Performance comparison between spatial interpolation and GLM/GAM in estimating relative abundance indices through a simulation study

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\section*{ABSTRACT}

Generalized linear models (GLMs) and generalized additive models (GAMs) are commonly used to standardize catch rates as relative abundance indices in fisheries stock assessments. Spatial interpolation (SI) is an alternative way to estimate relative abundance indices but there have been no comparisons of the effectiveness of the two types of approaches. In the present study, the performances of GLMs, GAMs and SI were compared through a simulation study based on fishery independent surveys of yellow perch in Lake Erie in 1990, 1991, 1992, 2000, 2001, and 2003. Simulated scenarios were tested with sample sizes of 60, 120 and 180 drawn randomly from the survey data, and random errors variances of 0.5, 1 and 2 \times the "true" estimate variances. For each combination of sample size and error, 100 simulations were calculated to estimate correlation between the "true" abundance and the estimated relative abundance indices from GLMs, GAMs and SI. The performances of all three methods improved with increasing sample sizes, but worsened with increasing magnitude of the simulated errors. SI performed better than GLMs and GAMs when the simulated errors were low, but SI was more sensitive than GLMs and GAMs to the magnitude of the simulated random errors. When simulated sampling covered the survey area incompletely, GLMs and GAMs performed better than SI.

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\section*{1. Introduction}

Standardized catch rate is commonly used as an index of relative abundance in fisheries studies. Catch rates are related to (and in most cases proportional to) population abundance in stock assessment models (Quinn and Deriso, 1999; Maunder and Langley, 2004; Maunder and Punt, 2004), but without standardization they may not correctly reflect abundance variation and therefore lead to biased stock assessment results. Catch rate standardization removes the effects of all factors other than population abundance variation (Maunder and Punt, 2004). This has been applied to population dynamics models in numerous research efforts (Gavaris, 1980; Lo et al., 1992; Harley et al., 2001; Walsh and Kleiber, 2001; Bishop et al., 2004; Maunder and Punt, 2004; Shono, 2008). Generalized linear models (GLMs) and generalized additive models (GAMs) are commonly used to standardize catch rates (O’Brien and Mayo, 1988; Punt et al., 2000; Ye et al., 2001; Campbell, 2004; Nishida and Chen, 2004; Damalas et al., 2007). Spatial interpolation (SI) is another way to estimate relative abundance indices (Rivoirard et al., 2000). The efficiency comparison of SI and catch rate standardization methods is important but less studied than the application of GLMs or GAMs.

GLMs and GAMs have been used to estimate abundance indices with their own advantages and limitations. GLMs were first introduced in the 1970s (Nelder and Wedderburn, 1972) and have been used to standardize catch rates since the 1980s (Gavaris, 1980). GLMs assume a linear relationship between a link function (e.g., identity, logistic, or log) of the expected response variable and the explanatory variables (Maunder and Punt, 2004). GAMs are extensions of GLMs but replace 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; Guisan et al., 2002). Nonlinear relationships are common between fish densities and environmental factors, and therefore GAMs are also widely used in catch rate standardization (Walsh and Kleiber, 2001; Denis et al., 2002). However, both GLMs and GAMs have disadvantages when standardizing catch rates, which include: (1) requirement of a number of explanatory variables, (2) error structure assumptions, (3) model selection uncertainties, (4) dealing with high percentage of zero catches, and

\[ E-mail address: haoyu@vt.edu (H. Yu). \]
(5) dealing with interaction terms (Maunder and Punt, 2004). When there is a high proportion of zero observations, zero-inflated models or delta models are often used to standardize catch rates (Punt et al., 2000; Martin et al., 2005). When the residuals are spatially autocorrelated, spatial-GLMs are often applied (Nishida and Chen, 2004; Yu et al., 2011). However, these new models often need a large number of observations of environmental factors besides catch data.

