A LEAST-SQUARES APPROACH TO IMPROVED SHORELINE MODELING

A Thesis

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By

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ABSTRACT

The primary objectives of this thesis are to develop and implement a quantitative method for predicting shoreline changes within reasonable temporal and spatial limits, and to better understand the processes controlling shoreline movement. A mathematical model for the prediction of future shorelines is developed for integration of the relevant spatio-temporal shoreline data to support continued analysis of on-going research in the coastal regions. This shoreline-erosion prediction model of Lake Erie can forecast shoreline changes in annual and 10-year increments. It was developed by using historical shoreline data of year 1973, 1990, 1994, and 2000 at Lake Erie provided and developed by NOAA, local government agencies and Mapping and GIS lab of the Ohio State University. The relationships among these previous shorelines are analyzed using a Least-Squares method. Erosion rates are then derived from shoreline changes. The research also involves method of acquiring, comparing, analyzing, and presenting historical shoreline positions for the Painesville region of the Lake Erie, Ohio. In this regard, a Geographic Information System (GIS) offers a potential platform to incorporate spatio-temporal characteristics, accuracy improvement, reliability and usefulness of the prediction model.

Dedicated to my Parents,

Smt. Ranjana Srivastava and Sri O. P. Srivastava

Brother, Anurag Srivastava and Friend, Ashish Jain

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CHAPTER 1

INTRODUCTION

1.1 Coastal erosion process

Erosion is a natural process involving loss of land mass and backward movement of land due to actions of natural forces like water and wind. This is most prevalent in coastal areas that are regularly subjected to the effects of both wind and water. Erosion in coastal region is specifically termed as **coastal erosion processes** to give it importance in research. The coastal erosion processes are cause of extensive damage to land property, beach and structure near the shore, and thus a serious problem throughout the U.S. coastal areas (Fletcher et al, 2003, Li, 1997). The large losses both in terms of financial and resources have made the study of coastal erosion an area of great interest as most of the causes of erosion are very difficult to prevent like hurricanes, tides and waves.

Coastal mapping and shoreline change detection is a first step towards understanding the level of erosion that takes place. Through the mapping and detection techniques we can quantify to some degree the loss of land mass and change in the surroundings due to erosion. This would in turn allow ability to use techniques to avoid losses in case of erosion and a measure of the benefits of those techniques. Erosion forms a big problem for coastal communities in their daily activities like navigation, coastal zone management, coastal environmental protection, and sustainable development. This problem is also exacerbated by water degradation and damage to the coastal ecosystem (Jonathan and David, 1996). Coastal ecosystem supports varied wildlife and human activities associated with it especially the seafood industry, thus any drastic changes affects not only the under water life but the human life that is employed on it.

In such scenarios prediction of the processes engaged in coastal erosion can enable people to take preventive measures thus saving them losses in terms of human life and property. Coastal zone managers, emergency management officials, and coastal property owners always need to be aware of the potential risks to coastal property before, during, and after severe storms and hurricanes. The importance of this issue was also raised in a recent report by the H. John Heinz III Center for Science (Heinz Center, 2000). The report pointed out that on the US coast approximately 1500 homes will be lost to erosion each year for the next several decades at an annual cost to coastal landowners of approximately $530 million. Thus it stresses the great importance of this area of research and its relevance in different facets of life.

Earth's shorelines constantly change through the erosion processes around oceans and lakes. Lake Erie (one of the Great Lakes) shorelines have also been drastically affected by the erosion processes owing to mainly wind, waves and ice (Ohio Coastal Management Program, 1997). In Ohio itself 95% of the Lake Erie shoreline is under erosion (Figure 1.1) and as a result nearly 2,500 structures are within 15 meter of destruction (ODNR, 1999).

Snapshot of summer of 1994 Snapshot of summer of 1996

Figure 1.1 Shoreline Erosion Scenario along Painesville region of Lake Erie (Coastal Imaging Lab, 2005)

The table 1.1 shows the recession rate statistics of the Lake Erie in different counties of Ohio. These long-term rates have been determined over the period of 100 years (1877 to 1973) and short-term rate prediction shows the statistics of 17 years (1973 to 1990). If we closely look at the data overall there is an estimation of less than 3 feet/year recessions while local recession rates are approximately 7 feet/year (Liu, 1998). In general very small recession rates are sufficient to threaten human activities.

County	Long-term Distances (ft.)	Long-term Rate(ft./yr)	Short-term Distances (ft.)	Short-term Rate(ft./yr)
Ashtabula	82	0.9	28	1.6
Lake	160	1.7	32	1.9
Cuyahoga	60	0.6	8	0.4
Lorain	80	0.8	12	0.7
Erie (lake)	103	1.6	42	2.5
Ottawa (lake)	208	2.0	27	1.6
Lucas	520	5.4	46	2.7
Erie (bay)	241	2.8	32	1.9
Ottawa (bay)	61	2.0	21	1.2

Table 1.1: County-wise Erosion rate statistics of Lake Erie (Ohio Geological Survey, 1993)

My work is a research on the prediction of the coastal erosion processes in the Painesville region of the Lake Erie, which is the great water body all along the Ohio's north shore. The major reasons behind this research have been to predict the occurrence of erosion so that its effects can be reduced and to make this research publicly available so that people that are affected by erosion can take full advantage of this study ahead in time.

1.1 Need for the shoreline prediction model

There have been significant changes in US shoreline as a result of the shoreline erosion. Every year federal and state agencies spend a great deal of financial resources in protecting beaches and structures from erosion (Galgano and Douglas, 2000). Since coastal areas are region of high economic investment because of means of transport and preferred areas of settlement the prediction of shoreline position are essential towards an effective coastal zone management. To help make informed and responsible decisions, coastal managers, shorefront landowners, and potential property buyers need information on both current and historical shoreline trends, including reliable measurements of erosion and accretion rates in non-stable areas (Williams, 2001). A detailed analysis of the shoreline change-rates assist a wide range of coastal management activities especially hazard zoning, development setback planning and regional sediment budget (Guy, 1999).

Coastal erosion process is highly nonlinear in nature. Shoreline change is one of the very good indicators of occurrence of coastal erosion. Accurate shoreline change rates are required to fully appreciate and analyze this complex phenomenon. Data also needs to be collected for wide range of coastal studies and coastal management applications mainly in Great Lakes Basin. Lack of reliable event history of erosion has made it extremely essential to establish a methodology of determining the shoreline change rates. Thus it is very crucial to find good models of shoreline for handling the nonlinearities involved. This system might help in locating the affected parcels, in land-use planning and in identifying the erosion hazard area (Li, 1996).

1.2 Shore line change: Spatio-temporal issue

Coasts can be considered extremely dynamic in nature as they continuously change their shape due to natural forces and human activities. Among the main causes of shoreline movement are natural forces such as wind, waves, currents, entrainment and transportation of sediment and littoral, and sea water levels. Winds, tides and waves acts everyday on coasts in the same and opposite directions causing great changes in their shape. Shorelines can thus be seen as a function of both temporal and spatial changes. The main challenge in shoreline prediction modeling thus has been to create models with sophisticated spatial-temporal numerical analysis, which can generate testable predictions about the functioning of a coastal erosion system (Fletcher et al., 2003).

These erosion causing forces also vary according to geographic location and seasonal variations and thus making it very difficult to develop more generalized models. Another major issue in modeling is in finding consistent model that can be applied from one coastal region to another.

A wide range of shoreline change data is available for its prediction analysis in coastal zone, such as spatial, temporal, social and economic. Spatial data contains the spatial information of the shoreline, topography, bathymetry and parcel (Li, 1997). City planning maps, census maps are the source of the decision making for various people involved in understanding the coastal erosion processes. These maps are developed through integration of the spatial data with the social economic data. Temporal data involves the time series tidal data and can be obtained by wind and wave observations using different location of the sensors.

1.3 Application of Geographic Information System (GIS)

A Geographic Information System (GIS) is an information system that is used to input, store, retrieve, manipulate, analyze and output geographically referenced data or geospatial data, in order to support decision making for planning and management of land use, natural resources, environment, transportation, urban facilities, and other administrative records. Prior to the widespread adoption of advanced GIS technology and digitization by coastal scientists there were errors in the process of identifying shoreline positions. This along with lack of spatial-temporal tools for analyzing trends in shoreline changes were among the potential causes for inability of models to give defensible shoreline change evaluations. These limitations in equipment also restricted the methods available to the scientists (Parker, 2003).

Modern analytical methods, including GIS-based analyses, provide more accurate estimates of shoreline change. In the presence of new sensors and new technologies more data is being generated and collected for the hazard mitigation along the coast. This data allows more accurate shoreline change modeling in both spatial and temporal dimensions (Dusen, 1997). A complete coastal GIS database can be developed by incorporating different shoreline change data - spatial, temporal and socio-economic (Liu, 1998).

Compilation of historical shoreline data and maps into geographic information system database is critical in conducting a modern shoreline change analysis. In the presence of modern GIS technology, the models will have greater reliability, accuracy, and analyzing/visualization capability. But at the same time it also allows revisions in previous prediction models that can account for more data in predicting the shoreline changes.

1.5 Objectives

The ultimate goal of this research is to present an analytical model for predicting the future shoreline in order to monitor the shoreline change along the Painesville region of the Lake Erie, Ohio. The initial step in this process is to create a digital database of historical shoreline positions, implement standardized geographic information system (GIS) technology and create a data inventory that can be used to facilitate current and future analyses of shoreline change.

In coastal management studies, four major points; identification of the causes involved in coastal erosion processes, prediction methods of shorelines, public access to prediction forecasts and management of the coastal resources have been discussed by Knecht et al. (1996). Based on the above defined categories, the main objectives of this project are: (1) to compile digital data the shoreline to study the past trend of the shoreline (2) to develop an analytical model of assessing and monitoring shoreline movement, (3) to compare the results of the developed analytical model with those of existing models for better understanding of the processes controlling shoreline movement (4) to develop an easily accessible interface to keep people up-to-date on the shoreline change prediction.

To achieve these objectives, this study (1) examines the original sources of shoreline data (maps, air photos, global positioning system (GPS), lidar), (2) selects the proper shoreline indicator (bluff edges, beach scarp, dune crust etc.) based on its visibility on the data sources (3) reviews previous analytical methods of shoreline change analysis, (4) determines the factors affecting shoreline movement and rates of change, (5) investigates alternative mathematical methods for calculating historical rates of change and forecasting future rates of change in order to set up a reliability of the developed model, and (6) describes error analysis associated with the developed analytical model and the reasons for those errors.

1.4 Organization of the thesis

The report presents an analytical shoreline prediction model, experimental results for the Painesville region of the Lake Erie using that model and comparison of these results with a traditional transect based approach to shoreline prediction. This report also provides explanations regarding the historical and present trends and rates of change of the shoreline movement. The thesis is organized in six chapters as follows. Chapter 1 introduces the coastal erosion phenomenon, its affect in the coastal areas and concepts related to this phenomenon. Chapter 2 presents existing statistical methods for future shoreline analysis evaluation of those models. Chapter 3 presents a detailed description of the analytical shoreline model for evaluating the future shoreline position. Chapter 4 provides description of the study area, shoreline data compilation methods and the results of implementing proposed shoreline analytical model on the case study data. Exhaustive error analyses of the model applied in the study area and discussion over those errors are explained in Chapter 5. In Chapter 6, there is a description of web-based interface to provide people an easy system to access the shoreline change prediction results in the study area. Finally, Chapter 7 summarizes the research conclusions and illustrates the topics for future research investigations.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

A wide range of applications could be made possible with the accurate estimation of the historical shoreline change rates. The calculations involved in the trend analysis of the shorelines are very complex due to its spatio-temporal variability. Future shoreline position prediction models are essential to effectively determine the changes to coastal line and allow us to save the structural and financial losses in the coastal region. As indicated in the earlier discussion a shoreline change prediction model would provide a better estimation of the coastal erosion. Modeling of shoreline changes can be done in two different approaches – erosion and recession. Often these two terms (erosion and recession) are used interchangeably and recession can be understood as the direct consequence of the erosion process but there are fundamental differences in both the terms. Erosion is the gradual wearing away of the coastal land while recession is the movement of features, such as bluff or dune crust, towards the land. The yardstick involved in conducting measurements for the two is also different. Erosion is based on volumetric measurement – change of volume while recession is expressed in change of distance for a given time period. Based on these fundamental differences in erosion and recession various mathematical models have been proposed to predict changes in shoreline over intervals of hours to years (Galgano and Douglas, 2000).

2.2 Erosion based shoreline change prediction

Shoreline erosion is caused by gradual rise in sea water level or wind or water current and results in loss of soil. But in many cases, it is accelerated by intensive use, construction, development, and mismanagement of the land. To understand the erosion based shoreline prediction the first requirement is to understand the factors involved in the coastal erosion process. To accomplish this several potential factors have been identified and analyzed that may cause the coastal erosion (US Army Corps of Engineers, 1993).

2.2.1 Geological factors

These factors involve earth's surface including the rock types and amount of sediment supply in a particular coastal region. Geological factors by themselves are important because the rate of coastal erosion can differ based on different geomorphology of the region. These factors can be summarized in the following points (Oldershaw, 2001):

a) Changes in the Earth's crust in the coastal region under consideration
b) Amount and rate of coastal region sediment transport from lakes and rives
c) Water table position in coastal slopes

d) Structural protection in rocks or sediments

e) Onshore and offshore coastal topography - types of rocks and sediments such as coastal marshes, high and low sand bluffs etc.

The geomorphology of the Lake Erie is made up of different types of rocks and sediments like rocky bluffs, flood plains, coastal marshes, sand dunes and artificial coastlines (Figure 2.1). Most of the Lake Erie coast is composed of the glacial till and lacustrine sediments but northeastern part of the Lake Erie coast is composed of resistant bedrock bluffs (Herdendorf et al., 1993).

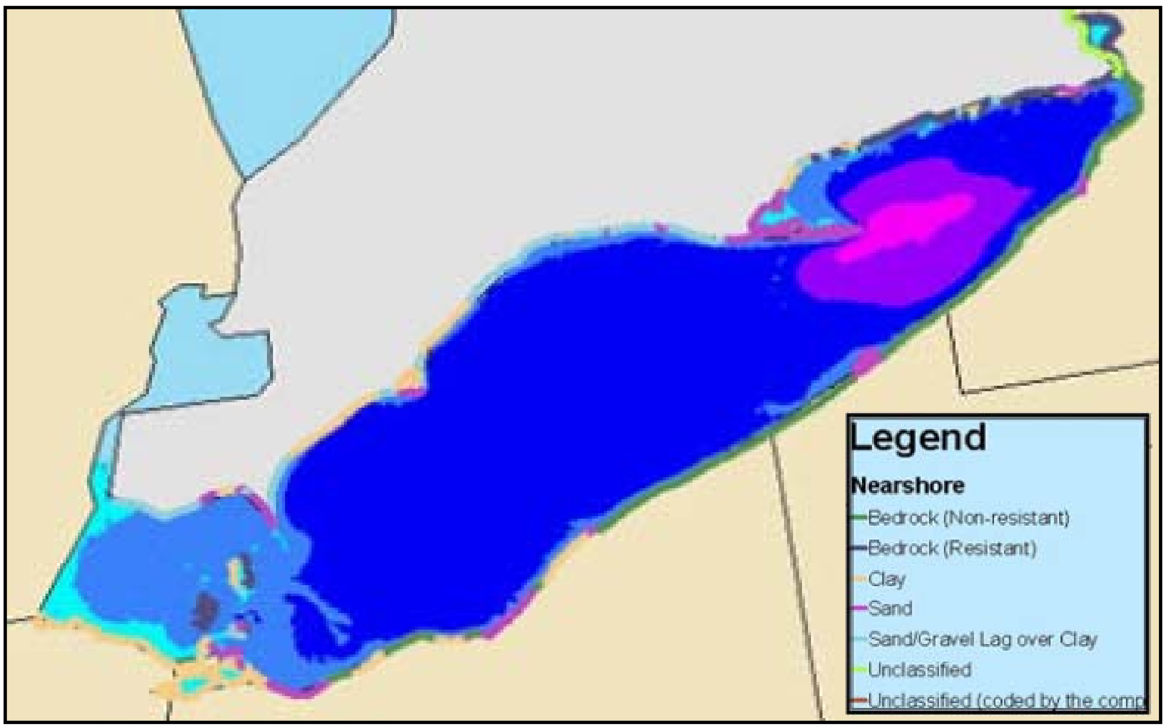

Figure 2.1 Lake Erie Geomorphology (Morrison et al., 2004)

2.2.2 Oceanographic and climatic factors

Climate provides another set of factors that can cause the coastal erosion process depending upon the geographical location. Winds and waves are the simplest factors of this form. A more complete set of such factors can be given as follows:

a) Waves influenced by the sea or the lake water level change and winds

b) Intensity and frequency of storms and tides

c) Frequency and amount of rainfall and rates of water level changes associated to the rainfall

2.2.3 Factors involving human activities

Besides all the above described natural processes there are several human activities that affect the rate of erosion in the coastal area. Such erosion rate is considered unnatural and needs to be identified and analyzed in shoreline change prediction model. These factors could be due to the following human activities in the coastal region:

a) Manmade structures to protect the shoreline in the coastal areas

b) Modification in the drainages to control the flow

Ideally, erosion based models would incorporate changes in above described factors occurring on annual and decadal scales.

Various erosion based models are being developed and analyzed by various researchers in the past two decades and suggestions on different data acquisition techniques are also made to develop such models (Sebnem and Paul, 2002).

2.2.4 Erosion based prediction models

Among the erosion-based prediction models, the most common one uses the concept of sediment mass conservation. In this concept, it is assumed that the shoreline will move in perpendicular direction to the shore due to sediment transportation and the geometry of the shoreline will not be affected by erosion process. Such models do not consider other factors that may change the shoreline (described in section 2.2.1, 2.2.2 and 2.2.3). U. S. Army Corps of Engineers used the following equation for sediment mass conservation in order to predict the shoreline-change (U.S. Army Corps of Engineers, 1992)

$$\frac{\Delta x}{\Delta t} + \frac{1}{D_B + D_C} . (\frac{\Delta Q}{\Delta y} \pm q) = 0 \tag{2.1}$$

Where, Δx is the change in the shoreline perpendicular to the shore, Δt represents the time interval of the analysis. Δy is the length of the shoreline under consideration. ΔQ represents the rate of sediment transport along the shore. D_C and D_B are offshore closure depth and berm crest elevation respectively. In this equation, Sand mining is considered through term q.

Allan et al. (2003) derived a method to measure the shoreline variability using water-level changes and beach slopes. This relationship can be presented by the following equation:

$$SE = \frac{VC}{S} \tag{2.2}$$

where, SE = Shoreline excursion due to water level changes

VC = Vertical changes in the water level and

S = Average Slope of the beach

They implemented this model in Tillamook beaches and Port Orford shoreline (Allan et al., 2003).

