Utilizing Geographic Information Science Advancements For Bathymetric Mapping and Dredging Assessment of a Small Urban Lake in Southeastern Minnesota

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Abstract

Currently emphasis on accurate and timely collection of fisheries data generates a need for investigation into advanced techniques in bathymetry, including recent refinements in Geographical Information Science (GIS) and Global Positioning Systems (GPS). The study area for this project was the east basin of Lake Winona, a small Mississippi River floodplain lake in Winona, Minnesota USA. Lake Winona was the site of recent dredging operations aimed at decreasing littoral zone areas to reduce plant growth and stunted fish populations. To assess potential effectiveness of dredging operations, bathymetric data were collected with a Garmin depthfinder and GPS unit, and interpolation techniques to produce lake morphometric characteristics (splining, kriging, and inverse distance weighting) were compared within ESRI's ArcMap 9.0. All interpolation methods produced similar outputs for cross validation statistical comparisons, although kriging produced the best predictive output of actual bathymetric contouring for Lake Winona. Calculation of morphometric characteristics from derived bathymetric information showed significant changes in Lake Winona compared to historic accounts. Lake dredging was successful in reducing littoral zone areas by 30 percent and increasing lake volume by 28 percent, while increasing the mean depth by 60 percent (from 2.6 feet to 4.3 feet). Habitat for stunted fish populations was substantially reduced. Today, information from this project is being used to assess the feasibility of further bathymetric studies and to refine management approaches to improve the Lake Winona fishery.

Introduction

Assessing the impacts of human interaction and development on the environment is often an arduous task. Information acquired quickly and accurately before information changes can be vital to implementation of appropriate management plans. Accurate bathymetric lake maps can be an important resource to area fish and wildlife managers, along with other stakeholders such as; fisherman, hunters, the general public, and area natural resource planners.

Within the past 10 years, the technological capability for inland bathymetric mapping has exploded, yet new techniques remain largely unexploited due to expense and the lack of research into proper techniques. Such innovation includes using Global Positioning Systems (GPS) for accurate mapping in combination with Geographical Information Science (GIS) for computer analysis.

Lake Winona is a 315 acre lake situated in the heart of Winona, MN (2000 census population 27,000+). Lake Winona, a hyper-eutrophic urban lake, is split into two sections by a major city thoroughfare. Approximately two thirds of the lake volume lies in East Lake Winona (215 acres), whereas the remaining one third of the volume lies in West Lake (100 acres).

Negative factors such as rain and fertilizer runoff, along with sedimentation from storm sewers are problematic more often with urban lakes such as Lake Winona. In an effort to control weed growth, and ultimately control stunted game fish, an extensive dredging project was conducted on East Lake Winona from 1999 to 2001. The goal of the project was to remove approximately 1.3 million yards^3 of sediment within an 80 acre area of the lake (Fremling et al, 1990).

The development of new techniques using GIS in conjunction with GPS technology for analysis will allow area ecological managers to obtain current and accurate bathymetric information for Lake Winona. This allows decision-makers to construct and evaluate management plans in a fraction of the time and expenditure as previously required. To assist with the development of new bathymetric techniques, this paper will investigate the process of using bathymetric data collection techniques which differ from traditional methods. I used GPS/GIS techniques to quantitatively and qualitatively compare interpolation techniques and to produce a quality bathymetric map for current and future comparisons needed for the fisheries management of Lake Winona.

Methods

Study Area

The area of interest for this study was East Lake Winona, a eutrophic 215 acre urban lake situated in the heart of Winona, Minnesota. Lake Winona is split into two basins by a major city thoroughfare, dividing approximately two thirds of the lake volume in the east basin known as East Lake Winona, and the remaining one third of the approximate volume within the west basin known as West Lake Winona.

Lake Winona's state is of concern to the local community due to the long history of troubled management concerns. Recent management solutions to control weed overgrowth and stunted fish populations included the recent dredging project undertaken between 1999 and 2001. This dredging project was done in an effort to increase the mean depth and reduce the widespread aquatic vegetation beds that were being used by overabundant populations of stunted sunfish (Fremling et al, 1990).

Data Collection Timeline

Three different datasets were obtained from Lake Winona for comparison and analysis by this study. Data for East Lake Winona was collected in November of 2004, while West Lake Winona and an East Lake Winona Validation data (to be referred to as "East Validation" from this point forward) were collected in April of 2005.

Equipment operation and survey design

The Garmin 168 Sounder, mounted on a 14 foot v-hulled boat, was utilized for data collection. The Garmin 168, is a WAAS (Wide Area Augmentation System) enabled chart-plotting receiver and depth finder and is equipped with a 200 kHz, 20˚ transom mount transducer. Surveys were conducted on calm days to minimize pitch and roll of the boat which can affect the accuracy of the sonar signals and accurate readings (Leonard, 1997).