GLMs and GAMs are used to account for the effects of other factors (e.g., environmental factors and spatial autocorrelation) on population abundances. However, SI, in contrast, uses spatial autocorrelation to estimate the values in un-sampled areas. Geographic information systems (GIS) are widely used to display and analyze spatial characteristics in fishery data (Rahel, 2004). SI is one of the applications of GIS, and it has been applied in estimating aquatic species densities since the 1990s (Simard et al., 1992; Maynou et al., 1996; Rivoirard et al., 2000; Wyatt, 2003). The densities of most fish species within their distribution ranges are spatially correlated because the environmental factors are more similar when the distances are closer, and therefore SI can be applied for estimating abundance indices. Kriging is one commonly used SI method (Cressie, 1993; Schabenberger and Gotway, 2005). The fundamental idea of kriging is to estimate the value of some quantity at an unknown point by using the combination of weights and the values at known local points. Therefore, it only requires sampled data and the coordinates of spatial locations. However, the disadvantages of kriging are also apparent: (1) marked sensitivity to measurement errors; (2) requirement for the coordinates of survey locations that were used to estimate the spatial distances among observations. According to different assumptions, kriging can be divided into many types (e.g., simple kriging, ordinary kriging, universal kriging, etc.). In the present study, ordinary kriging is used because it is the most commonly used SI method (Schabenberger and Gotway, 2005).

In this study, yellow perch catch rate data were used as an example to compare the performance of GLMs, GAMs, and SI. Yellow perch (Perca flavescens) is one of the most important commercial and recreational fish species in Lake Erie (Baldwin and Saalfeld, 1962; Regier and Hartman, 1973). Yellow perch abundance varies dramatically over time, and the catch rate data are spatially autocorrelated (YPTG, 2008). There is not a generally accepted method to estimate yellow perch relative abundance indices in Lake Erie, and the arithmetic mean (AM) of catch rates is currently used (YPTG, 2008). Therefore in this study AM is also included in the performance comparison. This is the first study that compares the performance of AM, GLMs, GAMs, and SI together in estimating relative abundance indices.

2. Materials and methods

2.1. Study area and survey method

Data used in this study are from the fishery-independent surveys conducted by the Ontario Commercial Fishers’ Association and the Ministry of Natural Resources Lake Erie Fisheries Management Unit in 1991–1993, 2000, 2001, and 2003 within the Canadian side of Lake Erie. These surveys include catch data as well as the information on gear and environmental factors (Table 1). The study area can be divided into western, central, and eastern basins and each basin was divided into 2 × 2 min cells using the ArcGIS software package (version 9.2, 2007, ESRI Inc., USA). The sample size is about 120 in each year and the sampling design is stratified random sampling. The catch rates and environmental factors of the un-sampled cells were interpolated in each year.

### Table 1

<table>
<thead>
<tr>
<th>Variables</th>
<th>Unit</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Catch number</td>
<td>Individual</td>
<td>Per species</td>
</tr>
<tr>
<td>Longitude</td>
<td>°</td>
<td>Converted to NAD 1983 UTM 17 N</td>
</tr>
<tr>
<td>Latitude</td>
<td>°</td>
<td>Converted to NAD 1983 UTM 17 N</td>
</tr>
<tr>
<td>Set duration</td>
<td>h</td>
<td>Standing time of gillnet in water</td>
</tr>
<tr>
<td>Bottom depth</td>
<td>m</td>
<td>Per sampling site</td>
</tr>
<tr>
<td>Gear depth</td>
<td>m</td>
<td>Depth to bottom of the gillnet</td>
</tr>
<tr>
<td>Transparency</td>
<td>m</td>
<td>Secchi depth</td>
</tr>
<tr>
<td>Water temperature</td>
<td>°C</td>
<td>At surface</td>
</tr>
<tr>
<td>Gear temperature</td>
<td>°C</td>
<td>At gear depth</td>
</tr>
<tr>
<td>Dissolved oxygen (DO)</td>
<td>mg/L</td>
<td>At gear depth</td>
</tr>
</tbody>
</table>