Another modeling approach presented by Ali (2003) is based on soil mass conservation. In this approach, the coastal terrain is represented by grid (3D-raster) cells and then volume of soil mass is calculated per cell basis. This model allows us to estimate the spatial distribution of the coastal erosion on the coastal terrain surface. In this method least-squares approach is used to estimate the soil-mass lost. The polynomial involved in deriving the relationship between the sediment loads and eroded soil can be given as follows (Ali et al., 2001):

$$S = a_0 + a_1 \times E + a_2 \times E^2 + a_3 \times E^3 \tag{2.3}$$

Where S represents mass of soil lost (kg), E is the estimated mass (kg) of the eroded soil using Revised Universal Soil Loss Equation (Ali et al., 2001). a_0, a_1, a_2 are the coefficients derived by the least-squares adjustments.

The major disadvantages of erosion based models can be summarized as the following points:

a) Involvement of exhaustive computation and a lot of money
b) Low prediction accuracy because of unavailability of model that could involve all the parameters that affect the shoreline change phenomenon

c) Requirement of extensive field study in order to include more parameters that affect the erosion process

To overcome all these limitations, there is certainly a need to research for new techniques that do not carry any information of the factors affecting the coastal erosion processes in its modeling. Recession based models or empirical models which deal only with the geometry of the shoreline and do not involve any information regarding the causal interactive factors of the coastal erosion processes are a step in this direction.

2.3 Recession based (Empirical) shoreline change models

Recession models use very empirical approach towards calculating changes in the shoreline. One such technique is bluffline-geometry modeling which does not involve sand transportation (Ali, 2003). In this empirical model shorelines are identified in increasing order of time (from past to future) and then the relationship between the time and the shoreline position changes is analyzed by using a numerical method. Shoreline modeling would become unstable in the presence of sand transportation due to its impermanency as sand can be transported back into the water. Moreover, the lack of consideration of sand transportation in the empirical model makes it easier to implement. However, it is reasonable to assume that by modeling the shoreline position changes we are taking the underlying coastal erosion processes into account because all of the changes in the geometry of the shoreline are the end result of erosion phenomena.

To measure changes in the position of the shoreline a minimum of several shoreline positions are generally plotted from various historical charts, aerial photographs and other resources. The distance between each shoreline position is then measured and is called "*rate of shoreline change*". Rate of shoreline change represents the dynamics of shoreline movement. This rate of shoreline change is based on measuring the movement of the shoreline over a specified length of time.

Various methods of determining shoreline rates-of-change have been described by Dolan et al. (1991). The following discussion borrows heavily from their paper. All methods used for calculating shoreline rates-of-change involve measuring the differences between shoreline positions through time. Rates of shoreline change are expressed in terms of distance of change per year. Negative values indicate erosion (landward movement of the shoreline); positive values indicate accretion (seaward movement of the shoreline). The following methods are discussed below: Transects based method, End Point Rate, Average of Rates and Linear Regression.

2.3.1 Transect based method

Transects based method has been a traditional and very popular mapping approach among the coastal engineers and planners for analyzing shoreline changes. This technique was proposed and implemented by the Division of Geological Survey in the Ohio Department of Natural Resources (ODNR). This approach involves the subdivision of available shorelines into smaller segments by creating transects at a master shoreline. Here, the master shoreline implies a shoreline with a good quality and transects are at the right angles to this master shoreline. Once these transects are created, then the rates of shoreline change are calculated along these transects to observe the historical shoreline movements. By using these change rates, the future shoreline position can be derived.

Coastal Erosion maps produced by the ODNR have the shoreline indicators (bluffline) of the year 1973 and 1990. Bluffline of year 1990 is chosen as the master shoreline and transects perpendicular to this shoreline are created to this shoreline (Figure 2.1). The change rate analysis along these transects is then carried out with respect to time and a linear extrapolation is used to predict the position of any future shoreline. The rates of historical shoreline change along each transect are tabulated in Lake Erie Coastal Erosion rates, Ohio Coastal Management Program published by the Lake Erie Geology Group of the Division of Geological Survey at the Ohio Department of Natural Resources in 1997. This method incorporates the spatial analysis in time domain and hence satisfies the spatio-temporal requirement of the shoreline change analysis.

2.3.2 End point rate (EPR) method

Another approach, the End Point rate (EPR) method, presented by Liu (1998) and Galgano and Douglas (2000), is based on an empirical equation which shows that the future position of a shoreline can be derived by a linear relationship between past shoreline positions and time. The change rate (m) and intercept (c) involved in this model are derived by a line ($y = mx+c$) extracted from the points on the earliest and latest available shorelines (y and x represent the shoreline position and time respectively). This model may not be applied widely because of the absence of positional quality information and due to undesirable results for short periods, for instance, less than eighty years (Galgano and Douglas, 2000).

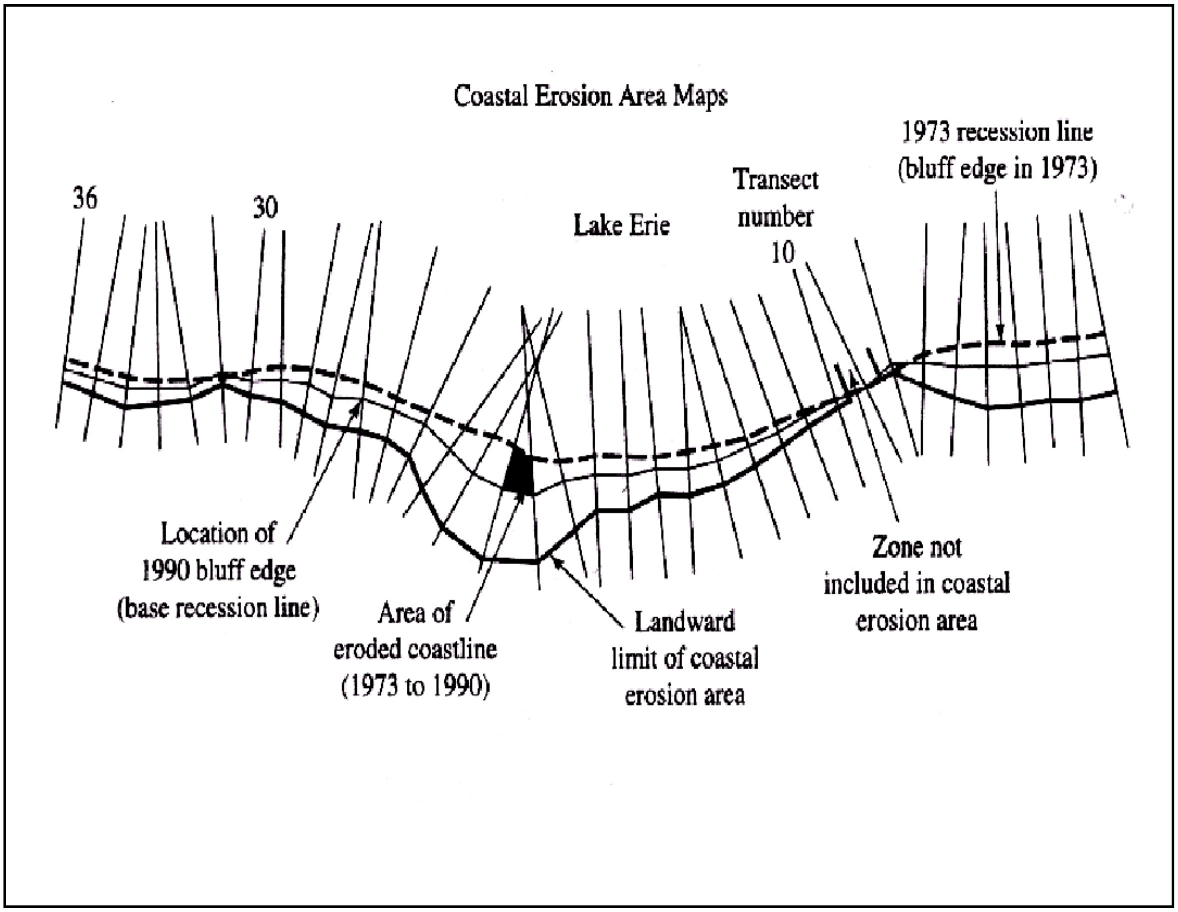

Figure 2.2 Coastal Erosion Map showing transects based approach (ODNR)

2.3.3 Average of Rates (AoR) method

This change-rate calculation method defines a minimum time criterion to provide the more accurate shoreline position data and the magnitude of rate of change. In 1989, Foster and Savage developed the average of rates method (Thieler, 2001). Minimum time criterion defines a term T_{min} which represents the minimum time that must elapse between measured shorelines in order to ensure that the average of rates calculation produces results that exceed measurement error. T_{min} is calculated by the following equation and requires the end-point rates for all the pairs of shorelines available (Dolan et al, 1991).

$$T\,\text{min} = \sqrt{E_1^{\,2} + E_2^{\,2}} \Big/ R_1 \tag{2.4}$$

Where E_1 = measurement errors in the first shoreline point

E_2 = measurement errors in the second shoreline point, and

R_1 = EPR of the longest time span for the transect

The AoR method also produces a measure of the standard deviation and variance of the data. The AoR method includes a means to filter unusable data by the measurement of errors. It also has an ability to reflect changes in trend and data variability. The major disadvantages are accuracy dependency on the minimum time span equation (Dolan et al., 1991), and the sensitivity of the results to the values used in the measurement error values. Also this model would produce the same results as the EPR if only two points are available (Thieler, 2001).

2. 3.4 Method of linear regression

Linear regression rate of change is the measurement of slope of the regression line obtained by fitting a least-squares to all shoreline points for a particular transect. This method is more robust because all the data are used, regardless of changes in accuracy. This statistical method requires no other analysis such as measurement errors used in the

Average of Rates (AoR) method. This method can be used if data is too noisy because least-squares adjustment will reduce the noise during the analysis (Galgano and Douglas, 2000). If only three historical shoreline datasets are available for the prediction of future shoreline's position then the proposed shoreline prediction model in this thesis can be seen as the improved linear regression model.

2.3.5 Dynamic segmentation concept

The concept of subdividing the continuous shoreline into smaller sections and then change trend analysis over these sub-sections was proposed by Liu (1998) and Li et al. (2001). The basic idea behind this approach is to maintain the continuity of the shoreline. Moreover, this model preserves the topological relationships between the shoreline and coastal features, which are essential for spatial analysis. Creating transects and then shoreline modeling and change prediction only leads to the point based analysis and the shoreline change prediction based on some chosen points from shoreline depictions cannot be fully justified because these points do not guarantee the continuity of the shoreline.

2.4 Conclusion

Transects based approach and shoreline change-rate models described in this chapter assume the determination of future shorelines is based on modeling points on past shorelines. Moreover, linear regression assumes linear behavior, which technically is incorrect because linear regression fails to recognize the potential for temporal differences in trend and accelerations or decelerations (Morton, 1991; Barton et al., 2003). A shoreline is a continuous and dynamic feature; a model for shoreline change analysis must maintain the continuity of the shoreline. In this regard, the method presented by Liu (1998) and Li et al. (2001) for shoreline change modeling and analysis by using a dynamic segmentation concept is more acceptable. This approach preserves the continuity of the shoreline by dividing the shoreline into various line segments. These line segments are continuous due to the fact that the end location of the first segment would be the same as the start location of the second segment, and these end points are not fixed in this process. This research implements the dynamic segmentation approach by modeling the changes with line segments of available past shorelines.

CHAPTER 3

BLUFFLINE ANALYTICAL MODEL

3.1 Introduction

In order to develop any analytical model for coastal mapping the first requirement is to choose a shoreline indicator. This indicator should be easily identifiable both in the coastal area and on aerial photographs. Morton and Speed (1998) and Pajak and Leatherman (2002) mentioned some of these shoreline indicators including bluff edges, vegetation lines, high water marks, beach crust, dune crust, beach scarp, etc.

Shoreline is defined as the line of contact between a land surface and a lake, river or ocean surface. Although there is significant difference between the shoreline and bluffline (Figure 3.1) but due to the scope of this research project, the top bluff edge is chosen as the shoreline indicator because of ease in its visibility on aerial photographs. Proposed method is based on the historic linear data and assesses future changes in the shape of the shoreline by reviewing historic snapshots of the bluffline. One of the purposes of this research is in developing standard repeatable methods for mapping and analyzing shoreline movement. This in turn will allow periodic updates regarding coastal erosion thus making it possible to evaluate land loss nationally through a systematic and internally consistent method.

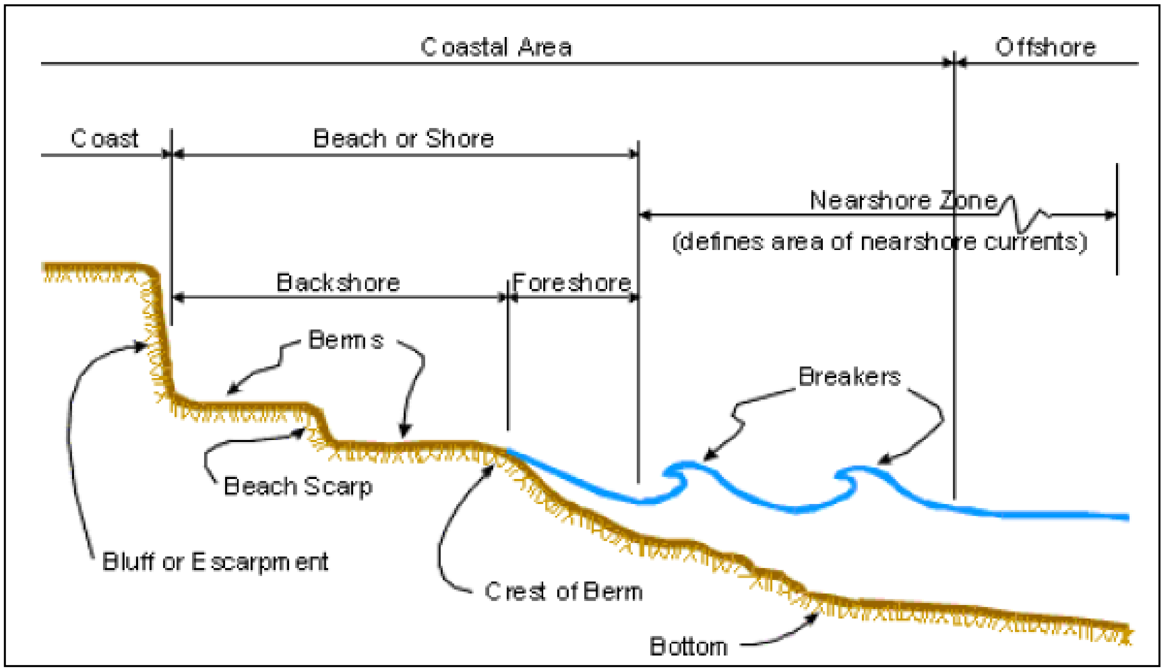

Figure 3.1 Beach Profile along the shore (Liu, 1998)

3.2 Methodology

The methodology involves data preprocessing (including georeferencing, projection), importation into a GIS (through digitizing), transformation to a common vector data model, and finally spatio-temporal analysis, error analysis and visualization. For a given area where attributes may change from site to site and from time to time, analysis is done by fixing the location, controlling time, and measuring attributes (Yuan, 2005). The basic idea of proposed modeling approach is to study the relationship between shoreline segments that belong to shorelines acquired at different times through a mathematical model that geometrically describes the relationship between them. The bluffline modeling is based on two main assumptions: a) The relation among available shoreline models can be represented in a two-dimensional space; b) A bluffline segment at time t1 can be transformed to its corresponding shoreline segment at time t2 (t2>t1) only by the action of erosion forces, which results in the change in the geometric representation of the two segments.

3.2.1 Linear representation of the bluffline

The shape of a bluffline within a reasonable length is generally irregular and cannot be expressed using analytical functions. To apply any numerical modeling approach in the analysis of the bluffline change, its geometry should be expressed under some assumptions as described in above paragraph. In this modeling approach the shoreline is divided into various segments that are defined by their end points. We divide a bluffline A_1A_{n+1} into a finite number (n) of segments $\overset{\frown}{A_1A_2}$, $\overset{\frown}{A_2A_3}$, $\overset{\frown}{A_3A_4}$, ..., $\overset{\frown}{A_nA_{n+1}}$ which are defined by their starting and ending points A_1 (x_1, y_1), A_2 (x_2, y_2), A_3 (x_3, y_3), A_4 (x_4, y_4), ..., A_n (x_n, y_n), $A_{n+1}(x_{n+1}, y_{n+1})$. Moreover, these segments with small spatial extents can be approximated to linear segments $\overline{A_1A_2}$, $\overline{A_2A_3}$, $\overline{A_3A_4}$, ..., $\overline{A_nA_{n+1}}$ (Figure 3.2).

3.2.2 Normalization of the blufflines

In implementing the linear approximation on all the available blufflines of different times, a standardized parameterization method is used (Schmidley, 1996).

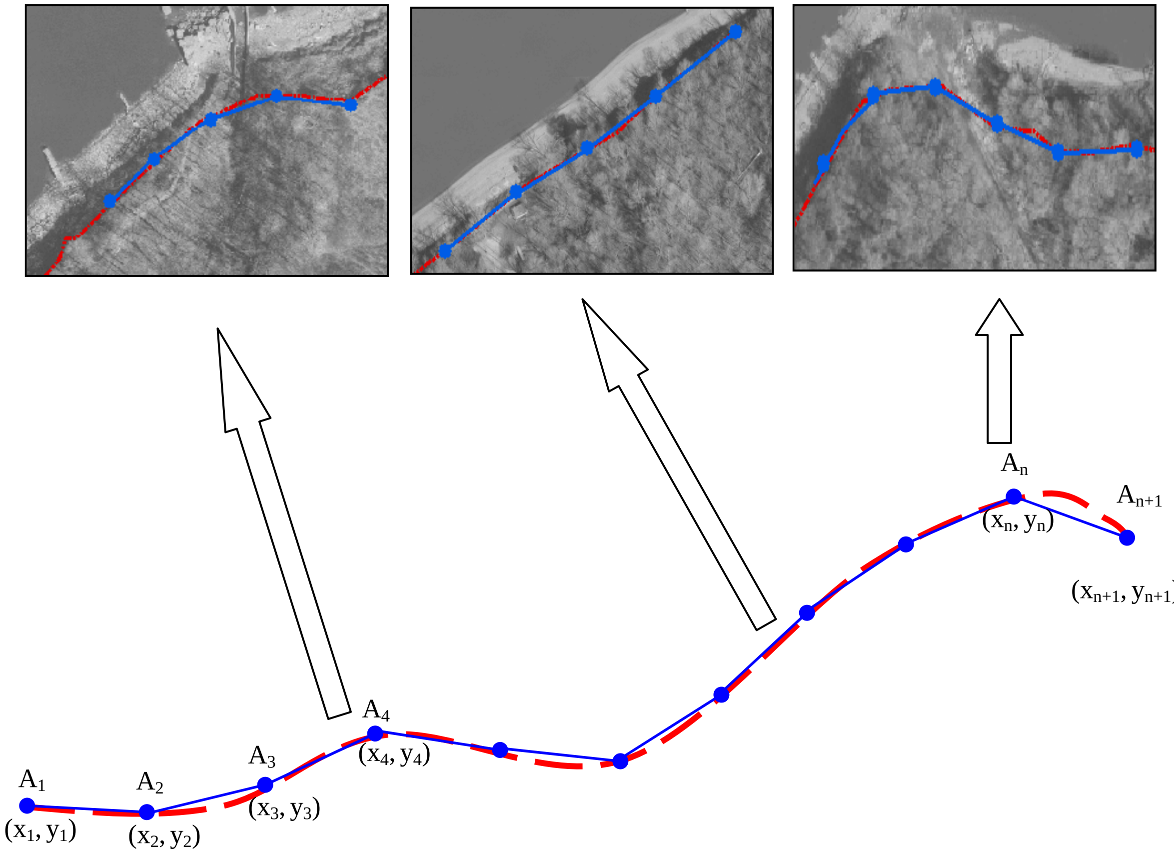

Figure 3.2 Linear approximation of the bluffline

According to this method each of the curves is normalized onto the interval of [0, 1] by considering their length equal to 1. These normalized curves are then divided into the same number of line segments. The end points of these line segments are normalized coordinates. The same division of each bluffline ensures that the line segments of a bluffline have the same constant length. The graphical representation for this procedure is shown in Figure 3.3, where the lengths of two blufflines A_1A_{n+1} (time $t = t_1$) and $A_1'A_{n+1}'$

(time $t = t_1 + t_2$) are normalized to 1 and equal-length line segments A_1A_2, $A_{p-1}A_p$, ..., A_nA_{n+1} and $A_1'A_2'$, $A_{p-1}'A_p'$, ..., $A_n'A_{n+1}'$ are created on both normalized bufflines.