Independent test trials found RMS values ranging between 4 – 6 meters and rarely above 7 meters, while position dilution of precision (PDOP) ranged from .5 – 1.5 and a high of 2.1. RMS and PDOP range values consistently fell within unit specifications for WAAS (Garmin Inc, 2002) as noted in the units literature. This literature indicates the goal for the unit is to "provide reliable signals with an accuracy of seven meters (21-22 ft), both horizontally and vertically, 95+% of the time."

To maximize mass point data collection along with efficient data collection, transects were spaced 30 meters apart and data were collected by the internal GPS data logger every 0.01 nautical miles (18.52 meters). Since the predictive accuracy of the interpolated surface is dependent on the intensity of data (McConville, 1995), transects were designed on a systematic grid along parallel transects, perpendicular to the longest shoreline for East and West Lake Winona, and parallel to the longest shoreline for East Validation.

Boat speed during surveys ranged from 3-4 knots when traveling along the course of a transect and between 2-3 knots when traveling between transects as suggested by Valley (2005). To avoid damage to the boat and instruments, the nearest transect course traveled to shore was one boat length away.

To test the accuracy of sonar depth measurements, 20 random test points were obtained upon completion of the main surveys. Test points for comparison were captured at random locations with a 20 foot survey rod from an anchored boat and compared to the Garmin 168 sonar depth reading.

The internal track logger within the Garmin 168 unit captured all information and was downloaded in the NAD83 map datum. Sample sizes for collected point data information throughout the entire stretch of both basins resulted in 803 points for West Lake Winona, 1342 points for East Lake Winona, and 1385 points for East Validation study. Data was transferred between GPS and a computer through use of the Minnesota Department of Natural Resources Garmin extension for use with ESRI's ArcMap 9.0 Geostatistical Analyst extension

Surveys from this project were compared to data derived from surveys conducted in 1985 (predredging of Lake East Lake Winona) and 2002 (post dredging of East Lake Winona) with both of these surveys developed using traditional bathymetric techniques. These traditional survey techniques used "line of sight" techniques and consisted of traveling transects by boat between visual landmarks on the shoreline and recording depth measurements from an electronic fishing depth finder at a specified time interval. Once collected, depth information was transferred to paper and contours were hand drawn at logical locations to depth information using a polar planimeter.

Geostatistics

Geostatistics is an applied form of statistics which utilizes a spatial component and assumes that all values in a study area are the result of a random process with dependence (ESRI, 2004). The geostatistical process of finding data values for unknown locations between observed data locations is known as interpolation. Through interpolation, a surface can be created that incorporates the statistical properties of the measured data, and for some methods, produces not only prediction surfaces but also error or uncertainty surfaces, providing an indication of how good the predictions are (ESRI, 2004). Interpolation is dependant on auto-correlation, assuming some relationship between distance and direction of known data values.

While all interpolation methods rely on the similarity of nearby data points for creation of output surface models, the process for determining interpolated values can be quite different. Two different groups of interpolation methods exist; deterministic, which utilize mathematical functions, and stochastic methods which utilize both mathematical and statistical functions to determine predicted surface values.

Interpolation

Deterministic interpolators include a group of surface prediction methods which assign values to locations based on the surrounding measured values. From the measured values, specified mathematical formulas are employed that determine the extent of similarity (e.g., Inverse Distance Weighted) or the degree of smoothing (e.g., Radial Basis Functions or Splining) (ESRI, 2004).

Inverse distance weighted (IDW), a deterministic interpolator, relies on local variability, assuming data values nearby are more likely to be similar than those further away. Calculated weight for surrounding points within IDW are proportional to the inverse distance raised to the power value, therefore as distance increases, weights decrease rapidly (ESRI, 2004).

IDW is an exact interpolator, forcing the predicted surface model through known data points. For IDW surface model calculation, prediction values are confined between the minimum and maximum known values, placing greater weight on observed values. Greater emphasis on observed values accounts for small scale variation, but also may create sensitivity for clustering and producing "bulls-eyes" around data points in high gradient areas (ESRI, 2004). IDW requires no assumptions and results are solely dependent on the distance to the prediction location for calculating interpolation values.

Radial basis function (e.g., RBF or splining), is also an exact interpolator, but unlike IDW can predict values above the maximum and below the minimum measured values (ESRI, 2004). RBF is unique in which it applies a "rubber sheet" through all known points, while minimizing slope curvature. RBF models are used for calculating smooth surfaces from a large number of data points where surfaces vary gently. This type of interpolation is inappropriate where there are large changes in the surface values within a short horizontal distance and/or when the sample data is prone to error or uncertainty (ESRI, 2004).

Within RBF, there are two functions which will be considered; completely regularized and spline with tension. The degree of smoothness parameter contributes to slight differences between RBF functions, which are often not significant, but may be tested through cross validation (ESRI, 2004).

Kriging and other stochastic interpolation methods utilize mathematical and statistical functions to create surface models. Stochastic methods use autocorrelation as well as complex geostatistics, such as variograms to create prediction maps and the resulting uncertainty assessment.