2.2. Generalized linear model

A basic GLM can be written as

\[
g(\mu) = X^T \beta \tag{1}\]

where \( g \) is the link function, \( \mu \) is the expectation of the observation, \( X \) is the vector of explanatory variables, and \( \beta \) is the vector of the regression coefficients (Montgomery et al., 2006). The log-transformation has been widely used in fisheries and has been found to be appropriate in many situations (Quinn and Deriso, 1999). Since there were zero observations in the survey data, delta-lognormal GLMs were used to generate “true” abundance data for yellow perch in the Canadian side of Lake Erie. The general form of delta-lognormal GLMs can be written as:

\[
Pr(Y = y) = \begin{cases} 
    w, & y = 0 \\
    (1 - w)f(y) & \text{otherwise}
\end{cases} \tag{2}
\]

where \( w \) is the probability of a zero observation, and \( f(y) \) is the probability function of the lognormal distribution. In the simulation procedure, we treated \( \mu \) as the expectation of the log-transformed observation of catch rates, and spatial-GLMs (hereafter GLMs) were used to standardize catch rates (Nishida and Chen, 2004; Yu et al., 2011). The residuals in GLMs were assumed spatially correlated, and the covariance, \( Cov(\epsilon_i, \epsilon_j) \) is the function of the distance \( d_{ij} \) between sample locations \( i \) and \( j \) and the range \( \theta \) (the maximum distance over which the significant autocorrelation occurs):

\[
Cov(\epsilon_i, \epsilon_j) = \sigma^2 f(d_{ij}, \theta) \tag{3}
\]

The spherical covariance model was used in this study:

\[
f(d_{ij}, \theta) = \frac{3d_{ij}}{2\theta} - \frac{d_{ij}^3}{2\theta^3} \tag{4}
\]

A backward stepwise selection procedure was used to choose the best combination of explanatory variables based on Akaike’s information criterion (AIC) (Akaike, 1973). The GLM catch rate standardization was conducted using the “gls” function in the R software package (Version 2.9.1, 2009, USA). The year effect was calculated and regarded as the relative abundance index after exponential transformation because it was initially log-transformed:

\[
l_t = \exp\left(\frac{b_t + \sigma_t^2}{2}\right) \tag{5}
\]

where \( l_t \) represents the estimated catch rate in year \( t \), \( b_t \) is the estimated year effect for year \( t \) and \( \sigma_t \) is the standard error of \( b_t \).

2.3. 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). A basic GAM can be written as

\[ g(\mu) = \alpha + \sum_{i=1}^{n} s_i(X_i) \]  

where \( g \) is the link function, \( \mu \) is the expectation of observations, \( \alpha \) is the intercept, \( X_i \) is the \( i \)th explanatory variable, and \( s_i \) is a smooth function for the \( i \)th explanatory variable. The cubic spline was used for each smooth function in this study. The smoothing parameters were selected by adding an extra penalty to each term in generalized cross-validation. Parameters in the GAM were estimated using the “mgcv” function in R software package (Version 2.9.1, 2009, USA). The delta-lognormal GAM was also used to generate the “true” abundance of yellow perch in each year.

### 2.4. Ordinary kriging

Ordinary kriging assumes that the constant mean is unknown, which may be reasonable for estimation of relative abundance indices for fish populations. The prediction of an unknown point is based on the statistical relationship among the surrounding measured points (Johnston et al., 2001). The general formula for prediction is

\[ \hat{Z}(s_0) = \sum_{i=1}^{M} \lambda_i Z(s_i) \]  