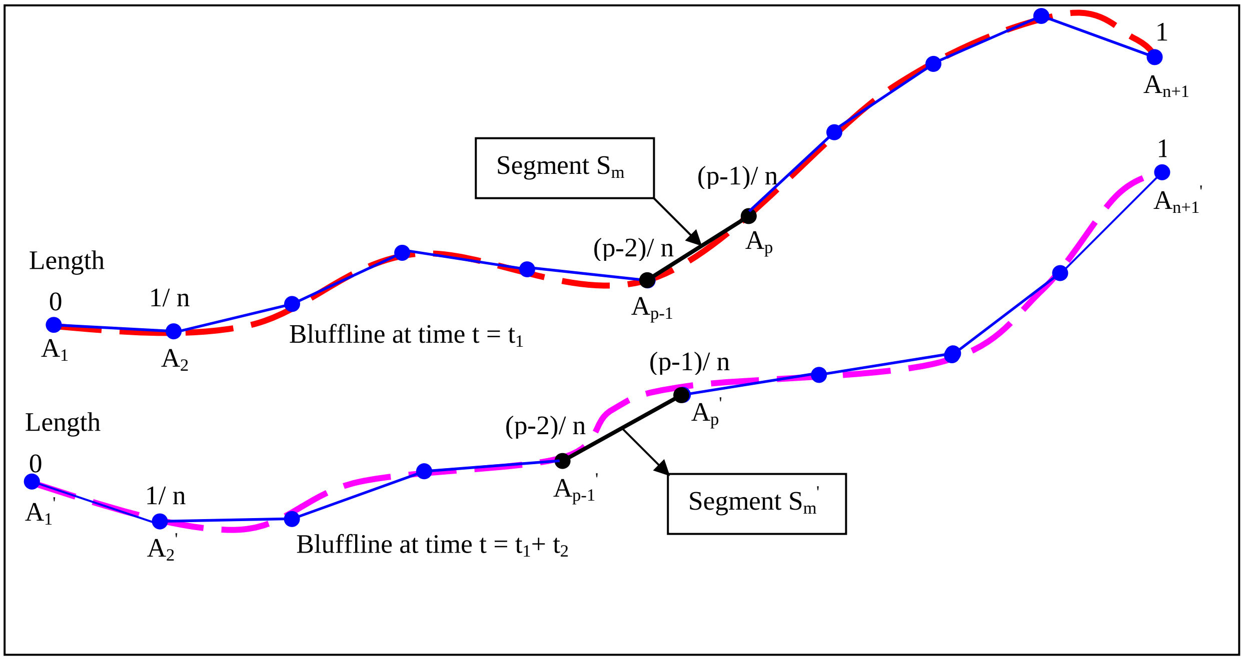

Figure 3.3 Concept of basic unit model in the analysis of buffline change

3.2.3 Basic unit model

The next step is to derive correspondences among bufflines. Setting up a correspondence between two bufflines is equivalent to deriving the correlation between every pair of divided line segments on both bufflines, for instance, A_1A_2 and A_1' A_2', or $A_{p-1}A_p$ and A_{p-1}' A_p'. Thus, the buffline change analysis is reduced to a problem of identifying parameters which are responsible for the change of the same line segment on different bufflines and establishing a method to predict the variability of these parameters in temporal dimension (Ali, 2003). For example, modeling the change of a pair of the line segments S_m and S_m' ($A_{p-1}A_p$ and $A_{p-1}'A_p'$) on different blufflines A_1A_{n+1} (time t $=t_1$) and $A_1'A_{n+1}'$ (time t $=t_1+t_2$) can be treated as a sub problem for the entire bluffline change analysis (Figure 3.3).

3.2.4 Transformation parameters of line segments

The transformation from one line segment to another line segment in a 2D plane can be done through translation, rotation and scale changes. In parametric form these three can be identified as translation (ΔT), rotation (ΔR) and scale change (ΔS) (Ali, 2003). In two-dimensional space, translation consists of only (Δx and Δy) change in the x direction and change in the y direction. This transformation is shown in Figure 3.4. Suppose that we want to transform a line segment $C_{(x3,\,y3)}D_{(x4,\,y4)}$ into another line segment $A_{(x1,y1)}B_{(x2,y2)}$ all we need to do is take four changes in the two axes x and y: $\Delta x_1 = (x_3 - x_1), \Delta x_2 = (x_4 - x_2)$ and $\Delta y_1 = (y_3 - y_1), \Delta y_2 = (y_4 - y_2)$ as is also illustrated in (Figure 3.4).

In general for any line transformation we need to consider all different parameters translation (ΔT) in x and y direction, rotation (ΔR) and scale change (ΔS). These unknown values similar to the above example can be determined from the coordinates of the end points of two corresponding line segments. Thus we need to obtain these end point coordinates for every pair of corresponding line segments (A_1, A_2,....., A_{p-1}, A_p, ..., A_n, A_{n+1} and similarly A_1', A_2',...., A_{p-1}', A_p', ..., A_n',A_{n+1}') from two different blufflines.

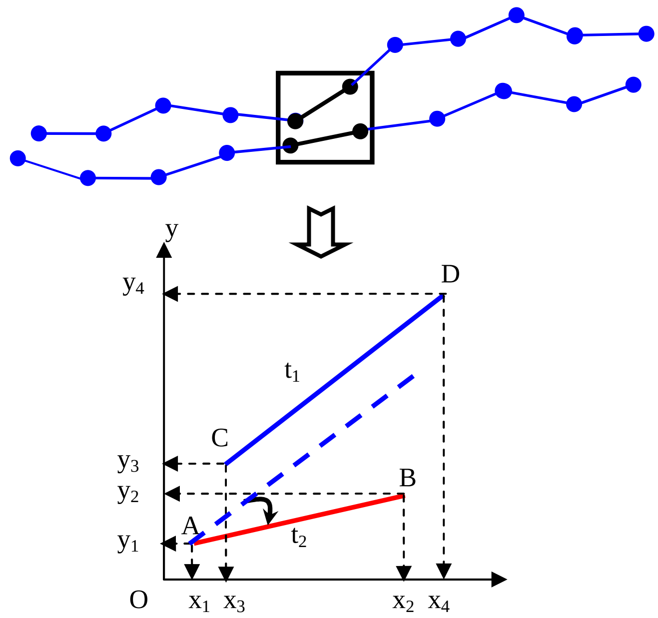

Figure 3.4 Transformation of one line segment to another line segment (Ali, 2003)

The correspondence is considered sequential so it is assumed that the first line segment of the first bluffline corresponds to the first line segment of the second bluffline and hence follows for all line segments in the two blufflines. For each of these corresponding line segments the parameters of transformation are obtained as follows.

$$\begin{bmatrix} x_1 \\ y_1 \\ x_2 \\ y_2 \end{bmatrix}_{t1} = (\Delta S)_{t1}^{t2} * (\Delta R)_{t1}^{t2} \begin{bmatrix} x_3 \\ y_3 \\ x_4 \\ y_4 \end{bmatrix}_{t2} + (\Delta T)_{t1}^{t2} \tag{3.1}$$

where $\Delta T = \begin{bmatrix} x_1 - x_3 \\ y_1 - y_3 \\ x_1 - x_3 \\ y_1 - y_3 \end{bmatrix}$, $\Delta R = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & \cos\theta & \sin\theta \\ 0 & 0 & -\sin\theta & \cos\theta \end{bmatrix}$ and $\Delta S = \left[\frac{Length(AB)}{Length(CD)} \right] = \left[\frac{\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}}{\sqrt{(x_3 - x_4)^2 + (y_3 - y_4)^2}} \right]$

3.2.5 A Least-Squares approach

Once the transformation parameters are found for every pair of corresponding line segments, change of these parameters needs to be studied in the temporal dimension. This analysis will allow us to predict the trend of these parameters. More pairs of blufflines will be helpful to obtain higher accuracy from the prediction model. For example, three historical blufflines (at time t_1, t_2, and t_3, where $t_3 > t_2 > t_1$) would make three different pairs of blufflines (t_1-t_2, t_2-t_3, t_3-t_1). For each identical line segment, therefore, three sets of transformation parameters can be derived. Based on these three sets of parameters, an analytical model can be set up to predict the future position of the line segment.

The continuity property of future blufflines should also be retained by the model. In this case, once the first point of a future bluffline is known, it will enable us to derive the Δx and Δy for the first segment of the future bluffline. Since every segment of the bluffline is connected, we can calculate the Δx and Δy for the remaining segments. Therefore, Δx and Δy are unnecessary to be modeled in transformation parameter analysis. Only two unknowns (rotation and scale change) need to be resolved in this model. To derive the position of future blufflines from available historical blufflines, a least-squares approach is used to determine rotation and scale change parameters.

In general, for m number of blufflines (at time t_1, t_2, t_3, …t_m) the calculation of rotation and scale change can be expressed as per the following polynomials.

$$\Delta\,\theta_{1-2} = a_1\,(t_2\text{-}t_1)^{k-2} + a_2\,(t_2\text{-}t_1)^{k-3} + a_3\,(t_2\text{-}t_1)^{k-4} + \ldots\ldots\ldots\ldots + a_{k-1}$$

$$\Delta\,\theta_{2-3} = a_1\,(t_3\text{-}t_2)^{k-2} + a_2\,(t_3\text{-}t_2)^{k-3} + a_3\,(t_3\text{-}t_2)^{k-4} + \ldots\ldots\ldots\ldots + a_{k-1}$$

. . . .

. . . .

where $k = m(m-1)/2$, is the total number of pairs that can be selected out of m blufflines. For a general interval of time ($t_p - t_q$), $\Delta\,\theta_{q-p}$ can be expressed as follows.

$$\Delta\,\theta_{q-p} = \sum_{i=1}^{k} a_{i-1}\,(t_q - t_p)^{k-i-1} \qquad (3.2)$$

Similarly, scale change modeling can be written by using the following polynomial.

$$\Delta\,S_{q-p} = \sum_{i=1}^{k} b_{i-1}\,(t_q - t_p)^{k-i-1} \qquad (3.3)$$

The number of unknowns (a_i, b_i) depends on the available number (m) of blufflines. The greater number of unknowns in these equations will increase the order of the polynomial and will increase the accuracy in determining the values of these unknowns. The chosen degree of polynomials shall affect the prediction results hence there must be some way to decide the degree of the polynomials. The issues related to the order of polynomials are not considered in this research due to lack of sufficient input datasets.

First, transformation parameters ($\Delta\,\theta_{q-p}$, ΔS_{q-p}) between all the available pairs of blufflines are calculated and then a numerical relationship between transformation parameters and time is established based on the above equations. The coefficients of the above polynomials can be calculated by using the least-squares approach as explained below. For calculation of a_i (for i=1 to k-1), equation (1) can be replaced by the following matrix form.

$$\begin{bmatrix} \Delta\theta_{1-2} \\ \Delta\theta_{2-3} \\ \ldots \\ \Delta\theta_{q-p} \\ \ldots \end{bmatrix} = \begin{bmatrix} (t_2 - t_1)^{k-2} & (t_2 - t_1)^{k-3} & \ldots & \ldots & 1 \\ (t_3 - t_2)^{k-2} & (t_3 - t_2)^{k-3} & \ldots & \ldots & 1 \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ (t_q - t_p)^{k-2} & (t_q - t_p)^{k-3} & \ldots & \ldots & 1 \\ \ldots & \ldots & \ldots & \ldots & \ldots \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ \ldots \\ a_{k-2} \\ a_{k-1} \end{bmatrix}$$

$$\begin{bmatrix} \Delta s_{1-2} \\ \Delta s_{2-3} \\ \ldots \\ \Delta s_{q-p} \\ \ldots \end{bmatrix} = \begin{bmatrix} (t_2 - t_1)^{k-2} & (t_2 - t_1)^{k-3} & \ldots & \ldots & 1 \\ (t_3 - t_2)^{k-2} & (t_3 - t_2)^{k-3} & \ldots & \ldots & 1 \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ (t_q - t_p)^{k-2} & (t_q - t_p)^{k-3} & \ldots & \ldots & 1 \\ \ldots & \ldots & \ldots & \ldots & \ldots \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \\ \ldots \\ b_{k-2} \\ b_{k-1} \end{bmatrix}$$

Which corresponds to $\quad Y_{k\times 1} \quad = \quad A_{k\times (k-1)} \quad X_{(k-1)\times 1}$ (3.4)

By least-squares method, the solution is $X = (A^tA)^{-1}A^tY$ which is obtained by minimizing the following function.

$$\sum_{i=1}^{k} \Delta\theta_i^{\,2} = (AX - Y)^t (AX - Y) \tag{3.5}$$

Similar calculations can be performed for scale change analysis. Now, in order to predict θ, ΔS for the future bluffline, we use equations (1) and (2) with known values of coefficients and time intervals (between the latest available bluffline and future bluffline). In the knowledge of Δx, Δy and estimated $\Delta\theta$, ΔS, the future bluffline can easily be derived.

3.3 Conclusion

The proposed model establishes the correspondence between shoreline based on shoreline-segment, which closely suits the nature of a shoreline as interface between land and water. The main assumptions in this model are a two-dimensional representation of the shoreline, use of bluff line as an indicator and incorporation of coastal erosion processes through the geometrical representation of the shoreline. This dynamic segmentation of shoreline provides a simpler and reliable tool to analyze the nature of its spatial dimension because of two main reasons.

a) The analysis over the approximated line segments can be carried out in a mathematical environment and hence provides a systematic direction for developing a numerical model for shoreline change analysis.

b) This arc length concept preserves the topological relationships between the parts of segmented shoreline which ensures the continuity of shoreline from the starting point to the end point.

CHAPTER 4

EXPERIMENTAL ANALYSIS OF THE MODEL

4.1 Study Area

The Great Lakes Basin is the world's single largest body of fresh water. This repository spans over 765,000 km^2 of area and its five lakes and connecting channels encompass over 20,000 km of the shoreline (Figure 4.1). Five lakes provide fresh water supply to the communities along its shore and area for recreational and sport-fishing facilities (Zuzek et al, 2003).

Lake Erie is the fourth largest lake of the five Great Lakes (Figure 4.2). The Ohio Geological Survey estimates that more than 3,200 acres of Ohio's Lake Erie shore have been lost to erosion since the 1870s, resulting in economic losses exceeding tens of millions of dollars per year (Ohio Geological Survey, 1993). Due to these factors it has become an important area of research to save these losses. To study various factors involved in shoreline erosion on Lake Erie an area of study is chosen at Painesville, Ohio, a fifteen-kilometer coastal region along the southern coast of Lake Erie. The shoreline under study spans over approximately 2.5 km in length (Figure 4.3). The reasons for choosing this area on Lake Erie are mainly two:

1) The availability of the historical blufflines in this region provides appropriate information for the analysis (The bluffline, a shoreline indicator, is used in this entire experiment).

2) The Division of Geological Survey in the Ohio Department Natural Resources (ODNR) considers this an important area of study as this region is highly vulnerable due to severe coastal changes (Zuzek, 2003).

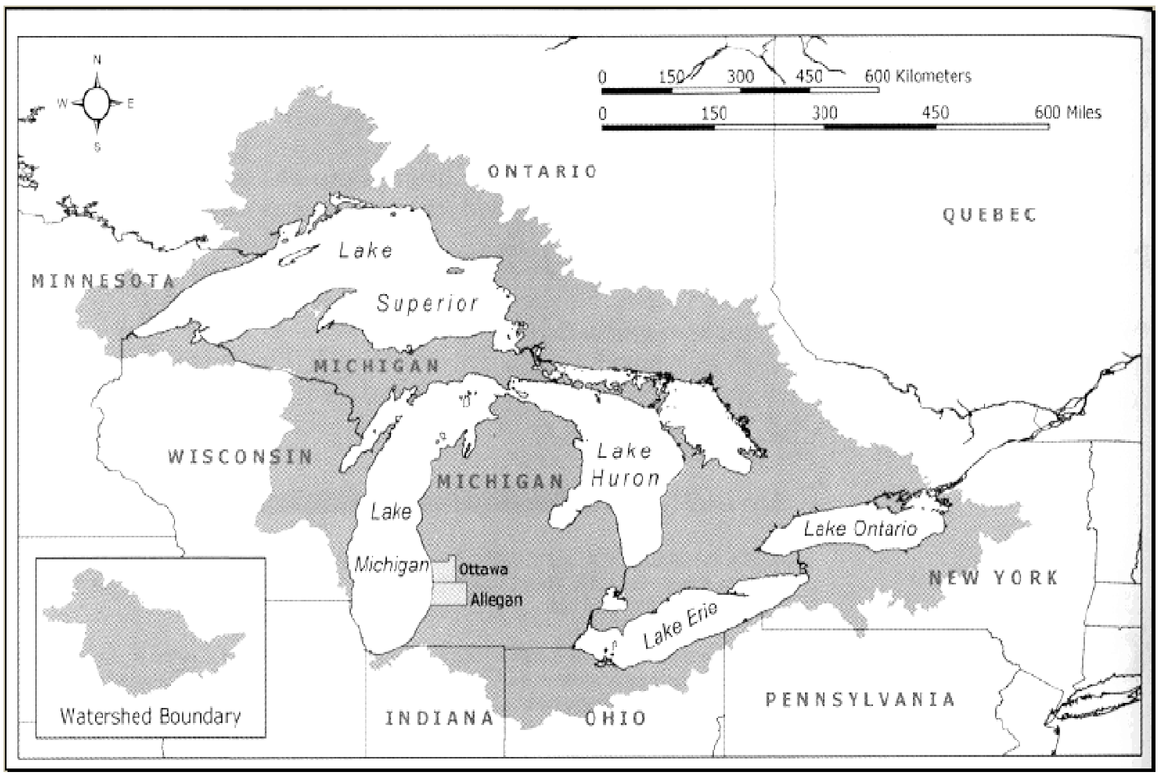

Figure 4.1 Great Lakes and their watershed boundaries (Zuzek et al, 2003)

4.2 Historical bluffline data compilation

Coastal scientists in universities and government agencies have been quantifying rates of shoreline movement and studying coastal change for decades. Ideally, extraction of shoreline position from the data sources involves geo-referencing and removing distortions from maps or aerial photographs, followed by digitizing shoreline position. Currently, historic data provides us with the ability to access the future changes in the shape of the shoreline by allowing historic snapshots of the shoreline.