Variograms, which include semivariograms and covariance functions, (to be discussed later) are used to graphically quantify the autocorrelation relationship. Autocorrelation theory suggests that nearby data pairs should have smaller differences than distant data pairs. A property of kriging is that it tends to under predict large values and over predict small values (ESRI, 2004).

When comparing weighted averages, kriging is the best unbiased predictor whether or not data are normally distributed and when the data are normally distributed, it is the best unbiased predictor (ESRI, 2004). Since kriging requires the greatest amount of user input (as compared with other interpolation methods), assumptions for data validity hold a greater importance. Within kriging, several methods exist, but only two, both with measurement error models (ordinary and universal) will be examined here.

Assumptions

To assess the effectiveness of various higher order interpolation methods such as kriging, assumptions of normality and stationarity are required for dependency rules to properly formulate predictions and assess uncertainty. Previous work (Rossi et al, 1992) recognized this need for a clear description of the underlying theory and assumptions for calculating interpolation models within geostatistics.

Since kriging methods rely on the normal distribution of data for accurate surface prediction, the assumption of normal distribution or normality, is desired before advanced interpolation may begin. Normal (i.e. Gaussian) models are convenient because they are classified not only by two parameters, the mean and the variance, but by their characteristic bell shaped symmetry (Journel, 1989). An appropriate log transformation or box-cox transformation may be performed on a data set to correct for skewness away from a normal distribution.

A fundamental assumption of geostatistical methods is that any two locations that are a similar distance and direction from each other should have similar difference squared values, a concept referred to as stationarity. The stationary principle is important because it relies on the theory that all data come from distributions that have the same variability and hence suitable replication (ESRI, 2004).

The assumption of stationarity may be validated by analyzing the semivariogram and covariance, functions of higher order interpolation surface modeling such as kriging. Detailed discussion of the variogram structure is offered by Isaaks and Srivastava (1989).

Data Analysis

Analysis of univariate and bivariate raw data statistics can lead to insight into trends and relationships within data and is therefore the first step before analyzing any geostatistics (Tukey, 1977), (Rossi et al, 1992). Raw data of interest for this analysis included; West Lake and East Lake Winona, along with an independent validation data set for East Lake Winona.

Using Exploratory Spatial Data Analysis; a histogram (univariate) may identify the mean, variance, skewness and kurtosis values, while a General Quarter-Quantile and Normal Quarter-Quantile show comparisons between a variable and log-normal data and then between corresponding data sets. Transformations and trend removal can help justify and satisfy the assumptions of normality and stationarity. (ESRI, 2004)

The Trend analysis helps to identify the presence or absence of a trend, which may aid in explaining some physical process (i.e. pollution or wind direction). Trends are nonrandom (deterministic) surface components, accounting for large-scale variation (ESRI, 2004). Trend analysis should always be investigated, since interpolation, in the presence of the trend can bias results by skewing the interpolation in a particular direction. (Isaaks and Srivastava, 1989) (Valley, 2005). Such problems introduced by trend include island contours around data points and weaving contours between high and low data points (Krum and Jones, 1992).

Model Parameters

When constructing an interpolated surface model, a variety of parameters are involved, depending on the complexity of the model and the degree of decision making. Interpolation methods such as IDW and

RBF require fewer decisions or parameters to manipulate in comparison to kriging methods. Parameters important for determining the validity of the surface model include (which may vary by model); surrounding point weight, neighborhood search, and anisotropy. IDW and RBF both have similar parameters for determining the small scale variation involved within the dataset. Kriging interpolation methods utilize functions such as semivariogram and covariance to assess the weight given to surrounding data points, based on distance and direction.

Finding the most suitable weight for IDW or RBF is accomplished easily in GeoStatistical Analyst 9.0 through the "optimize power" feature. With this feature, the GeoStatistical Analyst will try to minimize the root-mean-square prediction error (RMS), a summary statistic quantifying the error of the prediction surface. With the selected parameters, the GeoStatistical Analyst tries several different powers to identify the power that produces the minimum RMS. A curve is fit (quadratic local polynomial equation) to the points and from the curve, the power that provides the smallest RMS is determined as the optimal power (ESRI, 2004). When determining the influence of surrounding data points (i.e. neighborhood) for weighing interpolation calculations, careful analysis of the involved parameters is essential.

The neighborhood search is used to define the neighborhood shape and the constraints of the points within the neighborhood that will be used in the prediction of an unmeasured location. Neighborhood search sizes should be large enough to capture the variability in the data, but small enough to avoid capturing distant points, which create reduces spatial auto-correlation with the prediction location, hence jeopardizing the appropriateness of stationarity (Isaaks and Srivastava, 1989).

Cross Validation and Validation

Cross validation, a geostatistical tool, is an important means for discerning differences between interpolation methods. Cross validation is a process that uses all the data to estimate the trend and autocorrelation models by removing one data point at a time, predicting the value using the rest of the data. Cross validation helps to determine the appropriateness of the parameters surrounding the model and the interpolation method.