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, \( \lambda_i \) is an unknown weight for the measured value at the \( i \)th location, and \( M \) is the total number of measured values. The formula to estimate \( \lambda_i \) is

\[
\begin{pmatrix}
\gamma_{11} & \cdots & \gamma_{1n} & 1 \\
\vdots & \ddots & \vdots & \vdots \\
\gamma_{n1} & \cdots & \gamma_{nn} & 1 \\
1 & \cdots & 1 & 0
\end{pmatrix} \begin{pmatrix}
\lambda_1 \\
\vdots \\
\lambda_n \\
m
\end{pmatrix} = \begin{pmatrix}
\gamma_{10} \\
\vdots \\
\gamma_{n0} \\
1
\end{pmatrix}
\]  

\( \gamma_{ij} \) is the semi-variogram function, and it can be estimated by

\[ \gamma_h = \frac{1}{2|N(h)|} \sum_{(i,j) \in N(h)} (z_i - z_j)^2 \]  

where \( N(h) \) is the set of all pairwise Euclidean distances, \( h = i - j \), \( |N(h)| \) is the number of distinct pairs in \( N(h) \); \( z_i \) and \( z_j \) are observed values at spatial locations \( i \) and \( j \), respectively. A spherical model was fitted to the empirical semivariogram so that the semivariogram values can be calculated for various distance lags.

### 2.5. Simulation study

Three simulation scenarios were calculated with respectively AM, GLM, GAM, and SI to compare their performances across the survey area (Fig. 2). A common basis for comparing the results of these methods was created by interpolating the environmental factors from the surveys onto a 2' × 2' grid, using ordinary kriging. The survey area comprised 906 2' × 2' grid points (Fig. 1).

In the first scenario, delta-lognormal GLMs were fitted to the real survey data to calculate the coefficient of each explanatory variable (i.e., the year and the environmental factors) and the regression residuals. The “true” abundance at each 2' × 2' grid point was simulated by applying the coefficients from the delta-lognormal GLMs to their respective interpolated environmental factors and calculating the response variable. A spatially autocorrelated spherical

![Fig. 1. The Canadian side and the United States' side of Lake Erie. The Canadian side was divided into 2' × 2' cells. The gray area belongs to the United States. In the additional scenario, the blue grids were possibly sampled and the white grids would not be sampled. The units within the eastern basin of the lake had the same probability of being sampled; only half of the units in the central basin could be sampled, and the other half would not be sampled; and no units in the western basin could be sampled.](image)

![Fig. 2. The flow chart of simulation procedure to estimate the correlation coefficients between the “true” abundance and the relative abundance indices (RAIs).](image)
random error (mean = 0, sill = 0.05) was added to this “true” abundance at each grid point. Random samples without replacement of sizes 60, 120, and 180 were taken from the 906 2’ × 2’ grid points. These were added to randomly sampled residuals from the delta-lognormal GLM × 0.5, 1, or 2 to represent sets of new “surveyed” catch rates. The simulation process can be written as:

\[ C_{\text{survey}} = C_{\text{true}} + E_r + E_s \]  

where \( C_{\text{survey}} \) is the simulated catch rate, \( C_{\text{true}} \) is the “true” catch rate, \( E_r \) is the randomly sampled residual, and \( E_s \) is the spatially autocorrelated error.

Another random observation error was added to each environmental factor (mean of errors = 0 and standard deviation of errors = 0.1 × standard deviation of factors). Then AM, GLMs, GAMs and SI were fitted to the newly “surveyed” data respectively and
standardized catch rates were obtained. We assumed that 1% of the total fish at each sample location were caught during the survey period, i.e., the sum of interpolated catch at each location times 100 is the “true” abundance of yellow perch in the study area. Lastly we calculated the correlation coefficients between estimated relative abundance indices and the “true” abundance. One hundred simulations were conducted for this scenario.

In the second scenario, we used the same procedure except the coefficients of explanatory variables, the predicted catch rate, and residuals are from GAMs.

In the third scenario, SI was used to simulate catch rates and environmental factors at each location. Spatially autocorrelated error was not added to the “true” abundance in this scenario since the “true” abundance in each grid was generated using SI. The other steps were the same as the first two scenarios.