Depending on coastal location, data source, and scientific preference, different proxies for shoreline position are used to document coastal change, including the high water line wet-dry line, vegetation line, dune toe or crest, toe of the beach, cliff base or top, and the line of mean high water (MHWL). In this research blufflines are used for indicating the shoreline position. Historic blufflines of the years 1973, 1990, 1994, and 2000 are collected as data for analysis. The addition of more historical data can further improve the accuracy and reliability of the prediction model. For this future bluffline prediction analysis the blufflines of years 1973 and 1990 were digitized from the Lake Erie Coastal Erosion Area maps, Ohio Coastal Management Program published by the Lake Erie Geology Group of the Division of Geological Survey at the Ohio Department of Natural Resources in 1997. A systematic mapping approach was used in deriving the shoreline from these maps. The maps used for the years 1973, 1990 were in the paper format (Figure 2.2) and required to be converted in the digital format.

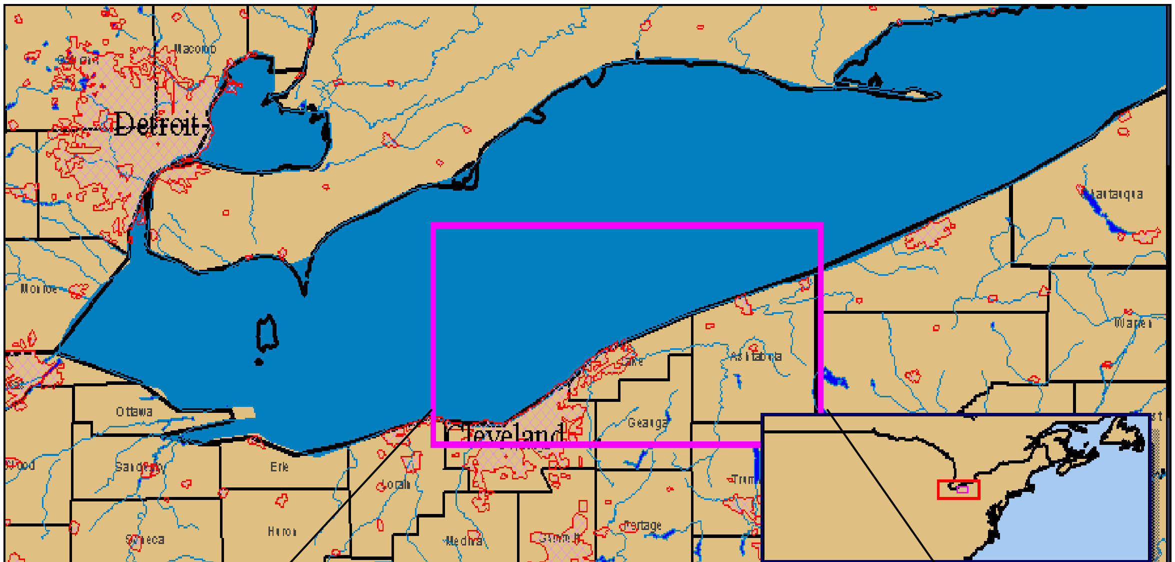

Figure 4.2 Study area location on the Lake Erie

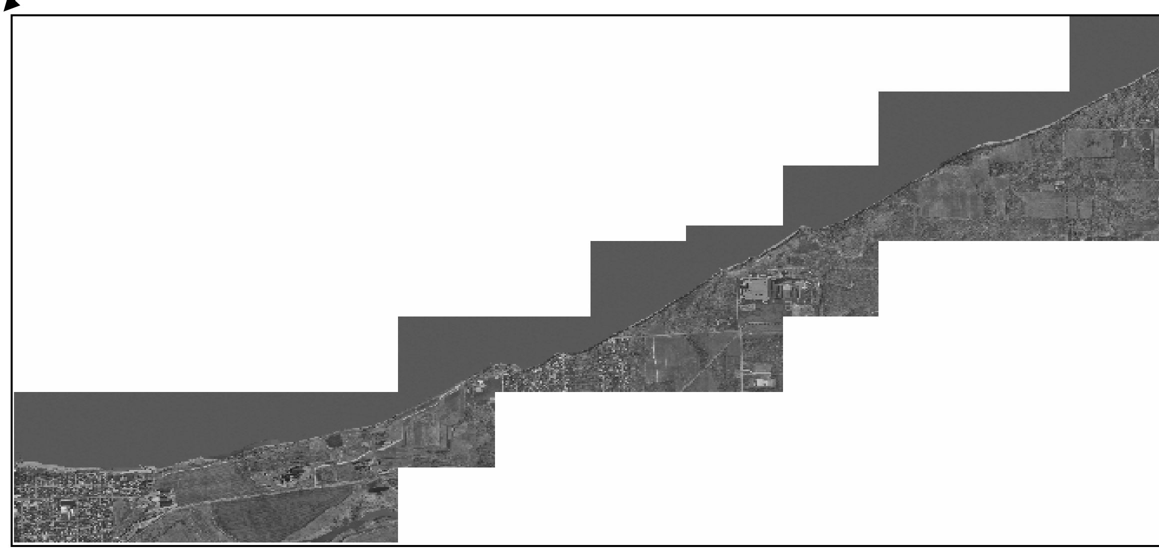

Figure 4.3 Study area

The bluffline of 1994 was interpreted from United State Geological Survey (USGS) DOQQ (taken in 1994) downloaded from the website (ftp://ftp.geodata.gis.state.oh.us) of Ohio Geographically Referenced Information Program (OGRIP) (Table 4.1). The bluffline of year 2000 was also derived from the orthophotos of the same year provided by the Lake County GIS Department. Figure 4.5 shows how this data for different years 1973, 1990, 1994 and 2000 was generated to carry out this analysis.

All these bluffline datasets were projected into the same horizontal coordinate system: State Plane, Ohio North - NAD 1983. In the analysis first the bluffline of year 2000 is predicted using least square prediction model and data from spatial dimensions of the shorelines in the year 1973, 1990 and 1994. This predicted value is then compared with the actual shoreline data collected for the year 2000 to perform error analysis of the prediction model and evaluate the accuracy of the model.

Year	Source
1973	Digitized from the Georeferenced Scanned Coastal Erosion Area Maps for Lake County by Ohio Division of Natural Resources, Division of Geological Survey, Lake Erie Geology Group, 1997.
1990	Digitized from the Georeferenced Scanned Coastal Erosion Area Maps for Lake County by Ohio Division of Natural Resources, Division of Geological Survey, Lake Erie Geology Group, 1997.
1994	Digitized from the DOQQ obtained from the OGRIP Website. Online Linkage: ftp://ftp.geodata.gis.state.oh.us/geodata/doqq/data/cleveland_north/cl114se3401.zip ftp://ftp.geodata.gis.state.oh.us/geodata/doqq/data/cleveland_north/cl115sw3401.zip ftp://ftp.geodata.gis.state.oh.us/geodata/doqq/data/cleveland_north/cl115se3401.zip

Table 4.1 Input datasets for the experiment and their sources

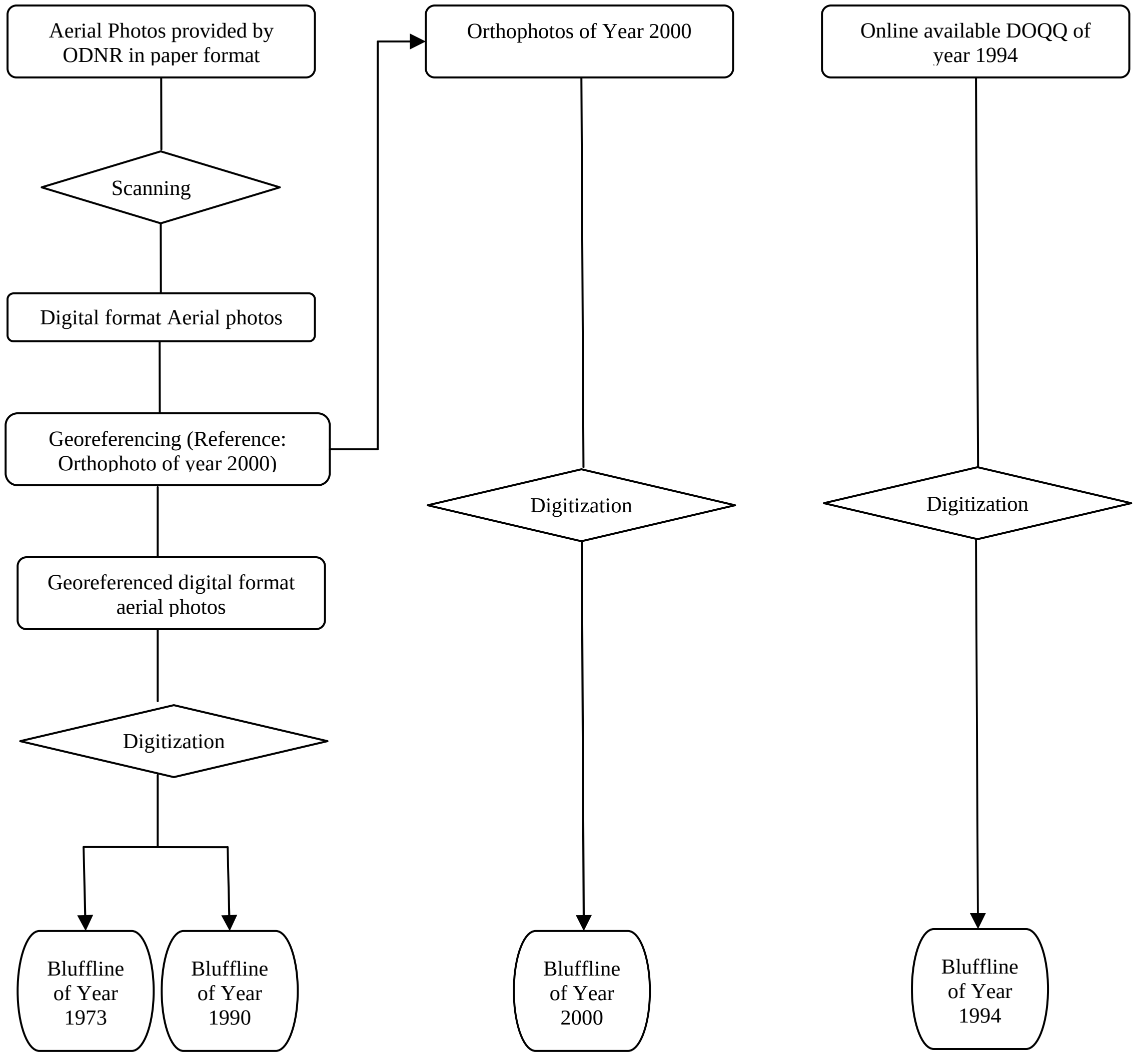

Figure 4.4 Flow chart of dataset collection of various years of shorelines

4.3 Experiment using the least-squares method

As mentioned before for prediction three pairs of blufflines for each year (1973, 1990 and 1994) were obtained through procedure shown in Figure 4.4. The scale and rotation parameters were then calculated between each of the pairs using the procedure described in the previous sections. Δx and Δy for each line segment was determined using the initial locations of the blufflines based on the continuous property of blufflines.

In order to determine the trends of scale and rotation for future use, their dependencies over time was predicted by setting up a polynomial (Equation 3.3 and 3.4). Although coastal erosion processes are nonlinear in nature as described in chapter 1 yet for this bluffline modeling experimental analysis the first order polynomial is used to derive the relationship of scale and rotation changing in time. The reason behind this limitation is the availability of only three years of blufflines. Ideally, the order of polynomials must reflect the nonlinearity of the process with some limitation on the highest power of the polynomial. The coefficients of this polynomial (a_1, a_2 and b_1, b_2) are solved using the least-squares method on the calculated values of the rotation and scale parameters for each pair of bluff-lines.

$$\Delta\theta = a_1 \Delta t + a_2 \text{ and } \Delta S = b_1 \Delta t + b_2 \tag{4.1}$$

$$\begin{bmatrix} \theta_{73-90} \\ \theta_{73-94} \\ \theta_{90-94} \end{bmatrix} = \begin{bmatrix} (1990-1973) & 1 \\ (1994-1973) & 1 \\ (1994-1990) & 1 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} \text{ and } \begin{bmatrix} S_{73-90} \\ S_{73-94} \\ S_{90-94} \end{bmatrix} = \begin{bmatrix} (1990-1973) & 1 \\ (1994-1973) & 1 \\ (1994-1990) & 1 \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \end{bmatrix}$$

Looking at the above matrices and comparing it with the general form of observation equation (Y = AX) the least- squares method will provide the solutions for the coefficients a_1, a_2 and b_1, b_2 as follows.

$$\begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = [(A^t A)^{-1} A^t] \begin{bmatrix} \theta_{73-90} \\ \theta_{73-94} \\ \theta_{90-94} \end{bmatrix} \text{ and } \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} = [(A^t A)^{-1} A^t] \begin{bmatrix} S_{73-90} \\ S_{73-94} \\ S_{90-94} \end{bmatrix}$$

where, $A = \begin{bmatrix} 17 & 1 \\ 21 & 1 \\ 4 & 1 \end{bmatrix}$

After determining these coefficients, substituting for the time difference (Δt =2000-1994) between the unknown bluffline (of year 2000) and latest known bluffline (of year 1994) into equation 4.1 we can calculate the rotation and scale change for every line segment of the bluffline of year 2000 from the latest available bluffline (of year 1994). Once the values of Δx and Δy for the first line segment are determined, the position of the bluffline of year 2000 can be derived.

CHAPTER 5

RESULTS AND ERROR ANALYSIS

5.1 Results

The end results of the least-squares model are the predicted bluffline for the years 2000, 2010 and 2020 for Painesville region of the Lake Erie. This least-square model can be used to predict the bluffline position for any given year under study. The presented experiment of the model in the study area seems to produce good results for the duration of 20 years. All data, including ones generated for this research and presented in this report, are being placed in a web-based Geographic Information System (ArcIMS) discussed later in chapter 6. Figure 5.1 shows some of the snapshots of the results derived by the least-squares model. In study area, bluffline is continuously moving landward due to coastal erosion. Proposed least-squares model is unable to incorporate the structural (done for protection) information and hence blufflines for the structurally protected region of the study area, marked in red, are not predicted in that region.

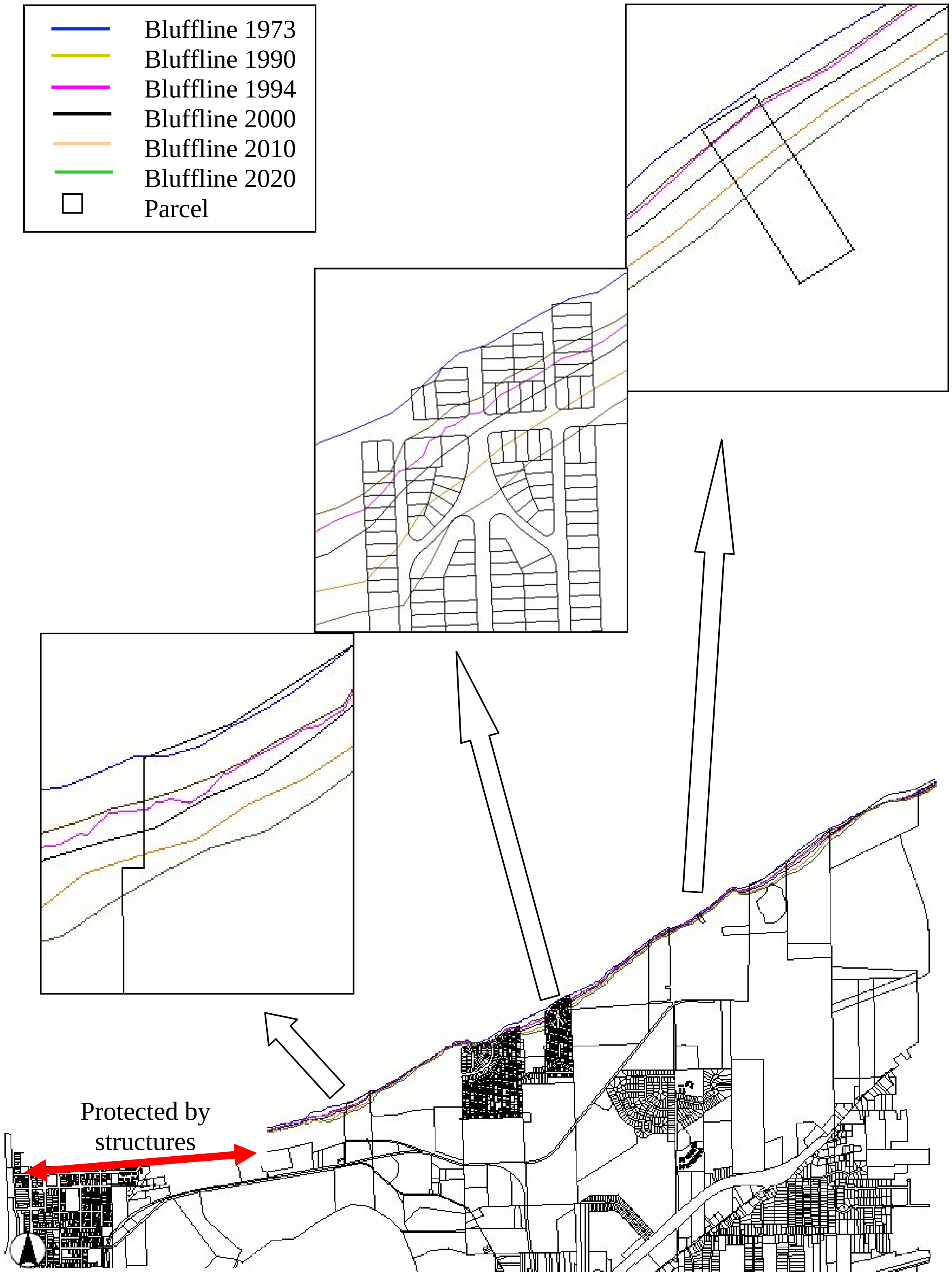

Figure 5.1 Results of least-squares predicted model

5.2 Error Analysis

The evaluation of the least-squares predicted bluffline of year 2000 is done by comparing it to the orthophoto-digitized bluffline of year 2000. This reference bluffline of year 2000 is digitized by visual inspection of the orthophoto. Moreover, erosion-rate based bluffline for year 2000 is derived by using the erosion rates mentioned in the book published by the geological section of the ODNR. These erosion rates of the points on the study area bluffline are the annual rates calculated along transects described in the figure 4.4. These rates (mm/year) are the linear function of the time measured in years. Both, the least-squares predicted bluffline of 2000 and bluffline calculated based on the erosion rates are compared with reference to the orthophoto digitized bluffline of 2000. The idea behind these two sets of comparisons is to present the error analysis between the bluffline based on the traditional method of erosion rate and the predicted bluffline from the least-squares model (Figure 5.2).

