of yellow perch in Lake Erie. Traditional sampling designs and adaptive sampling designs for fishery-independent surveys were compared. ATS performed better than the traditional SRS and StRS, and the adaptive sampling designs of ACS and ATSS for yellow perch fishery-independent survey data in Lake Erie. The reason that ATS had better precision than StRS is the advantages of ATS in samples allocation in each stratum. In Lake Erie, yellow perch density varies temporally and spatially, so it is difficult to find an appropriate strata division for each year. When the density in each stratum is heterogeneous and sample size is small, StRS performed even worse than SRS. ACS and ATSS in this case are not as good as expected. The reason is very likely to be the insufficiently clustered population of yellow perch. Besides efficiency, ATS is more flexible and practical in reality also than StRS. The formula used to calculate variance is not fixed. A subjective weighting factor derived from prior knowledge may be added to it. In a conventional sampling, it is often possible that some strata will be under-sampled or not sampled due to bad weather and vessel or gear problems. Traditional sampling designs lack the ability to deal with this situation because the sample plan is determined before the sampling activities. In contrast, ATS is able to decrease the negative effect of under sampling. This is because once the first phase sampling is done, theoretically there are negative influences if the samples in the second phase are not totally allocated. ACS and ATSS have their practical limitations. For ACS, if prior knowledge about the population distribution before survey is limited, selecting an appropriate critical value can be difficult; "edge units" do not involve later statistical estimation, but require much effort. ATSS avoided "edge units" and neighborhood sampling, but it still has to face problems of critical value and initial sample size as in ACS. Both ACS and ATSS cannot count the exact total sample size before sampling. However, the problems mentioned above do not exist in ATS which make calculations in ATS easier and plausible. The only difficulty of using ATS is the sample size in Phase 1. My results showed that 80% was a reasonable proportion to apply. My simulation study suggested that in different fisheries, the best sampling design can be different.

In Chapter 3, GLM and GAM models and geostatistical models were compared in analyzing the temporal and spatial variation of yellow perch population. A new type of model, SI, was applied to estimate yellow perch relative abundance index. The un-standardized catch rates may not correctly reflect the real fish abundance. Although GLM and GAM are most commonly used models to standardize catch rate in fisheries, they are not suitable for all kinds of survey data due to their limitations. For the selection of continuous explanatory variables, stepwise regression is often applied. However the procedure of choosing explanatory variables is difficult when two or more variables are highly correlated (multicollinearity). Furthermore, interactions among explanatory variables are more difficult to choose than single variables. We do not need to consider these problems when SI is used. From this point, SI is more convenient to use than GLMs or GAMs. AIC is the most commonly used criterion for model selection. But based on my results from this study, the recommended models according to correlation coefficients of estimated catch rate and "true" abundance from GLM and GAM did not match these from AICs. In addition, dealing with zero catches in GLMs and GAMs is also a common difficulty. Both zero-inflated models and delta models will increase the complexity of analysis. SI can avoid all these difficulties in relative abundance index estimation. When the error term was small, the performance of SI was better than GLM, GAM, and AM shown as the higher r values. When the error term was amplified, the performance of SI decreased dramatically. GLM and GAM were affected by the magnitude of error term less than SI and AM because the environment factors were included in these two models, which can reduce the influence of measurement error in the dependent variable. In general, AM method is only preferred when neither environment factors nor spatial information of sampling locations are available. If the survey can not cover the distribution area of the population due to biased design or lack of sampling locations, GLMs and GAMs are preferable to SI. Otherwise, SI is a good alternative model to estimate relative abundance index.

Spatial and temporal population dynamics play an important role for the stock assessment and fisheries management of yellow perch in Lake Erie. Both model-based and design-based approaches were used for this purpose. Adaptive sampling designs may be considered when both spatial and temporal variations were obvious for the fishery. After survey data are collected, spatial autocorrelation is suggested to be considered when model based methods are used, and the geostatistical model is very useful when sampling is complete in spatial coverage but is not suggested when the sampling coverage is incomplete. These models used in this study and the methods of model comparison can be applied in other fisheries.

REFERENCES

Booth, A.J. 2000. Incorporating the spatial component of fisheries data into stock assessment models. ICES J.Mar. Sci. 57: 858-865.

Bolker, B.M. 2008. Ecological models and data in R. Princeton University Press, New Jersey.

Casselman, J.M.2002. Effects of temperatures, global extremes, and climate change on year class production of warmwater, coolwater and coldwater fishes in the Great Lakes basin. McGinn, N.A., editors. Fisheries in a Changing Climate. Am. Fish. Soc. Sym. 32. Bethesda, Maryland.

Chubb, S., and Liston, C.R.1985. Relationships of water level fluctuations and fish. Prince, H.H., and D'Itri, F.M., editors. Coastal Wetlands. Lewis Publishers, Inc., Chelsea, Michigan.

Environmental Objectives Sub-Committee (EOSC). 2005. Lake Erie Emvironmental Objectives. Report to Lake Erie Committee, Great Lakes Fishery Commission.

Hartman, W.L. 1972. Lake Erie: effects of exploitation, environmental changes, and new species on the fishery resources. J. Fish. Res. Bd. Can. 29: 931-936.

Lenters, J.D. 2001.Long-term trends in the seasonal cycles of Great Lakes water levels. J. Great Lakes Res. 27(3): 342-353.

Lofgren, B.M., Quinn, F.H., Clites, A.H., Assel, R.A., Eberhardt, A.J., and Luukkonen, C.L.2002. Evaluation of potential impacts on Great Lakes water resources based on climate scenarios of two GCM's, J. Great Lakes Res. 28:537-554.

Petitgas, P. 2001. Geostatistics in fisheries survey design and stock assessment: models, variances and applications. Fish Fish. 2: 231-249.

Quinn, F.H. 2002. Secular changes in Great Lakes water level seasonal cycles. J. Great Lakes Res. 28: 451-465.

Ryder, R.A. 1977. Effects of ambient light variations on behavior of yearling, subadult, and adult walleye (*Stizostedion vitreum vitreum*). Can. J. Fish. Aquat. Sci. 34: 1481-1491.

Swartzman, G., Huang, C., and Kaluzny, S. 1992. Spatial analysis of Bering Sea groundfish survey data using Generalized Additive Models. Can. J. Fish. Aquat. Sci. 49: 1366-1378.