Incomplete surveys are often observed in fisheries for reasons such as lack of effort or lack of knowledge of the overall distribution of the target species. We added one additional scenario to test the performances of the models with an incomplete survey. In this scenario, the study area was divided into western, central, and eastern basins (Fig. 1). In the western basin, no units were sampled; in the central basin, every second grid unit was available to be randomly sampled; and in the eastern basin, every grid unit was available to be randomly sampled. The data were generated from the delta-lognormal GLM (as in the scenario 1), random sample size was 60, and the residual magnitude was 1×. This combination of sample size and random variation of the catch rate is close to the real sampling conducted in this survey. One hundred simulations (the procedure was the same as scenario 1) were conducted for this scenario.

<table>
<thead>
<tr>
<th>“True” data</th>
<th>Sample size</th>
<th>Real error × 0.5</th>
<th>Real error × 1</th>
<th>Real error × 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>GLM</td>
<td>GAM</td>
<td>GLM</td>
</tr>
<tr>
<td>GLM</td>
<td>60</td>
<td>688.5</td>
<td>528.0</td>
<td>1057.4</td>
</tr>
<tr>
<td></td>
<td>120</td>
<td>1331.2</td>
<td>1079.9</td>
<td>2059.0</td>
</tr>
<tr>
<td>GAM</td>
<td>180</td>
<td>1961.0</td>
<td>1606.3</td>
<td>3076.4</td>
</tr>
<tr>
<td>SI</td>
<td>60</td>
<td>1175.0</td>
<td>887.4</td>
<td>1465.5</td>
</tr>
<tr>
<td></td>
<td>120</td>
<td>2228.4</td>
<td>1773.7</td>
<td>2919.1</td>
</tr>
<tr>
<td></td>
<td>180</td>
<td>3246.2</td>
<td>2672.8</td>
<td>4335.1</td>
</tr>
</tbody>
</table>

Fig. 4. The relationship between estimated relative abundance indices and the “true” abundance after 100 simulations. The “true” abundance was estimated from GLMs, the sample size was 120, and the error term was the real error. The relative abundance indices were estimated from GLMs, GAMs, AM, and SI respectively. The red dots represented the relationships between catch rates and abundances in the surveyed years after 100 simulations. The fitted lines from linear regression (abundance – catch rate) which was forced to passing the origin were added to the scatter plots.
2.6. Performance comparison

Linear relationships were assumed between the relative abundance indices and the “true” abundances, and the Pearson correlation coefficient (r) was used to compare the models. The model with the highest correlation coefficient is preferable. GLMs and GAMs were also compared for model fit using AIC.

3. Results

Yellow perch catch rate distribution varied spatially and temporally in Lake Erie (Fig. 3). In 1991, the highest catch rate area was between the central and eastern basins, and a few areas with high catch rate were patchily distributed in the western and central basins. The catch rate distribution patterns were similar in 1992, 1993 and 2001: the western basin had the highest value, and the western part of the central basin had higher value than the eastern part of the central basin and eastern basin. In 2000 and 2003, the highest catch rate area was the western part of the central basin, and the western basin and eastern part of the central basin had higher density than the eastern basin. The mean catch rate in the lake was also variable over time. The mean catch rates of 2000, 2001, and 2003 were higher than those of 1991–1993.

The environmental factors showed different spatial and temporal variation patterns in Lake Erie. The lake gets shallower from east to west in general. The water temperature distribution varied over time. In 1991, the high temperature area was between the central basin and eastern basin. In 1992, the eastern basin, western basin, and eastern part of the central basin were high temperature areas. In 1993, 2000, 2001, and 2003, the western basin and part of the eastern basin had highest 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 2001. In 2001, the western basin had a higher value than the central basin.