The importance of accuracy analysis for any model can not be underestimated. Keeping this in mind, special efforts have been made for the accuracy analysis of the developed least-squares model. The main concern was to choose the methods which could compare the two linear datasets after having the desired datasets.

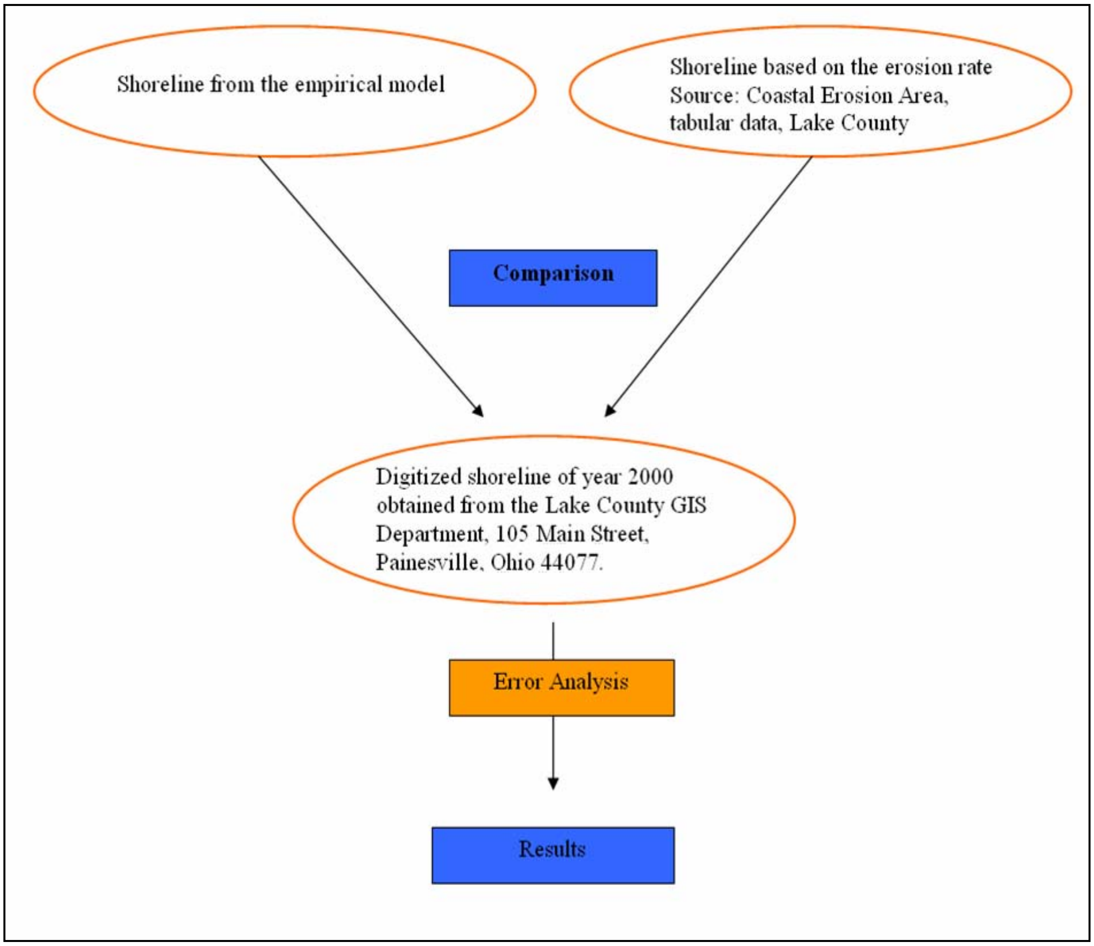

Figure 5.2 Error analysis flow chart for the bluffline of year 2000

In spatial data quality, the comparison of the two-point datasets for the positional quality information is fully defined but the estimation for the positional quality of any linear dataset with respect to the reference dataset is still a topic of ongoing research. The extensive accuracy analysis of the least-squares model comprises of following two methods

1. Error analysis using transect

2. Error analysis using quality metrics (Ali, 2003)

5.2.1 Error analysis using transects

In this first method, a finite number of transects are digitized from the coastal area erosion maps produced by the Division of Geological Survey of ODNR (Figure 5.3). Along these digitized transects, intersection points of transects and blufflines represent the bluffline movement. Once distances (movements of points from reference bluffline to erosion based and least-squares model-based blufflines) are measured, the average errors are derived by dividing the sum of those distances by the number of transects (Appendix A). This approach approximately estimates the accuracy of the predicted bluffline and erosion-rate- based bluffline as compared to the digitized bluffline. The accuracy of this comparison method depends upon the number of transects taken into consideration. A denser network of transects will ensure a more exhaustive comparison between the blufflines. The results show comparable values of average and same minimum errors between the two datasets along transects (Table 5.1).

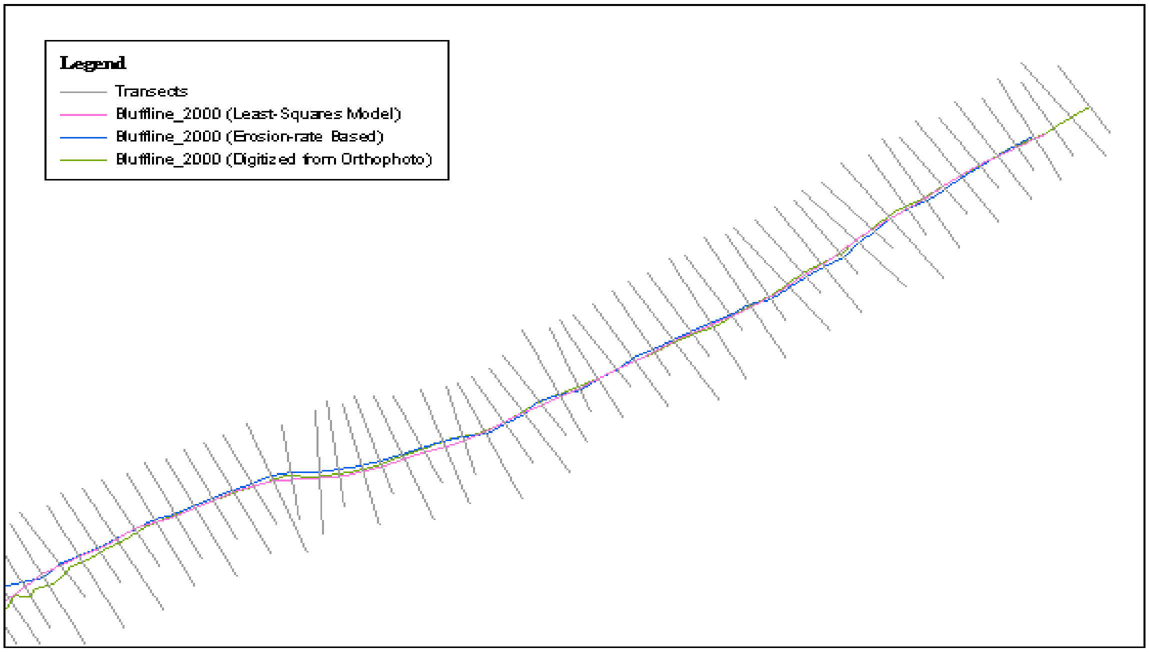

Figure 5.3 Error analysis using transects

However, while comparing the maximum errors for two datasets we find that the bluffline predicted by the least- squares model is more accurate in comparison to the traditional erosion rate based bluffline with reference to the digitized bluffline from the orthophoto. The detailed analysis and explanation for the errors are discussed in rest of this chapter.

Bluffline pairs	**Average error**	**Maximum error**	**Minimum error**
Least-Squares Predicted vs. orthophoto digitized	4.99 m	23.86 m	0.00 m
Erosion rate- based vs. orthophoto digitized	4.94 m	40.54 m	0.00 m

Table 5.1 Error analysis results from transects method

An overview map of the blufflines obtained from least-squares model, erosion-based model and orthophoto digitization is presented in Figure 5.1. This model may be very useful to disseminate coastal geospatial data and coastal erosion information to end users including coastal residents in erosion areas and to assist them in making their decisions such as property protection measures, property purchasing/selling, and small community planning activities. For the study area the proposed model is applied using the linear behavior of the 'change in transformation parameters (rotation change and scale change)' with respect to the time. This linear relationship of these parameters with time can lead to some error if we are dealing with the curvature part of the bluffline. If more number of blufflines pairs (more than 3) is available in any region then this model can be tested for better accuracy by using the higher order polynomials. The second issue arises for the west-most part of the bluffline where the bluffline is protected by man-made structures. Implementation of the least-squares model in its simplest (methodology presented in Chapter 3) form does not involve any criterion for the analysis of such region. The bluffline change in the protected region would behave differently than the other part of the bluffline. In such regions, bluffline would retaliate in lesser amount due to the protection structures. Moreover, errors in digitization of the bluffline from the orthophoto and aerial photos can be major source of error in the prediction model. For detailed analysis of the study area the region is further subdivided in four consecutive regions- A, B, C and D (Figure 5.4). The analysis over subdivided regions shall allow observations on bluffline changes in different regions based on their different curvatures and characteristics.

Figure 5.4 Overview map

Part ‘A’ of the bluffline starts with the co-ordinates of 2330910.03 Easting and 777109.89 Northing and ends at the co-ordinates of 2323671.59 Easting and 772666.65 Northing (Figure 5.6). Over this region total 86 transects were obtained through digitization of the coastal erosion area maps (T1- T86, Appendix A). The statistics of average error analysis along the transects shows that the least-squares predicted bluffline has better accuracy (17.32 meter) than the erosion-rate based bluffline (25.82 meters) (Table 5.2). The maximum errors also strengths the fact that bluffline of year 2000, derived by the least-squares model, has the better accuracy with reference to the orthophoto-digitized bluffline of year 2000.

Bluffline pairs	**Average error**	**Maximum error**	**Minimum error**
Least-Squares Predicted vs. orthophoto digitized	17.32 m	73.54 m	0.00 m
Erosion rate- based vs. orthophoto digitized	25.82 m	133.01 m	0.00 m

Table 5.2 Error analysis results for section ‘A’ from transects method

Figure 5.6 shows the error analysis in graphical view for both the model for each transects in section ‘A’. Graphical analysis enables us to understand the error behavior of both the models along each transects. The errors in erosion-rate based bluffline are more almost along each transects (Figure 5.6). The error-prone zone in this section is shown in the green ellipse and has been magnified for greater detail (Figure 5.5). The error along each transects of this region has been tabulated in Table 5.3.

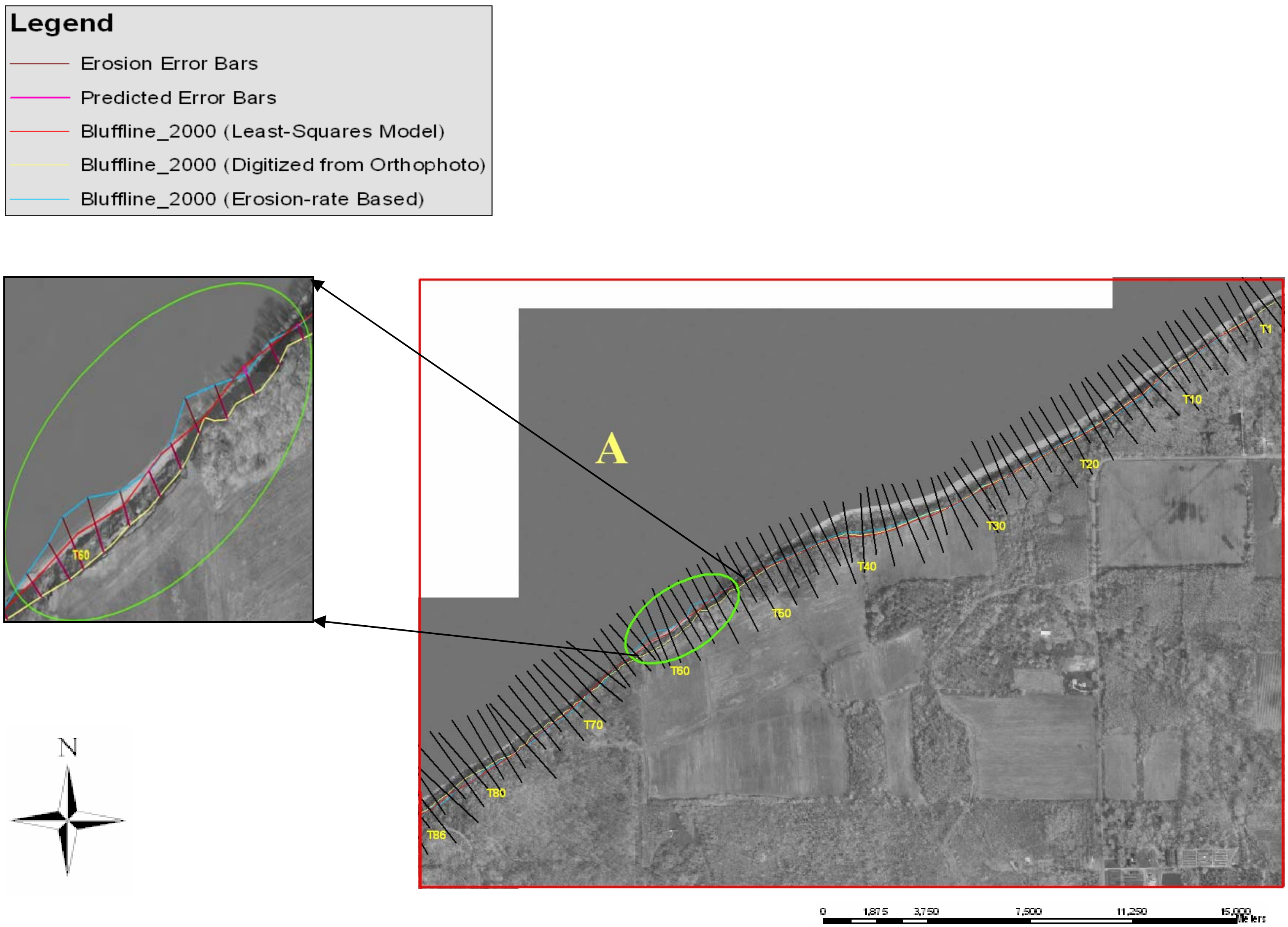

Figure 5.5 Subdivided study area ‘A’

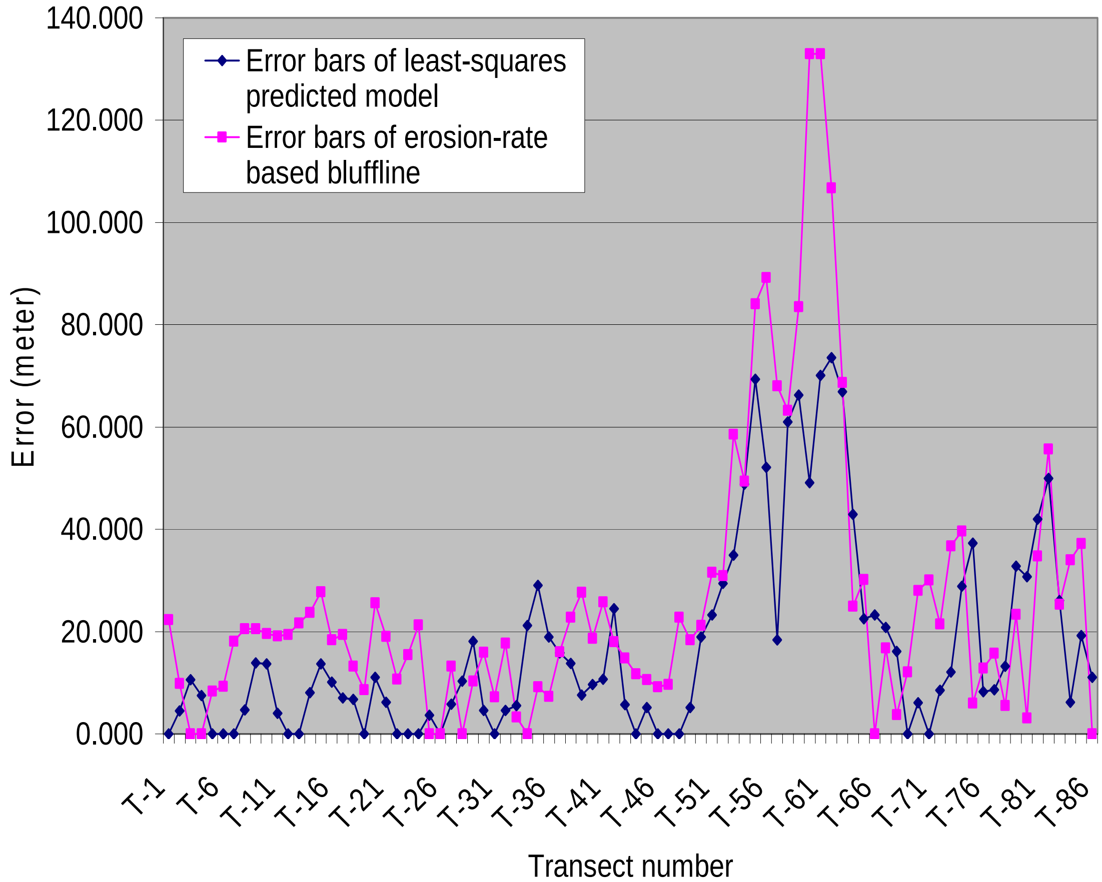

Figure 5.6 Error analysis along each transects in section ‘A’ of the study area

In the error prone region the bluffline predicted by the least-square model is more seaward with respect to the bluffline digitized by the orthophoto. The cause of this unexpected result in the error-prone area of this region could be the mapping errors such as in digitization, involved in depicting the historical blufflines in the area. Maximum errors, marked in red, for the blufflines predicted by both the models lie in the error prone region (Table 5.3).