Cross validation provides an array of statistical and graphical outputs for comparison of different parameters before surface model creation, allowing for manipulation of parameters if needed. Among the prediction error output statistics for cross validation of deterministic and stochastic interpolation methods is the mean prediction error (MPE) and root-mean-square (RMS). The RMS statistic is a measurement of how close the predicted values are to the measured values, in which smaller values are preferred. The mean prediction error statistic (MPE), is a measure of the bias within the model, which will produce values centered around zero for unbiased models.

Stochastic methods provide additional statistics as an extra measure of uncertainty and potential error for the prediction model. The kriging standard error, a statistical measure of uncertainty in the prediction, is calculated by the square root of the kriging variance. RMS and MPE values can be "standardized" to account for scale dependence, by dividing the RMS and the MPE each by the standard prediction error to produce RMS standardized and MPE standardized. The RMS standardized is a measure of variability in addition to the kriging standard error, in which RMS standardized values will underestimate the variability when greater than one and overestimate variability where values are less than one (ESRI, 2004).

The use of cross validation prediction error statistics can be a beneficial tool for finding differences among interpolation methods, however may fall short of clear determination for finding the "optimal" interpolation method. In such situations, Pearson's correlation coefficient and r squared values calculations may be beneficial for interpolation model determination (Isaaks and Srivastava, 1989).

The Pearson correlation coefficient is useful for determining linear relationships between an independent variable (i.e. observed values) and dependent values (i.e. prediction values). Positive Pearson values near 1 indicate a strong relationship between them, while negative Pearson values indicate an inverse relationship. The r square is a similar statistical measure, calculated by squaring the Pearson value, explaining the fraction of the variance not clarified by the regression.

The process of validation, another useful tool for model suitability, is conducted with an independent data set from the modeling process through a separate data collection or creation of subset from the original dataset. Validation creates error prediction statistics similar to those for cross validation, and is beneficial for assessing the validity of the model parameters.

Results

Exploratory analysis indicated positively skewed data for all three data sets, requiring a lognormal transformation to satisfy the first assumption of normality. The log transformation in a histogram of 10 classes did significantly impact the orientation of the histogram graph and consequent makeup of univariate statistics, the mean and median. Table 1 illustrates changes in mean, median, and standard deviation values before and after log transformation. Statistical mean and median data values in close proximity are characteristic of normal distribution, thereby satisfying the normality assumption.

The average squared deviation of all values from the mean, referred to as the variance, and the square root of the variance, referred to as the standard deviation, are important for measuring the spread of values around the mean of a frequency distribution. Smaller values of variance and standard deviation indicate tighter clusters of measurement around the mean (ESRI, 2004). Between standard deviation and variation statistics, standard deviation is considered a better measurement statistic, since variation is negatively effected by erratic high values (Isaaks and Srivastava, 1989).

The coefficient of skewness for Gaussian distributions is a measure of the symmetry of distribution after log transformation, where perfect symmetric distributions the skewness equals zero (ESRI, 2004). The coefficient of skewness after log transformation for all three data sets was calculated at 1.236 (West Lake), 0.1784, (East Lake) and 0.1747 (East Validation). Positive skewness values for West Lake imply positively skewed data which results from the high percentage of smaller values (i.e. shallow depth values) within the data set. East Lake and East Validation, analogous data sets, exhibit skewness values very near zero, suggesting virtually near symmetry in the frequency distribution after log transformation.

Detrending for each of the three data sets did not exhibit any sort of trend when the 1st order polynomial (linear behavior) was applied through the projected points. However, a 2nd order polynomial (quadratic) fit did demonstrate evidence of trend, exhibiting an upside down "U" shape in East Winona and Validation data sets. This polynomial fit behavior is the result of the trending process finding abnormal behaviors within depth information and indicates the presence of trend in the northeast to southwest direction of the lake. Further examination of the unusual linear trend behavior within East Lake and Validation data sets was attributed to the abnormal bathymetric points created to the dredging of the lake along this region.

The second order polynomial applied to the West Lake Winona exhibited a right side "U" shape on the same northeast to southwest direction, indicating a trend, not in the northeast to southwest direction, but in the northwest to southeast direction. This abnormal trend behavior can be attributed to West Lake Winona being very shallow with the exception of a confined, but deep area along the southeastern end of the lake.

To create a consistent search neighborhood, 32 neighbors were used (except for kriging, in which 64 neighbors were used) for calculation along with a standard location (X = 609131.7, Y = 4876923), which for consistency was picked arbitrarily in the middle of the lake. For IDW and RBF, differences in anisotropy were tested and found to be negligible.