The range, partial sill and nugget of fitted semivariogram of catch rate were estimated each year. The patterns differed among years. They all showed an apparent nugget effect except 1991...
and 1992. The ranges from 1991 to 2003 were 51.1 km, 23.4 km, 11.4 km, 55.2 km, 119.6 km, and 79.4 km respectively; the partial sills were 3954, 3792, 1060, 44,258, 32,217, and 41,674, respectively.

The mean AIC values increased when the error term was amplified or sample size increased (Table 2). The median values of AICs were consistent with the mean values (values not shown), which indicated the distribution of AICs was symmetric. In most cases, AIC values from the GAMs were smaller than those from GLMs; when the “true” data came from the prediction of SI and errors were small, AIC values from GAMs were larger than those from GLMs. To illustrate the relationship between the relative abundance index (RAI) and the “true” abundance, the scatter points and their fitted lines were plotted for 100 simulations for the scenario of sample size 120 and 1× residual (Fig. 4). In this scenario, SI performed better than the other three models. The RAI’s estimated from GLMs and GAMs were close to each other while RAI’s estimated from AM showed highest variability.

In the first scenario, the “true” abundance was calculated from the GLM, and the correlation coefficients (r) between the “true” abundance and RAI’s varied with the magnitude of the error (Fig. 5a). When the magnitude of the error was half of the real error, the median of r values was larger than 0.8 for every model, and the median of r from the GLMs was the highest and had the narrowest range than when the other three models were used. GLMs and GAMs resulted in similar median of r values, but the r values from GAMs had wider range. When the magnitude of the error term was equivalent to the real error, GLM still resulted in the highest median of r values, but the ranges of r were larger than when the magnitude of the error term was half of the real error. When the magnitude of the error term was two times the real error, the median of r values when GLMs and GAMs were used were higher and the ranges of r values were narrower than when SI and AM were used. SI had higher median of r values and smaller ranges than AM. The median of r values decreased when we amplified the error term or reduced the sample size. Comparing with Table 2, the patterns of AICs and r values did not completely match: GLMs resulted in higher r values in most situations (77.8%), but GAMs usually resulted in smaller AICs than GLMs did (92.6%).

In the second scenario, the “true” data were calculated from the GAM (Fig. 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 GLMs and GAMs were used. The ranges of r values were narrower when GAMs were used than when GLMs were used. When the magnitude of the error term was equivalent to the real error, the ranges of r values from GLMs were smaller than when the error term was half of the real error. When the magnitude of the error term was equivalent to two times the real error, both SI and AM resulted in smaller medians and wider ranges than when GLMs and GAMs were used. In terms of medians and ranges of r values, GLMs and GAMs performed nearly the same, and SI performed better than AM.

In the third scenario, the "true" data were calculated of the SI (Fig. 5c). When the magnitude of the error was equivalent to half of the real error, GLMs and SI performed similarly, and they resulted in larger medians and narrower ranges than when GAMs and AM were used. The medians of r values were very close when GAMs and AM were used, but AM had wider ranges than GAMs, especially when the sample size was 180. When we amplified the error term, the medians from each model decreased and the ranges increased. When the error term was equivalent to the real error, GLMs resulted in the narrowest ranges and largest medians. GAMs, SI, and AM were very close. When the error term was equivalent to two times the real error, GLMs were still the best model in terms of the medians of the r values. When the sample size was 60, SI and AM resulted in narrower ranges of r values than when GLMs and GAMs were used. When we increased the number of samples from 60 to 120, the estimation of relative abundance indices from GLMs and GAMs improved, but it did not improve when SI and AM were used.

The performance of the models was compared between incomplete surveys and the complete survey (Fig. 6). The performances of GLMs and GAMs were not significantly affected much by the incomplete sampling. However, the performances of SI and AM decreased with incomplete sampling as shown by decreases of their median r values.