Transect Number	Error measurements of least-squares predicted model (meter)	Error measurements of erosion-rate based bluffline (meter)
T-52	29.42	30.92
T-53	34.95	58.57
T-54	48.79	49.37
T-55	69.38	84.02
T-56	52.10	89.17
T-57	18.36	68.01
T-58	61.01	63.24
T-59	66.26	83.45
T-60	49.07	133.01
T-61	70.08	132.97
T-62	73.54	106.76

Table 5.3 Error measurements along each transects in error prone region of section ‘A’

Part ‘B’ of the bluffline starts with the co-ordinate of 2323671.59 Easting and 772666.65 Northing and ends at the co-ordinates of 2316447.29 Easting and 768182.15 Northing (Figure 5.7). This region has 88 transects in total (T87-T174, Appendix A). The average, maximum and minimum errors in this region are shown in Table 5.4. These error analysis results show that the least-squares predicted bluffline has better accuracy (17.32 meter) than the erosion-rate based bluffline (25.82 meters) in terms of average error calculation (Table 5.4). Maximum error for the erosion based bluffline is found in error prone region ‘B2’ while that of least-squares predicted model lie in error prone region ‘B1’ (Figure 5.7). This is justified because of curvature natures of the region ‘B1’ which could not be considered in the least- squares model. The error-prone zones are shown by green ellipses and have been magnified for greater detail (Figure 5.7). Graphical view of errors and error measurements along each transects in Table 5.5 and Table 5.6 also supports these regions.

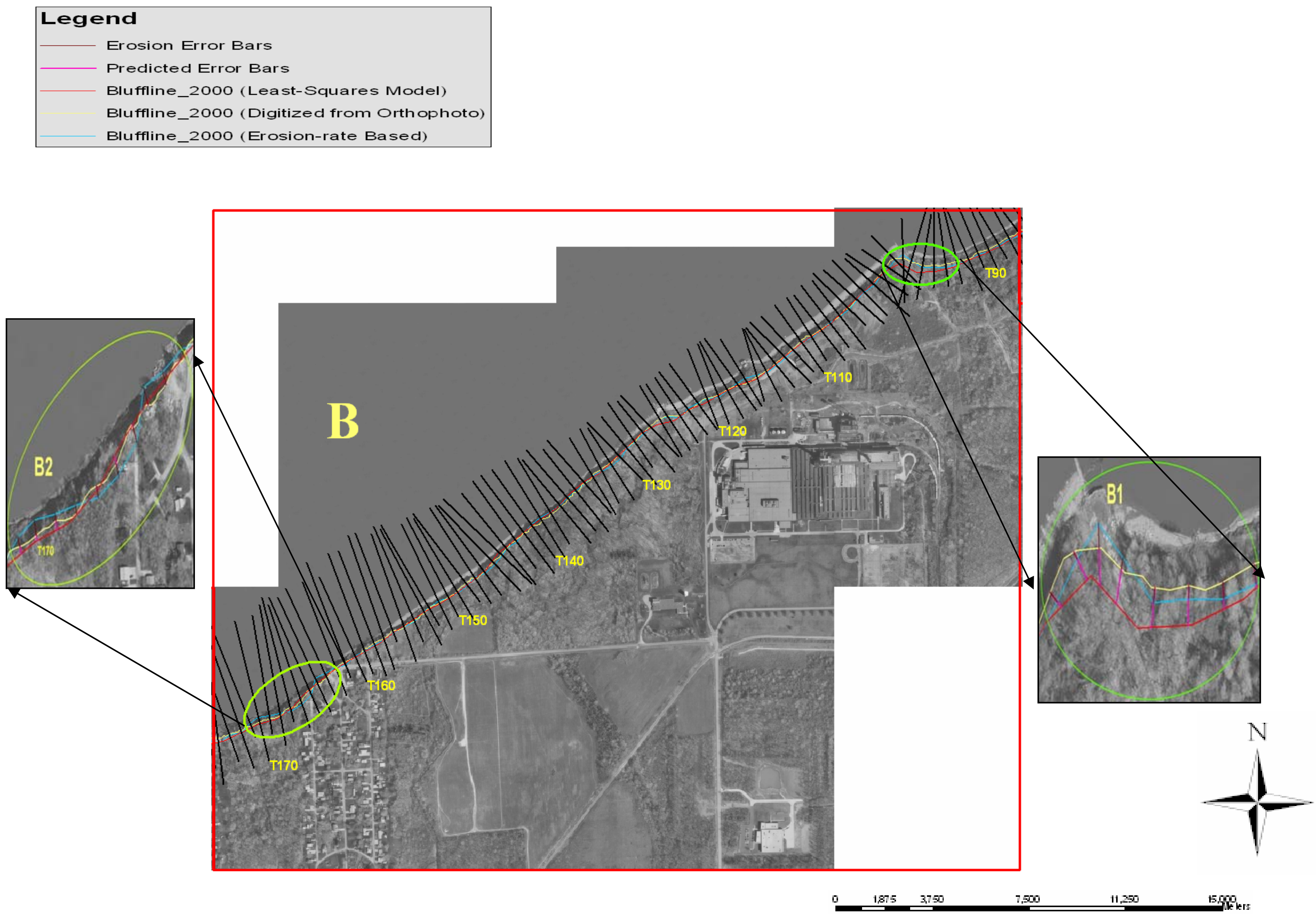

Figure 5.7 Subdivided study area ‘B’

Bluffline pairs	Average error	Maximum error	Minimum error
Least-Squares Predicted vs. orthophoto digitized	15.18 m	59.44 m	0.00 m
Erosion rate- based vs. orthophoto digitized	17.51 m	51.47 m	0.00 m

Table 5.4 Error analysis results for section 'B' from transects method

In region 'B1' the bluffline predicted by the least-square model is more landward with respect to the bluffline digitized by the orthophoto. The cause of this unexpected result in the error-prone area of this region could be the use of the linear polynomial equation in the least-squares changes. As it can be observed from Figure 5.7 the error-prone area 'B1' lies in the region of sudden curvature change and due to limitation on the available number of datasets the model is unable to incorporate the curvature behavior of the bluffline. Error zone 'B2' in this section is error prone zone for the erosion-rate-based bluffline. In this region least-squares predicted bluffline shows considerably better results (Table 5.6).

Transect Number	Error measurements of least-squares predicted model (meter)	Error measurements of erosion-rate based bluffline (meter)
T-90	10.12	37.60
T-91	59.44	14.718
T-92	57.99	15.61
T-93	36.08	18.03
T-94	56.08	30.44
T-95	40.46	20.25
T-96	40.41	25.77
T-97	60.82	26.07
T-98	61.06	23.16

Table 5.5 Error measurements along each transects in error prone region 'B1'

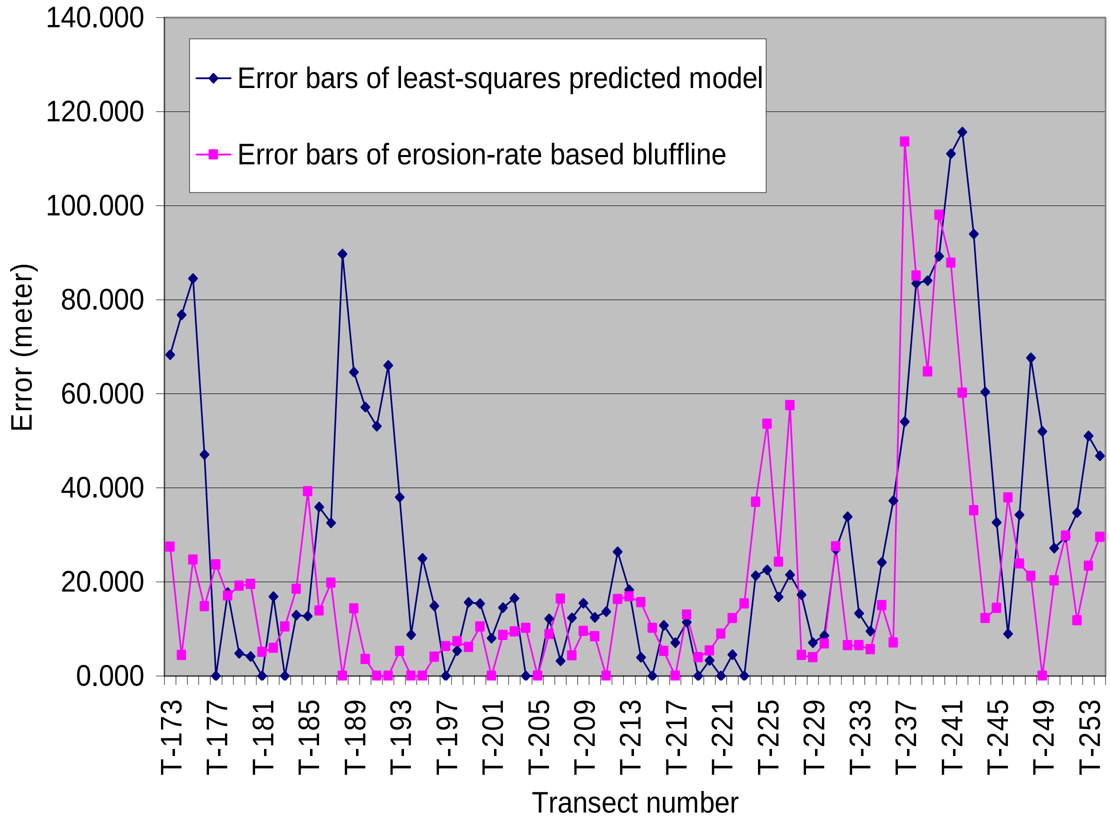

Figure 5.8 Error analysis along each transects in section 'B' of the study area

Transect Number	Error measurements of least-squares predicted model (meter)	Error measurements of erosion-rate based bluffline (meter)
T-161	13.92	36.40
T-162	8.67	50.33
T-163	7.95	42.47
T-164	21.72	30.12
T-165	11.76	31.23
T-166	0.00	22.11
T-167	24.89	15.95
T-168	14.13	40.81
T-169	19.17	26.87
T-170	25.11	23.94
T-171	36.81	0.00
T-172	41.89	51.47

Table 5.6 Error measurements along each transects in error prone region 'B2'

The starting co-ordinates of Part 'C' of the bluffline are 2316447.29 Easting and 768182.15 Northing and ending co-ordinates are 2309114.67 Easting and 765162.65 Northing (Figure 5.8). Over this region total 81 transects were obtained through digitization of the coastal erosion area maps (T175-T256, Appendix A). In this region, the average and maximum errors are greater for the least-square predicted model which implies the lesser accuracy of the least-square model in comparison to erosion-based model (Table 5.7). The reason behind this lesser accuracy could be the presence of two curve regions in this section – region C1 and C2 (Figure 5.8).

Bluffline pairs	Average error	Maximum error	Minimum error
Least-Squares Predicted vs. orthophoto digitized	19.25 m	115.62 m	0.00 m
Erosion rate- based vs. orthophoto digitized	18.85 m	113.62 m	0.00 m

Table 5.7 Error analysis results for section 'C' from transects method

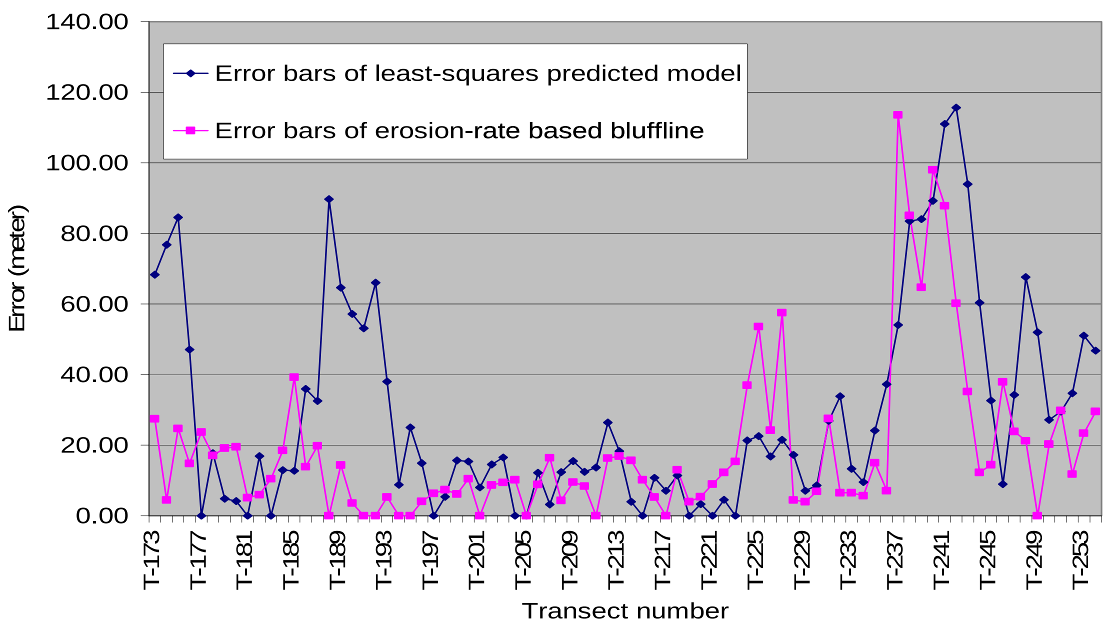

Figure 5.9 Error analysis along each transects in section 'C' of the study area

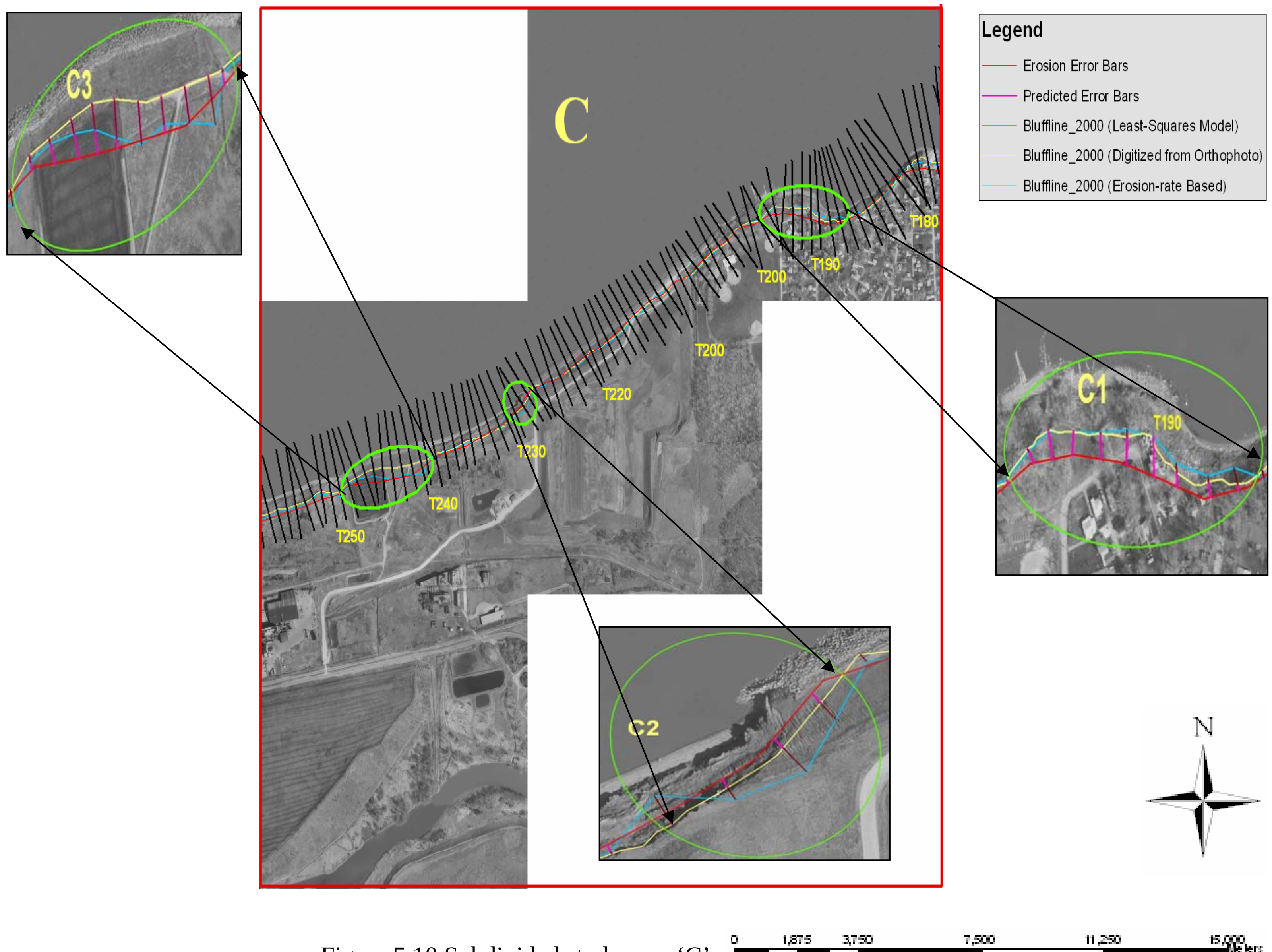

Figure 5.10 Subdivided study area ‘C’

In this section ‘C’ three error-prone areas are identified (Figure 5.8). In region C1 the bluffline predicted by the least-squares model is more landward with respect to the orthophoto-digitized bluffline. For this error prone region, sudden curvature change of the bluffline adversely affects the results (Table 5.8).

Transect Number	Error measurements of least-squares predicted model (meter)	Error measurements of erosion-rate based bluffline (meter)
T-189	64.63	14.31
T-190	57.15	3.63
T-191	53.13	0.00
T-192	66.03	0.00
T-193	38.02	5.25
T-194	8.75	0.00
T-195	24.97	0.00

Table 5.8 Error measurements along each transects in error prone region ‘C1’

Error prone region ‘C2’ mainly shows the poor results of the erosion-based shoreline. In this region results for the least-squares predicted bluffline approximately match with the average error of the region (19.25 m).

Transect Number	Error measurements of least-squares predicted model (meter)	Error measurements of erosion-rate based bluffline (meter)
T-224	21.30	37.00
T-225	22.57	53.59
T-226	16.83	24.21
T-227	21.53	57.59

Table 5.9 Error measurements along each transects in error prone region ‘C2’

The west-most part of the bluffline (error-prone area C3) could be analyzed as the unexpected result due mapping errors involved in digitization the historical blufflines in the area. The maximum error of this section for both the blufflines are observed in this region. Table 5.10 shows the error measurements for blufflines of the models along each transects in this region with maximum errors marked in red.

Transect Number	Error measurements of least-squares predicted model (meter)	Error measurements of erosion-rate based bluffline (meter)
T-236	37.24	7.04
T-237	54.05	113.62
T-238	83.50	85.08
T-239	84.01	64.73
T-240	89.25	98.02
T-241	111.04	87.80
T-242	115.62	60.15
T-243	94.00	35.21
T-244	60.38	12.31
T-245	32.69	14.45

Table 5.10 Error measurements along each transects in error prone region 'C3'

The rest of the part of the region (region D) is identified protected region (Figure 5.9). This region is protected by the structures. The bluffline for this region is not predicted by the least-squares model because of the fact that the proposed methodology does not carry any information regarding the structures. In the presence of structures the bluffline would certainly retaliate in lesser amount than in its normal condition. Differentiating between natural rates of erosion and the influences of beach nourishment is difficult because experiments have not been conducted to specifically address this issue. In addition, available data may be inadequate to address this issue because there are not enough shoreline positions immediately before, after, and between nourishment projects.