Some variation, albeit minor, did exist for comparison among interpolation methods. All methods statistically (RMS, MPE, and where applicable, RMS standardized) produced a quality output surface. RMS values, a measure of the paired relationship between observed and measured values, indicated greater accuracy with lower RMS values, which varied from 3.74 with RBF regularized spline to 3.92 with IDW. RMS values for the other interpolation methods used here fell between these RMS values for IDW and RBF methods.

Another measure of data variability is the mean prediction error (MPE), which is a measurement of data bias within the prediction surface model. MPE values, when unbiased, exhibit the tendency to center around a value of zero, ensuring the model chose the most appropriate prediction value. Biased data, when not appropriately checked, may inappropriately skew away from a "true" data value.

Table 1. Presence and absence of log transformation in a histogram distribution for all Lake Winona data sets.

Transformation	Mean	Median	Std Dev
West	1.62	1.39	0.62
East	2.42	2.2	0.73
Validation	2.4	2.2	0.83
No Transformation	**Mean**	**Median**	**Std Dev**
West	6.39	4	5.4
East	14.65	9	10.47
Validation	15.32	9	11.96

MPE values for all methods exhibited minimal bias for the predicted surface. MPE values for all interpolation methods measured included; IDW (-0.006) and RBF (regularized, 0.019 and spline with tension, 0.023), which were slightly less bias than kriging values (ordinary, -0.112 and universal, -0.049).

Since the MPE value is dependent on the scale of the data, kriging models provide a better representative of the MPE and the standardized MPE (the MPE divided by the kriging standard error (i.e. the square root of the variance prediction)). The standardized MPE values for ordinary (-0.020) and universal (-0.041) fall much closer to MPE values for other models, rather than MPE values for kriging. Therefore, when using standardized MPE values for kriging in comparison with MPE values for IDW and RBF, all calculated models exhibited low variability.

Examination of Pearson correlation coefficient and r square values (Table 2) between observed and predicted values showed virtually no difference between

Table 2. Pearson Correlation Coefficient and r squared values for all interpolation methods.

	Pearson correlation	r squared
IDW	0.93	0.86
Ordinary Kriging	0.93	0.87
Universal Kriging	0.93	0.87
RBF- Regularized Spline	0.93	0.87
RBF- Spline with Tension	0.93	0.87

interpolation methods. Further examination of Pearson correlation coefficient and r square statistics did show strong similarities between observed and predicted values for all interpolation methods.

The East Validation data set was useful for assessing the protocol of the parameters used to build the original model, using an independent data set. For a valid set of surface model parameters, the validation data set should yield prediction error statistics similar to those produced in cross validation. MPE values (Table 3) for validation data departed slightly from their desired direction (zero) indicating greater bias in the data. RMS values (Table 3) increased slightly away from zero indicating a greater difference between observed and predicted values. Such indicated variation between cross validation and validation prediction error statistics signify the incorporation of small scale variation within the original surface model.

With each of the six interpolation output models calculated, a derived vector output feature class produced morphometric statistics for each model. Using the summary statistics from the raw data, the known depths of East Lake Winona ranged from 0 to 40 feet in depth, creating 8 depth classes at 5 foot intervals. Calculation of segment area for each depth interval in relation to those deeper depth intervals was useful for determining the change of surface area.

From calculating to total segment area, it was determined that the area of East Lake Winona was 905829.95m² compared to 783120.31m² found in 1985 and 2002. Differences in area calculations are the result of different shoreline maps used in 1985 and 2002. Recent Farm Service Agency (FSA) air photographs were utilized in 2004, for the greatest accuracy in shoreline delineation. To correct for differences in total area, relative area and relative volume were used for all experimental calculations here.

Calculations for relative segment area were conducted among all six interpolation models conducted among all six interpolation models for comparison with bathymetric survey information conducted in 1985 and 2002. Comparison of segment area and segment volume calculations for all surveys revealed substantial depth and volume changes within the littoral zone from dredging operations.

Hypsographic curve calculations illustrated littoral zone segment area reduction from 90% in 1985, to 63% in 2004, corresponding to similar results by Mundahl (2001) using traditional surveys. Hypsographic curve calculations for segment volume within the littoral zone illustrated substantial reduction from 92.6% of total lake volume in 1985 to 64.3% in 2004, corresponding as well results from Mundahl (2001).

The dredging project had drastic and substantial effects on the overall mean depth throughout the east basin of Lake Winona. The average calculated mean depth of 4.4 feet shown by this study compared favorably with the mean depth of 4.1 feet in 2002 and indicated an approximate 60% change in the mean depth in 1985, previously 2.6 feet.

Testing accuracy of sonar depth readings using a T-Test, paired sample for means, revealed depth measurements with surveyors rod and Garmin 168 were

Table 3. Comparison of Cross Validation and Validation prediction statistics.
*(C) denotes Cross validation, (V) denotes Validation

	MPE (CV)*	MPE (V)*	RMS (CV)*	RMS (V)*
Ordinary Kriging	-0.112	-0.458	3.837	4.683
Universal Kriging	-0.049	-0.395	3.797	4.576
IDW	-0.006	-0.393	3.928	4.683
RBF- Regularized Spline	0.019	-0.362	3.741	4.439
RBF- Spline with Tension	0.023	-0.351	3.792	4.427

statistically similar (n=21, r=0.9838).