4. Discussion

SI was showed to be a good alternative of estimating fish abundance indices in the present study, especially when the environmental factors are not available. GLMs and GAMs are commonly used to estimate fish relative abundance indices; however, the observations of environmental factors often are missing in many fishery datasets. Therefore researchers in this situation usually use
the AM method to estimate fish abundance indices though its reliability is limited. SI performed better than AM and is more flexible than GLMs or GAMs. The change of the relationship between fish distribution and the environmental factors over time and space is critical for exploring the real fish abundance variation. SI is able to capture this kind of temporal and spatial variation because the data can be divided into many groups based on time (or spatial) scale and then analyzed separately in each group. In the present study, although we only used the survey data in 6 years, the range of time reaches 12 years (1991–2003). SI solved this problem by fitting different geostatistical models year by year.

AIC is the most commonly used criterion for model selection when GLMs/GAMs are 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 most complex model (Shino, 2005). In this study, model selection uncertainty was also found to be high using AIC as a criterion of model selection. The recommended models based on the correlation coefficient of estimated relative abundance index and “true” abundance from GLMs and GAMs, did not always match those recommended by their AICs, and vice versa. For example, in most situations (92.6%), GAMs resulted in smaller AIC values, which indicates that GAMs should be preferable to GLMs if AIC is the model selection criterion. However, 77.8% of the correlation coefficients from GLMs were higher than those from GAMs, which means that the relative abundance index estimated from GLMs could represent the abundance better.

Dealing with zero catches in GLMs and GAMs is also a common difficulty (Maunder and Punt, 2004). The zero catch can cause computational problems when the natural logarithm of catch rates is used in models. Zero-inflated models and delta models are often applied for survey data with many zeros. However both of them need to divide the dataset into two components and then fit two models with different distribution assumptions, which increases the complexity of the analysis. In addition, each part will face the problem of selecting appropriate explanatory variables. SI is capable of avoiding this difficulty in dealing with zeros, and the computation is straightforward. Ordinary kriging used in the present study requires no distributional assumptions of the data (Schabenberger and Gotway, 2005; Negreiros et al., 2010).

The magnitude of random error significantly influenced the performance of SI. When the error term was small (half of the magnitude of the real error), the performance of SI was better than or similar to that of GLMs, GAMs, and AM because the correlation coefficient (\( r \)) was higher. When the error term was amplified, the performance of SI and AM as shown by the \( r \) values decreased accordingly, but SI performed better than AM. The reason is that AM only calculated the numeric value of the data, whereas SI also include the spatial relationship among sampling locations. The performances of GLMs and GAMs were less affected by the magnitude of the error term than SI and AM. The disadvantages of SI include the requirement for high quality sampling designs and plenty of observations. In a good sampling design, the samples can represent the population efficiently. Incomplete sampling can impact SI much more than GLMs and GAMs. In the present study, we used a simple random sampling design to sample the population in the lake. Yellow perch density is heterogeneously distributed in the lake and varies over time. Adaptive sampling designs may perform better than simple random sampling or stratified random sampling design (Yu et al., 2012). However the estimator from adaptive sampling designs is often biased, which will cause new problems in practice (Thompson and Seber, 1996). The application of adaptive sampling designs in fish relative abundance indices estimation is worth further study in the future. Sample size may affect the accuracy of ordinary kriging prediction; however, there is no widely accepted rule for an appropriate sample size (Negreiros et al., 2010).

In the present study, using 10–15% of population size as sample size is appropriate for abundance index estimation.

In general, GLMs, GAMs, and SI showed good performance for relative abundance index estimation in the present study. However, different models are suitable for different situations and data sources. The AM is only preferred when neither environment factors nor spatial information of sampling locations are available. When the observation error of the survey catch is limited, SI performs better than the other methods shown as high \( r \) values. SI is also capable of avoiding computation difficulties, such as dealing with zeroes. If the survey cannot cover the distribution area of the population due to biased designs or lack of sampling locations, the estimated relative abundance index will not reflect the real abundance level when SI is used. In this situation, GLMs and GAMs are preferable to SI.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.fishes.2013.06.002.

References