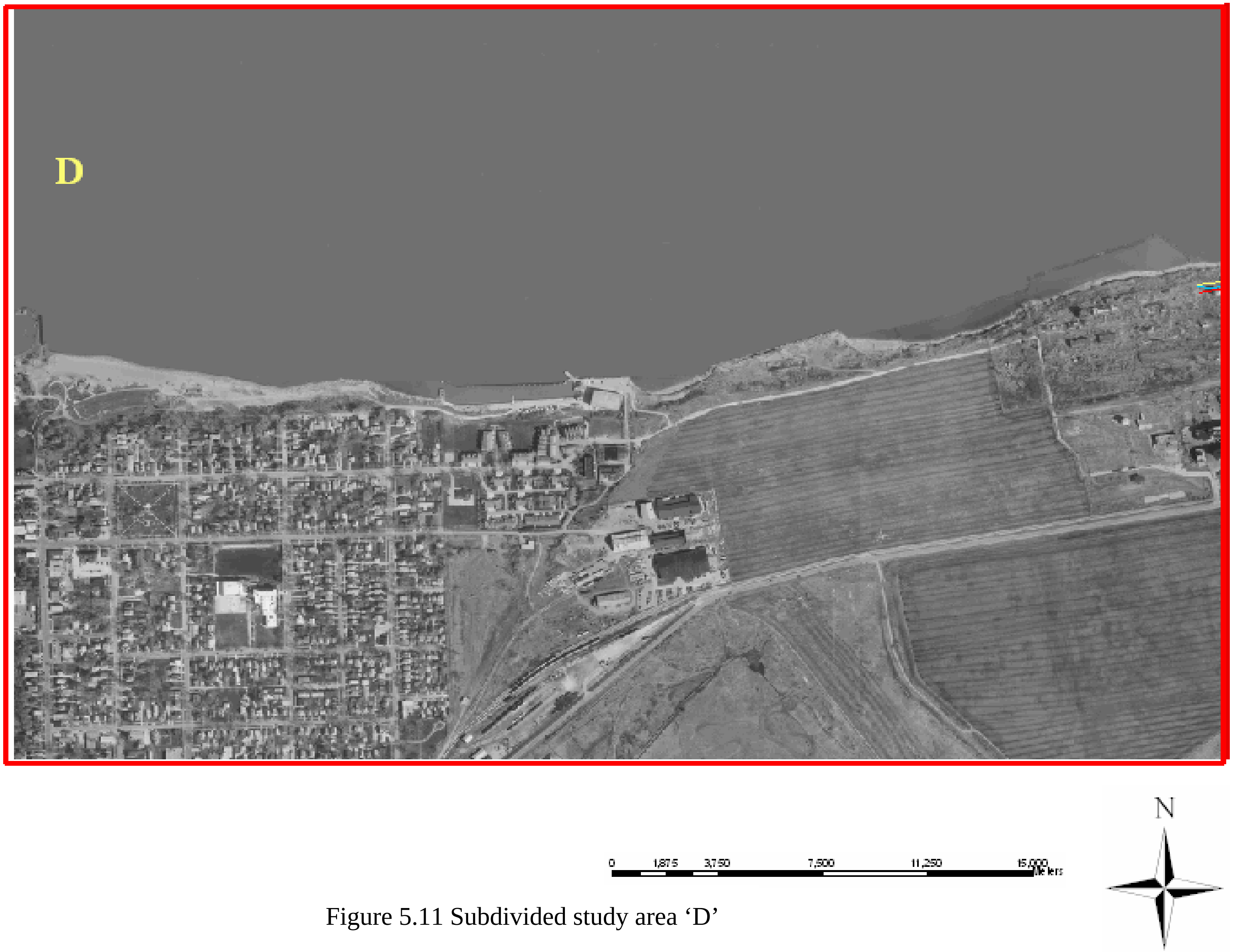

Figure 5.11 Subdivided study area ‘D’

5.2.2 Error analysis using quality metrics

The second error analysis approach is based on the metrics developed by Ramirez (2000) for the positional quality assessment of the linear features. He developed four quality metrics (distortion factor, generalization factor, bias factor, and fuzziness factor) and an automated interface for calculating these metrics in order to access the positional quality of any linear dataset quantitatively. An overview of these quality metrics and calculation of these metrics are shown in figure 5.4. For the error analysis of this research, the distortion factor seems to be more important than all the other factors because in the calculation of distortion factor the bluffline is divided into smaller sub segments which are meaningfully comparable under the measure of closeness. The analysis over the sub segments provides a detailed comparison between two available blufflines. Generalization factor only compares the length of the two bluffline and could be a measure of accuracy for very basic analysis. Bias factor compares the relative location of the bluffline segments which is not a concern of this analysis due to main focus upon the comparison of the geospatial locations of the segmented blufflines. Fuzziness factor concentrates upon the analysis of the end-points of the blufflines and can also be omitted due to less significance.

Distortion factor is the measure of average deviation of the corresponding points produced on the blufflines. The corresponding points are established by locating the points on each normalized bluffline at the same interval. Normalized bluffline refers to the vector-valued representation of the bluffline in the interval [0, 1]. The value of distortion factor near to zero will represent the more accuracy of the bluffline under consideration with respect to the reference bluffline. While comparing the two pairs of blufflines the lesser amount of the distortion factor will refer to the more accuracy.

In the metrics error analysis of the experimental results the distortion factor of the pair of digitized bluffline and least-squares model bluffline is found to be less than the other pair of digitized bluffline and erosion-based bluffline (Table 5.2).

Factor	**Digitized vs. Least-Squares predicted**	**Digitized vs. Erosion-based**
Distortion Factor	0.467	0.794

Table 5.11 Error analysis using distortion factor

The lesser value of the distortion factor in the pair of digitized bluffline and least-squares model bluffline shows that the average deviation of the geo spatial locations of the comparable points is smaller in least-square predicted model with respect to the digitized bluffline. Hence, in terms of distortion factor the bluffline predicted by least-square model is more accurate in comparison to the erosion-based bluffline while using the digitized bluffline as the reference.

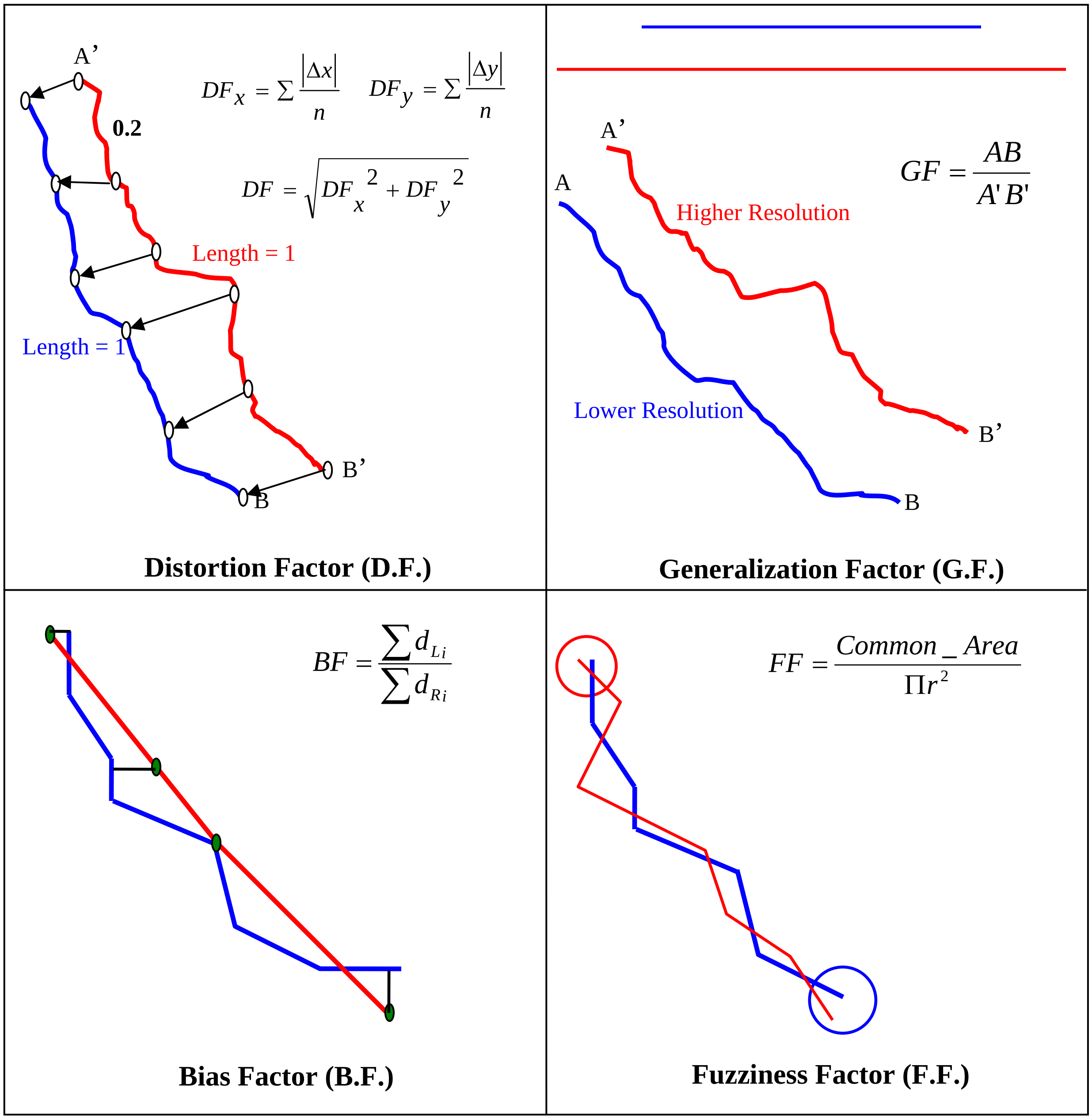

Figure 5.12 Quantitative matrices to compare two blufflines (Ali, 2003)

CHAPTER 6

WEB BASED APPLICATION OF THE MODEL

6.1 Introduction

As described earlier in this report coastal erosion prediction results and management are very important for several engineering applications and financial health of coastal societies. In presence of a tool that can forecast or predict changes in their surroundings will benefit the people living along the coastlines and research on coastal areas. This would speed up lot of engineering initiatives towards protecting the shores and decrease their cost of operations by letting them know ahead in time. Important coastal decisions could only be made based on erosion monitoring data of long period of time (Li, 1996). Publishing such data in public would help planners in identifying the regions of high risk so that decisions are taken sensibly in use of land for residential or other purposes.

In order for this system to be useful it needs to have an easy-to-access and user friendly environment so that it provides the needed information to the concerned parties without any headaches. Also a system which has global access will allow people from outside Ohio to conduct new studies on Lake Erie that would benefit the state eventually and allow ease in implementation of new technologies in this area. In today's internet era easy and global access is only achievable over World Wide Web, hence the right platform for keeping the data in a user friendly form.

6.2 Painesville-Ohio shoreline erosion awareness system

With this in mind a web based erosion awareness system is developed for the Painesville region of Southern Lake Erie coast. This internet based system is capable of fulfilling the primary requirements of easy-to-use and user friendliness (Niu and Li, 2004). This Shoreline Awareness System (Figure 7.1) has three components to provide information regarding the coastal area change:

1. Coastal Resident Support Module
2. 3D Erosion Visualization
3. Bluff-Erosion Scenario

The initial concept and framework of this erosion awareness system was developed by Dr. Tarig Ali, a doctoral student at the GIS and Mapping lab, The Ohio State University. Later on, this system is modified (specially the Coastal Resident

Support Module) as part of this thesis research work with invaluable contribution of Dr. Xutong niu, a post-doctoral researcher of the lab.

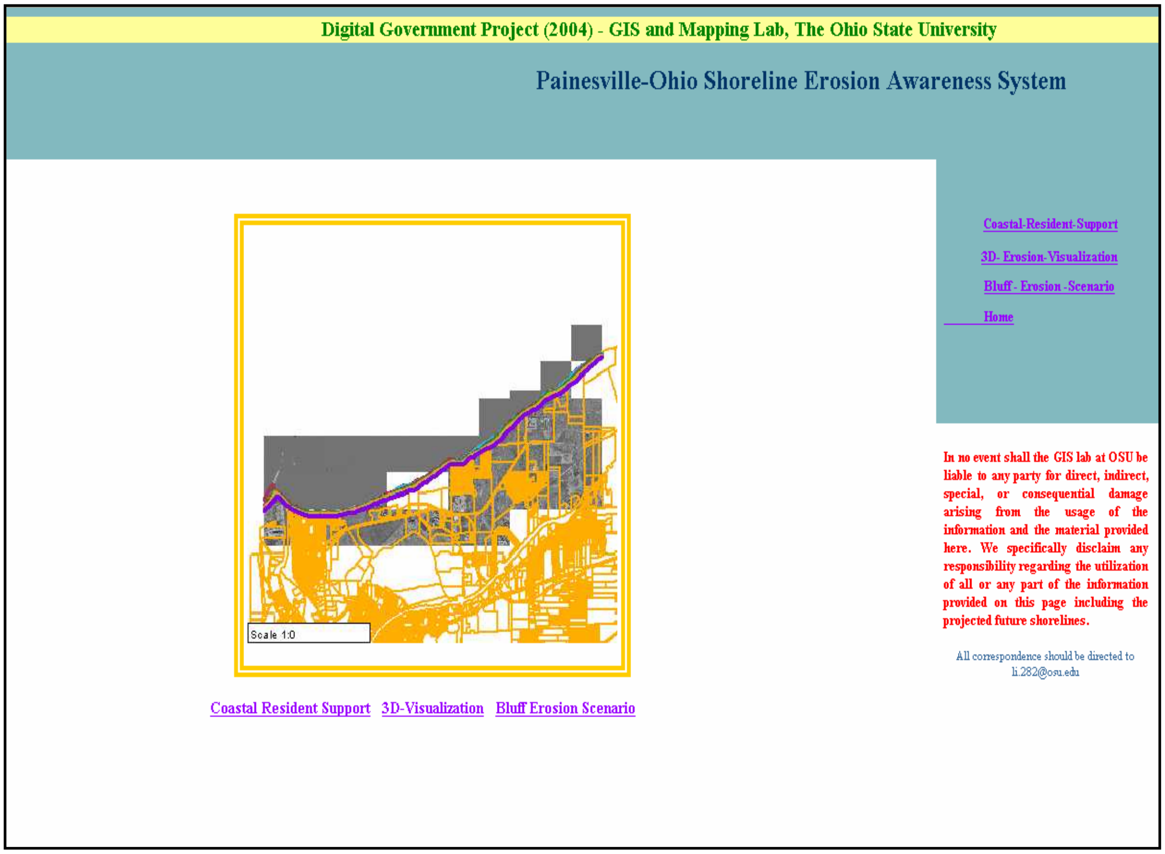

Figure 6.1 Painesville-Ohio shoreline erosion awareness system

6.2.1 Coastal –Resident-Support module

This is the main component of the Painesville-Ohio Shoreline Erosion Awareness System. Along with the historical shorelines of years 1973, 1990, 1994 and 2000 this Coastal Resident Support module (Figure 6.2) shows the future shorelines of years 2000, 2010 and 2020 predicted by the least-squares model. The main purpose of this module is the visual overlay of the past and future shoreline on the property parcel data obtained from Lake Erie County (Niu and Li, 2004). This model was developed through modifications to already designed internal JavaScript of the ArcIMS tool of ESRI, Inc.

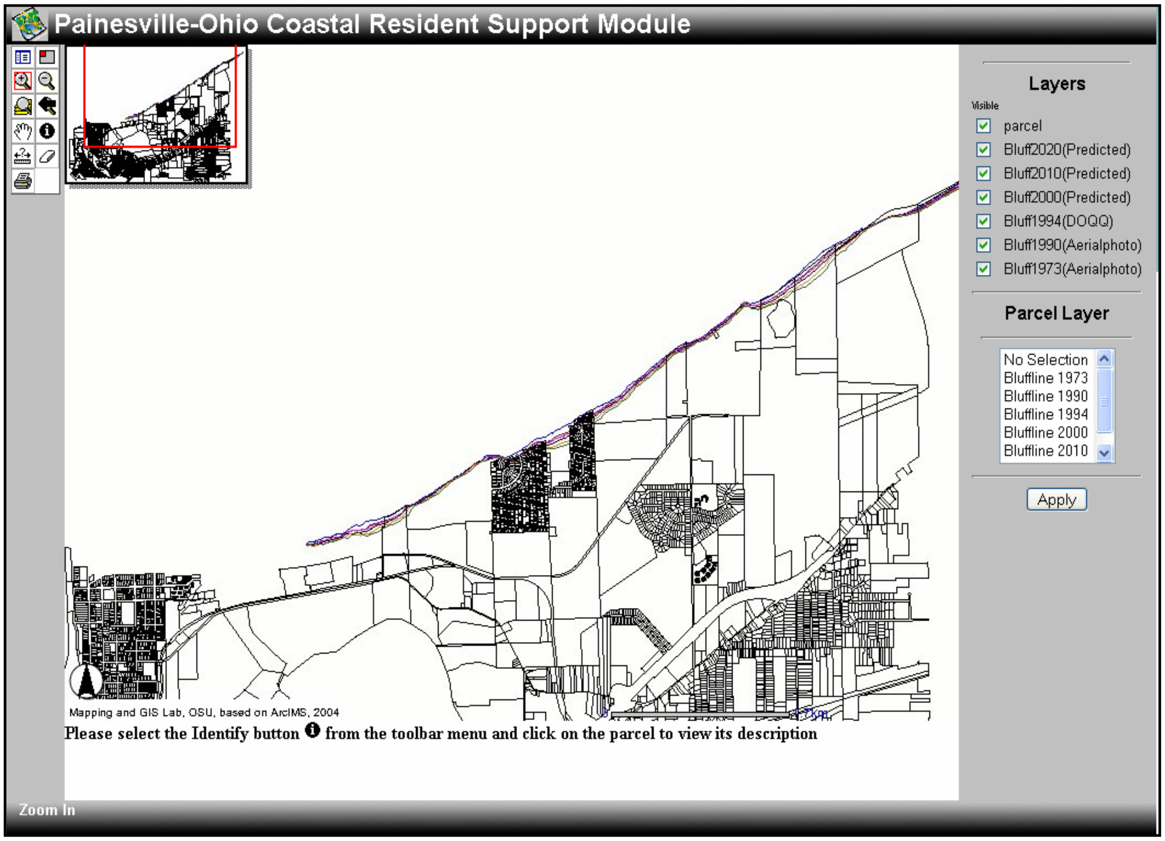

Figure 6.2 Coastal resident support module for Painesville region of Lake Erie

In this subsystem, parcels affected by erosion in the future are highlighted in yellow to allow easy identification of parcels in danger (Figure 6.3). Along with supplying the information of shoreline trends in the study area, this system can also be utilized to provide necessary information, regarding the parcels near the coastline, such as parcel area, parcel owners' addresses, their contact numbers etc. (Figure 6.3). People interested in buying or selling the properties along the shore can use this system extensively to locate the current status of the parcel with respect to the past, present and future shoreline/bluffline positions.