Discussion

Model Decision

Confirmation of assumptions and general trend relationships, where kriging was concerned, did appear to prove useful for calculating an accurate and unbiased surface model. General reasoning for trends is answered by explainable physical processes such as the abnormal depth behavior in the northeast to southwest direction caused by dredging in East Lake Winona. With a lognormal transformation applied to satisfy normality assumptions, kriging models produced unbiased results only after detrending removed a 2nd order polynomial trend and removed an abnormal depth behavior for the modeling of the final surface model.

Globally, little bathymetric variation occurred throughout the floor of East Lake Winona in each of the interpolated surface method outputs. All interpolation methods created similar drop offs (due to dredging) and gradual increases in depth towards shore along similar areas of the lake. The global similarities among methods were correlated to the similarity of generated statistics for each method. On a smaller scale, some qualitative variation did exist across all three interpolation methods. The IDW surface model, based on the extent of smoothing, produced “bulls-eye” patterns, especially along higher gradient areas (due to dredging) and connected similar areas together. Generally such bulls-eyes patterns such as produced here are not characteristic of the true bathymetry and are therefore not typically featured in bathymetric maps. Thus even though IDW produced respectable statistics for both cross validation and validation, it was not considered a suitable final surface model choice.

The RBF methods, based on the degree of smoothing, are also drastically affected by these same gradient changes. RBF methods typically produce high error or uncertainty in areas where gradient abruptly changes due to the rubber sheeting applied to the data. In many areas RBF method here tried to “connect the dots” of similar areas, creating connected “coves” of similar depths. RBF statistically produced the highest quality prediction statistics, although the types of features being modeled must account for part of the decision making, ruling out both RBF and IDW for this model.

Kriging models, although over-whelmed by parameter decisions, also included an important aspect of prediction error. It is important to note that kriging models require considerable understanding of the aspects of the model which have significant impacts on the output. Additional assumption requirements (stationarity and normality) were easily satisfied through log transformation and inspection of the derived variogram for proper autocorrelation around the weighted least-square fit line.

Pearson correlation coefficient and corresponding r square values were only minimally useful for determining between interpolation prediction models. All interpolation methods displayed strong positive correlation between observed and predicted values. For true statistical correlation assessment, multiple datasets for comparison would be required.

Prediction error maps for kriging surface output models exhibited minimal error output within the study area, although revealing potential error at the outer boundaries (i.e. shoreline). Information at such outer boundaries in most cases should be considered known (i.e. < 5 feet, within the smallest depth interval), since these areas represent sections of the transect between the shoreline and the end of the transect too shallow for travel by boat. Situations such as this require additional knowledge of the study area for external influencing factors. As with any study, there is no substitute for understanding the various factors affecting the data and the resource being sampled or the collection of additional data points.

Caution should be stressed when using interpolated values, since interpolated values are usually less variable than the original data values and make the contoured surface appear smoother. Although smoother surface models are more visually aesthetic, a smoother surface understates the variability and may be misleading from a qualitative point of view (Isaaks and Srivastava, 1989). In terms of bathymetric measurement for East Lake Winona, comparison of universal and ordinary kriging produced similar results (more than other interpolation models), both in prediction statistics and of output map features. Universal kriging compared with ordinary kriging appeared to contain less bias and lower RMS values in cross validation and validation statistics, thus the more qualified surface modeler. In choosing a suitable optimal model for modeling a final surface, universal kriging did stand out when all aspects (cross-validation, validation, and output product) were examined.

Lake management and survey feasibility

Development of the most accurate unbiased interpolated surface output is important for calculation of other statistics within the lake and comparisons with previous bathymetric surveys. Calculated statistics for area and volume for 8 depth classes at 5 foot intervals indicate significant change from the current East Lake Winona bathymetric model and the pre-dredging 1985 bathymetric map. Additionally, similarities exist among location of depth interval and relative morphometric calculations from this study and traditional studies done by Mundahl (2001).

Similarities for preparatory field work (1 day) and collection of data (1 day) for traditional and the advanced techniques used here are relatively similar for similar size lakes (Zytkovicz, 2005). Generally 2 personnel are needed to conduct traditional techniques as opposed to 1 with newer techniques, creating additional cost differences between bathymetric techniques.