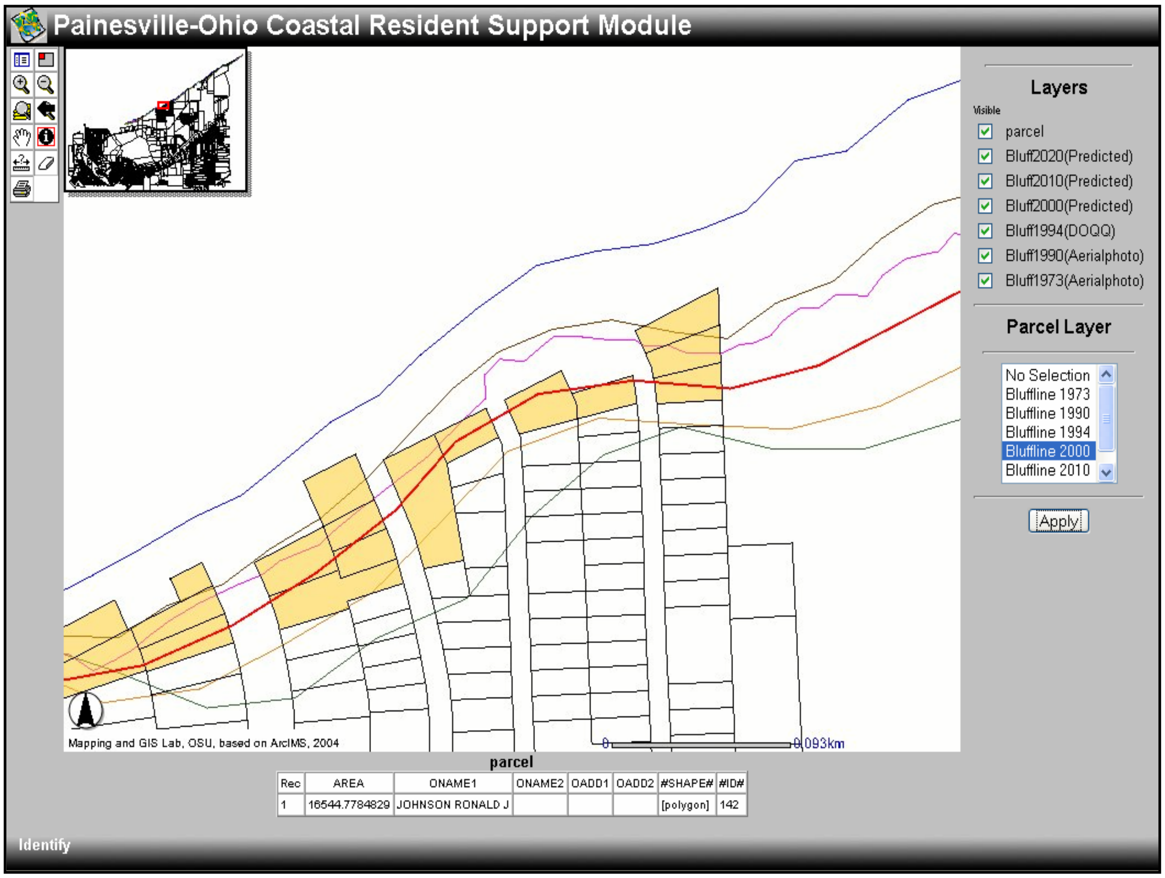

Figure 6.3 Highlighted parcels and information regarding the parcel in danger

6.2.2 3D-Erosion-Visualization

This subsystem provides 3D visualization of the coastal terrain model and water surfaces. Embedded with full navigational tools and using the virtual reality, 3-D erosion visualization model can greatly enhance the analysis of the coastal region under consideration. This visualization would benefit coastal residents, engineers and managers (green colored in Figure 6.4). For this virtual reality model, the files were created using the Arc/Info and Arc/GIS tools of the ESRI.

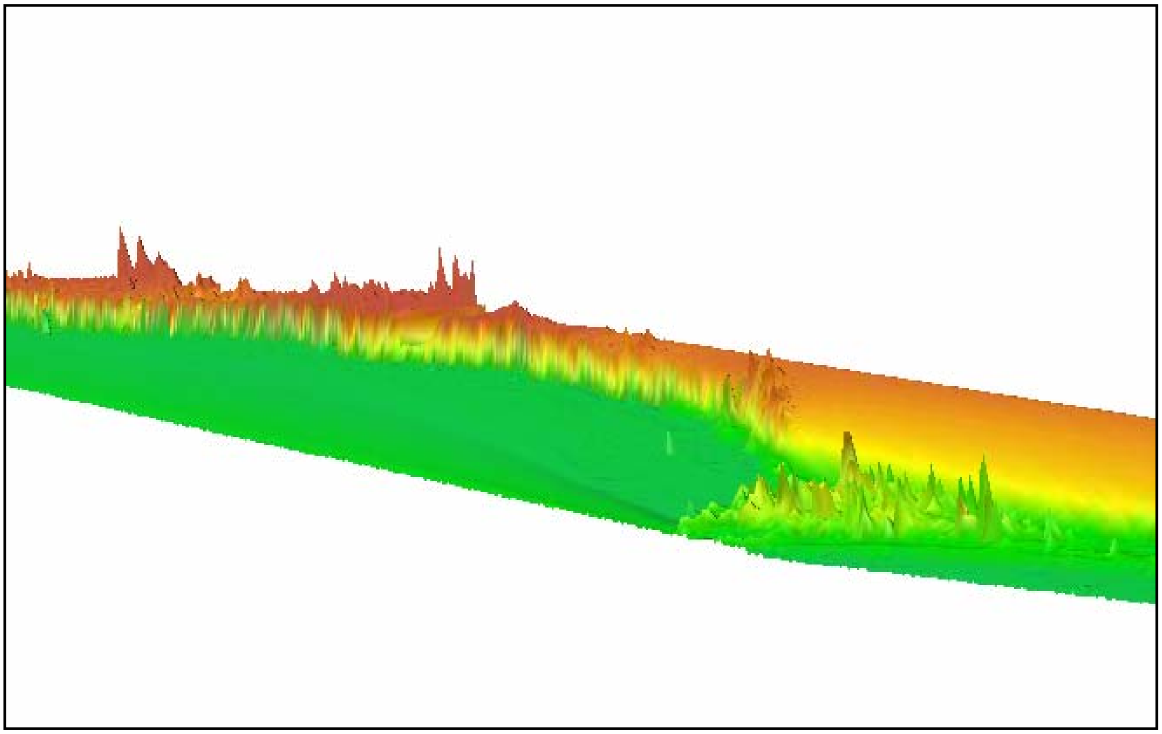

Figure 6.4 3D erosion visualization system for the Painesville region of the Lake Erie

6.2.3 Bluff-Erosion scenario

This segment of the Painesville-Ohio Shoreline Erosion Awareness System is an animation of the bluff erosion in the study area. This animation is created using five image frames of the south shore of Lake Erie, in Ohio for summer of the years 1994, 1995 and 1996 (Figure 1.1). The image frames is obtained from the web-page of the Coastal Imaging Lab, at The Oregon State University (Coastal Imaging Lab). These images frames are termed as “snaps” and are the snapshot images of the beach or cliff. This video image series was recorded by a United States Geological Survey (USGS) video camera placed in the study area and data was generated from the collected images using automated image processing stations known as Argus Stations. Several such stations are currently installed, and the images from these stations are available at the Coastal Imaging Lab.

CHAPTER 7

CONCLUSION AND FUTURE SCOPE

7.1 Conclusion

This report summarizes historical changes in the Painesville region of the Lake Erie shoreline emphasizing the erosion hazard because it impacts natural resources and the economy. The brief introduction of coastal land loss provides a more comprehensive view of coastal processes and key references that can be used to learn more about coastal change in a broader context. The least-squares model is easy to implement and showing greater accuracy in the study area in comparison to the traditional transect based approach. The demarcation of shoreline indicator from the aerial photographs, as well as errors in surveying and the digitization process can be major sources of prediction errors of blufflines. These types of errors can be characterized as random errors. The seasonal changes and storm-inducing erosion can be classified as systematic error sources in the presented research. These errors can be removed by using the total stations and Global Positioning System (GPS) receivers except for very small sites (Li, 1995).

Another reason for the lower accuracy in the prediction model experiment could be the sudden curvature change in the region which leads to inaccuracy as the prediction model is based on a linear equation. The least-squares model can be improved by employing a high-order polynomial if more numbers of shorelines of previous years are available. We believe that the use of a higher-order polynomial will lead to a better result as it can take into account the curved nature of the shoreline.

7.2 Future Scope

In the presented least-squares model the coefficients (a_i and b_i) are the constants (Equations 3.2 and 3.3). If more number of blufflines is available then the model could be further researched for the spatio-temporal variability of these coefficients. Incorporating the spatial and temporal dimensions to these parameters would depict the more realistic situation of the area. The bluffline modeling is an outcome of spatial temporal analysis and to maintain this spatio-temporal behavior of the model these coefficients must be a function of space and time rather than just being constants. To monitor the long term shoreline changes, aerial photographs of the shoreline of Lake Erie should be taken every 5 years (Li, 1995).

It is hard to distinguish between natural rates of shoreline movement and those influenced directly by human activities. In order to make a more reliable model there is a need of identifying the regions with natural rates of shoreline change. Moreover, rates of shoreline change would be influenced by the protection structures applied for the stabilization of the shorelines. Shoreline protection would change the coastal erosion process and hence the prediction for the future shoreline positions would be influenced.

Another, future research direction could be in the direction of incorporating the structural information in the least-squares model. In the presence of structural information the model can be used for both types of areas: protected and non-protected. The basic idea in implementing this concept would be as follows:

$$\Delta\,\theta_{q-p} = \sum_{i=1}^{k} a_{i-1}(t_q - t_p)^{k-i-1} - C$$

Where, $\Delta\ \theta$ is the change in the rotation. Here, a new constant C has been introduced to take care of the structures. The coefficient 'C' could be function of several parameters associated with the structures.

C = f (structural material corrosion rate, time, positional information of the structure)

The same method can be used to correct the model for scale change determination in the protected region. On the whole, the implementation of the above strategy may provide the results with better accuracy.

A complete study to quantify historical shoreline change rates must consider all aspects of spatial and temporal scale in the context of Seasonal to decadal changes in the bluff line position and a shoreline modification attribute, therefore, was added to the shoreline change rate point file so that statistics and causes of shoreline change could be determined separately for natural and unnatural shoreline settings. A long shoreline change rates are required for the complete analysis of the coastal areas which would help the coastal maganagment for planning purposes.

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APPENDIX A

ERROR MEASURMENTS ALONG TRANSECTS

Transect Number	Error measurements of least-squares predicted model along transects (meter)	Error measurements of erosion-rate-based model along transects (meter)
T-1	0.00	22.30
T-2	4.47	9.84
T-3	10.60	0.00
T-4	7.53	0.00
T-5	0.00	8.36
T-6	0.00	9.26
T-7	0.00	18.05
T-8	4.72	20.52
T-9	13.86	20.54
T-10	13.65	19.55
T-11	4.02	19.12
T-12	0.00	19.38
T-13	0.00	21.66
T-14	8.06	23.72
T-15	13.70	27.75
T-16	10.10	18.40
T-17	7.05	19.42
T-18	6.77	13.21
T-19	0.00	8.64
T-20	11.02	25.56
T-21	6.18	19.03
T-22	0.00	10.68
T-23	0.00	15.50
T-24	0.00	21.31
T-25	3.66	0.00
T-26	0.00	0.00
T-27	5.77	13.23
T-28	10.35	0.00
T-29	18.08	10.31
T-30	4.56	15.93
T-31	0.00	7.18
T-32	4.56	17.73
T-33	5.54	3.28
T-34	21.17	0.00
T-35	29.06	9.18
T-36	18.91	7.35
T-37	15.87	16.05
T-38	13.74	22.74
T-39	7.58	27.67
T-40	9.68	18.64
T-41	10.70	25.79
T-42	24.48	18.00
T-43	5.76	14.81

Transect Number	Error measurements of least-squares predicted model along transects (meter)	Error measurements of erosion-rate-based model along transects (meter)
T-44	0.000	11.739
T-45	5.143	10.566
T-46	0.000	9.169
T-47	0.000	9.671
T-48	0.000	22.808
T-49	5.200	18.412
T-50	18.916	21.150
T-51	23.220	31.545
T-52	29.420	30.923
T-53	34.946	58.567
T-54	48.789	49.367
T-55	69.383	84.024
T-56	52.103	89.174
T-57	18.358	68.010
T-58	61.010	63.236
T-59	66.259	83.451
T-60	49.070	133.006
T-61	70.079	132.970
T-62	73.539	106.755
T-63	66.881	68.696
T-64	42.873	24.950
T-65	22.500	30.200
T-66	23.251	0.000
T-67	20.849	16.799
T-68	16.094	3.717
T-69	0.000	12.065
T-70	6.055	28.059
T-71	0.000	30.112
T-72	8.502	21.455
T-73	12.104	36.754
T-74	28.855	39.628
T-75	37.277	6.021
T-76	8.279	12.841
T-77	8.586	15.768
T-78	13.227	5.489
T-79	32.807	23.342
T-80	30.699	3.132
T-81	42.004	34.784
T-82	49.932	55.688
T-83	26.011	25.259
T-84	6.190	34.000
T-85	19.190	37.165
T-86	11.051	0.000
T-87	15.25	37.35

Transect Number	Error measurements of least-squares predicted model along transects (meter)	Error measurements of erosion-rate-based model along transects (meter)
T-88	26.30	16.62
T-89	23.45	12.56
T-90	24.78	31.78
T-91	32.75	18.42
T-92	10.12	37.60
T-93	59.44	14.72
T-94	57.99	15.61
T-95	36.08	18.03
T-96	56.08	30.44
T-97	40.46	20.25
T-98	40.41	25.77
T-99	60.82	26.07
T-100	61.05	23.16
T-101	9.57	11.06
T-102	0.00	21.88
T-103	0.00	7.03
T-104	0.00	9.65
T-105	13.84	12.47
T-106	11.66	4.35
T-107	0.00	7.00
T-108	5.20	8.36
T-109	11.53	21.95
T-110	21.85	16.85
T-111	8.27	13.13
T-112	0.00	18.52
T-113	5.72	21.29
T-114	0.00	19.35
T-115	9.47	20.09
T-116	11.50	48.57
T-117	4.55	15.95
T-118	0.00	7.69
T-119	0.00	16.33
T-120	0.00	0.00
T-121	11.80	11.15
T-122	0.00	20.16
T-123	0.00	9.31
T-124	0.00	10.66
T-125	46.35	0.00
T-126	0.00	0.00
T-127	3.15	10.07
T-128	10.80	8.00
T-129	5.55	3.91
T-130	0.00	29.52
T-131	5.46	26.30

Transect Number	Error measurements of least-squares predicted model along transects (meter)	Error measurements of erosion-rate-based model along transects (meter)
T-132	16.44	16.44
T-133	11.34	0.00
T-134	17.57	4.82
T-135	27.92	7.06
T-136	21.61	15.24
T-137	18.77	8.87
T-138	13.60	16.06
T-139	17.65	30.64
T-140	10.60	19.85
T-141	0.00	4.45
T-142	10.15	14.25
T-143	14.57	0.00
T-144	20.12	16.36
T-145	11.76	25.50
T-146	6.15	16.55
T-147	0.00	14.67
T-148	19.25	24.55
T-149	10.44	19.74
T-150	7.60	5.71
T-151	9.90	13.08
T-152	0.00	8.19
T-153	6.21	4.25
T-154	15.39	0.00
T-155	11.71	0.00
T-156	17.00	23.41
T-157	10.24	15.95
T-158	18.29	10.89
T-159	20.92	17.44
T-160	0.00	13.37
T-161	3.31	23.06
T-162	0.00	19.58
T-163	13.92	36.40
T-164	8.67	50.33
T-165	7.95	42.47
T-166	21.72	30.12
T-167	11.76	31.23
T-168	0.00	22.11
T-169	24.89	15.95
T-170	14.13	40.81
T-171	19.17	26.87
T-172	25.11	23.94
T-173	36.81	0.00
T-174	41.89	51.47
T-175	68.27	27.41

Transect Number	Error measurements of least-squares predicted model along transects (meter)	Error measurements of erosion-rate-based model along transects (meter)
T-176	76.82	4.43
T-177	84.53	24.68
T-178	47.11	14.79
T-179	0.00	23.65
T-180	17.69	17.03
T-181	4.80	19.11
T-182	4.11	19.57
T-183	0.00	5.11
T-184	16.89	5.93
T-185	0.00	10.45
T-186	12.94	18.50
T-187	12.75	39.24
T-188	35.94	13.84
T-189	32.55	19.83
T-190	89.68	0.00
T-191	64.63	14.31
T-192	57.15	3.63
T-193	53.13	0.00
T-194	66.03	0.00
T-195	38.02	5.25
T-196	8.75	0.00
T-197	24.97	0.00
T-198	14.87	4.08
T-199	0.00	6.33
T-200	5.36	7.31
T-201	15.70	6.15
T-202	15.37	10.49
T-203	8.00	0.00
T-204	14.50	8.66
T-205	16.47	9.46
T-206	0.00	10.15
T-207	0.00	0.00
T-208	12.16	8.87
T-209	3.25	16.40
T-210	12.35	4.38
T-211	15.50	9.55
T-212	12.41	8.41
T-213	13.66	0.00
T-214	26.38	16.28
T-215	18.29	16.88
T-216	3.98	15.69
T-217	0.00	10.18
T-218	10.79	5.26
T-219	7.06	0.00

Transect Number	Error measurements of least-squares predicted model along transects (meter)	Error measurements of erosion-rate-based model along transects (meter)
T-220	11.40	13.04
T-221	0.00	3.92
T-222	3.30	5.37
T-223	0.00	8.96
T-224	4.57	12.30
T-225	0.00	15.36
T-226	21.30	37.00
T-227	22.57	53.59
T-228	16.83	24.21
T-229	21.53	57.59
T-230	17.22	4.42
T-231	7.06	3.99
T-232	8.56	6.93
T-233	26.93	27.54
T-234	33.84	6.49
T-235	13.28	6.49
T-236	9.52	5.70
T-237	24.14	14.98
T-238	37.24	7.04
T-239	54.05	113.62
T-240	83.50	85.08
T-241	84.01	64.73
T-242	89.25	98.02
T-243	111.04	87.80
T-244	115.62	60.15
T-245	94.00	35.21
T-246	60.38	12.31
T-247	32.69	14.45
T-248	8.97	37.97
T-249	34.26	23.83
T-250	67.69	21.19
T-251	51.95	0.00
T-252	27.16	20.25
T-253	29.54	29.85
T-254	34.69	11.83
T-255	50.99	23.36
T-256	46.77	29.53