However, great differences reside in post processing of data between techniques. Post processing with traditional methods, using a planimeter may take up to 8 hours or more, while an hour or less time of post processing for advanced techniques. Although this survey and the 2002 survey produced similar results for map features and morphometric calculations, it would be expected that the GPS methods would produce a higher quality map for larger

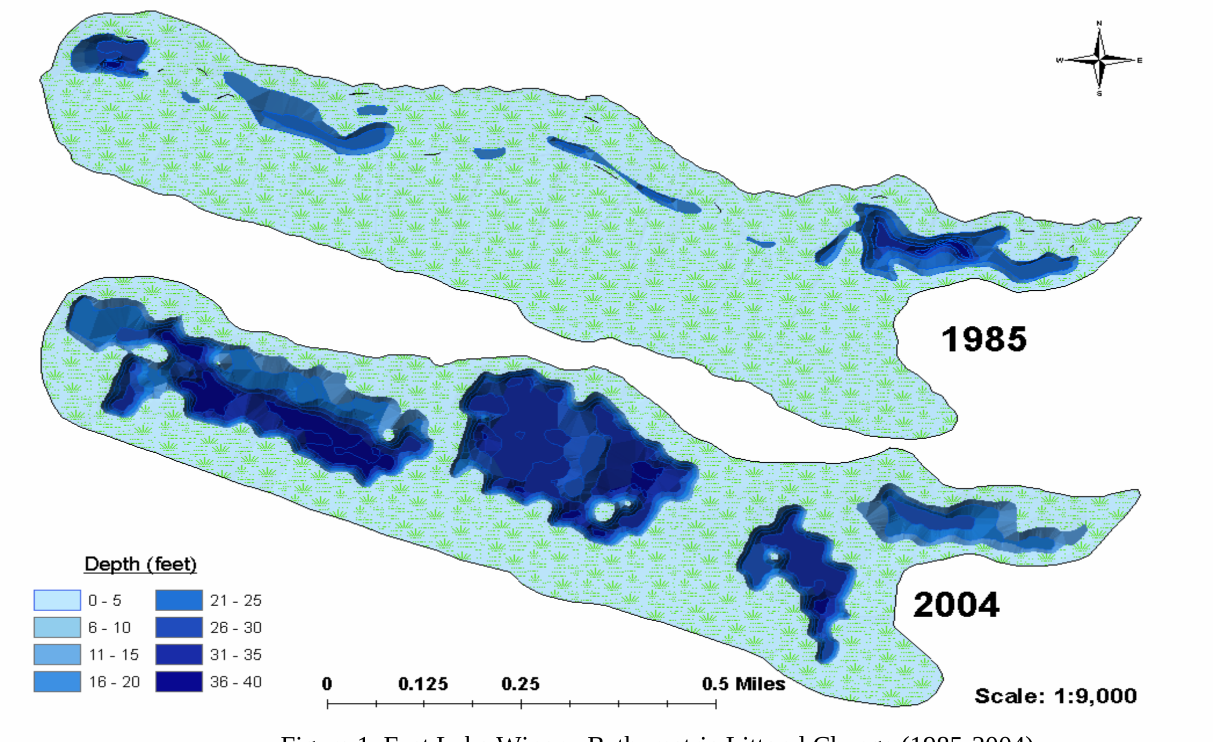

Figure 1. East Lake Winona Bathymetric Littoral Change (1985-2004).

lakes where GPS capabilities better track transect paths.

Previous bathymetric surveys (Leonard, 1997) with similar advanced techniques noted larger bodies of water (2000+ acres) did show drastic differences in map output quality and cost per unit effort over traditional techniques with up to 274 hours less time and a 98% cost savings. Although lakes typically do not exhibit a great deal of bathymetric variation, advanced surveys provide a reliable method for quickly processing survey information in lakes where frequent sedimentation occurs, or as in the case of East Lake Winona, to monitor the potential for slumping of dredge areas.

Dredging analysis

This survey and the prior 2002 bathymetric survey helped to determine if the dredging goals (Fremling et al, 1990) of decreasing mean depth within the littoral zone and increasing the lake volume for dissolved oxygen were achieved. The creation of steep drop offs near the lake's north-northwestern shoreline and removal of expansive shallow areas were beneficial for eliminating extensive weed beds used as habitat for overabundant Sunfish populations. Loss of widespread aquatic vegetation habitat provides greater opportunity for Largemouth Bass (Micropterus salmoides) and other predatory fish to forage on prey species. Comparison of littoral zone change areas from this study and 1985 surveys (Figure 1) show the extent of the dredging and the general areas in which new habitat was created. (It should be noted that since different techniques produce varying amounts of generalizations, the two maps should not be expected to be exactly identical). Shallow areas located between dredge holes also provide new habitat types in the form of shallow humps for fish structure, previously unseen in the lake.

Goals for the dredging of several

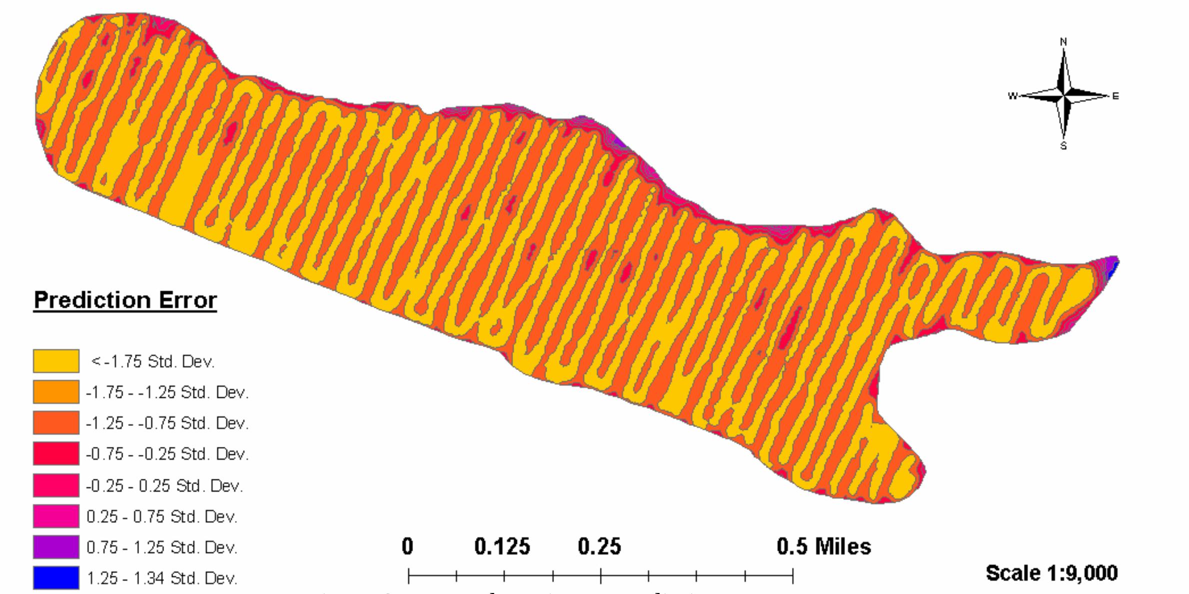

Figure 2. East Lake Winona Prediction Error Map.

deep holes to 60 feet (Fremling et al, 1990) were not noted by this study or by the 2004 surveys, where maximum depths of approximately 40 feet were observed. Although creation of greater maximum depths was intended, deposits of mud (up to 20 feet) in many areas complicated obtaining these desired depths.

Curlyleaf Pondweed *(Potamogeton crispus*) and other common aquatic vegetation plague both basins of Lake Winona, but the west basin to a greater extent, where vegetation growth frequently tops out on the surface throughout the entire basin. Since minimal locational changes of vegetation growth in deep (>2m) littoral zones occurs (Chambers, 1987) (Duarte and Kalff, 1990), current vegetation beds in East Lake Winona are expected to persist. Water levels within the lake have remained consistent, with a maximum variation of less than 1.5 feet over the past 10 years (Minnesota Department of Natural Resources, 2005).

Sources of Error

Error and error recognition is an important aspect of any survey, especially with the use of technology. The use of technology can both create error due to measuring devices and detection where it was previously immeasurable. Positional errors result from discrepancies between the observed, measurement location and the actual location. In historic line of sight methods, slight deviation from transect line between visual shoreline locations was almost unnoticeable. With use of GPS technology, deviation from the intended transect can be quickly noticed and transect can be rerun, ensuring high correlation between data collection and data mapping.

The use of measurement error statistics such as RMS and PDOP (Position Dilution of Precision) can help determine when errors might occur. The RMS error, factoring the possibility of distance off course, is reliant on the quality of GPS, and among other things such as cloud cover and satellite locations. The results from the Garmin 168 were satisfactory, never calculating an RMS error to be over 7 meters or a PDOP over 2.1. Understanding the GPS unit and its average RMS is important when considering transect spacing, such that the RMS error values should fall under half the transect spacing.

An advantage for use of kriging is the ability to calculate error with the measurement. Creating a prediction error measurement map as part of the surface model can help determine which areas error was highest, and if the parameters are outside the ability of the collection unit. Figure 2 represents both transect and prediction error surrounding each data point within the transect. If the data comes from a normal distribution, the true value will be within prediction ± 2 times the prediction standard errors about 95 percent of the time (ESRI, 2004). Special concern should also be taken when using interpolated maps since the original error involved in map creation is often lost when applied to secondary uses.

Conclusions

Using GPS to collect bathymetry data in combination with GIS for analysis of interpolated surface modeling proved slightly better than traditional bathymetric map creation techniques. The comparison of interpolation techniques such as Inverse Distance Weighted, Radial Basis Functions, and kriging, demonstrated similar modeling procedures along with similar qualitative and quantitative results. When comparing all interpolation methods, universal kriging produced the highest quality statistics and graphical output, in addition to error checking capabilities, making it the best choice given all considerations for modeling and lake characteristics. Using the kriging model to calculate and compare statistics from bathymetry here and surveys of 1985 and 2002 illustrated that the goals of the 2001 dredging project to East Lake Winona were achieved.

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