The Application of Remote Sensing and GIS for Improving Modeling the Response of Wetland Vegetation Communities to Water Level Fluctuations at Long Point, Ontario

by

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AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Coastal wetlands are complex and dynamic environments which are of high environmental, social, and economic importance. With the acceleration of climate change and global warming, it is necessary to monitor and protect dynamic coastal wetlands. Wetland ecosystem simulation modeling is one approach to help produce better wetland protection and management strategies. The application of remote sensing and Geographic Information System (GIS) in wetland ecosystem simulation models can help with better spatial modeling of wetland ecosystems. In addition, coastal topographic models can achieve digital representations of terrain surfaces and aquatic environments.

This study applies remote sensing and GIS technologies for improving wetland vegetation simulation modeling. First, the study integrates multiple topographic data sources (i.e. Light Detection and Ranging data (LiDAR) and bathymetry data) to generate a coastal topographic model. Shoreline data are involved in the generation process. Second, a pre-existing wetland simulation model is updated to a new version to model the response of wetland vegetation communities to water level fluctuations at Long Point, Ontario. Third, different coastal topographic models have been employed to explore how a coastal topographic model affects the wetland simulation results. Model sensitivity analysis is conducted to explore the variation of model simulation results to different vegetation transition baselines parameter.

Findings from this study suggest that a high accuracy coastal topographic model could yield a higher accuracy simulation result in a wetland ecosystem simulation model. Second, the application of remote sensing and the integration of multiple topographic data (e.g. LiDAR data and bathymetry data) could provide high accuracy and high density elevation information in coastal area, especially in land-water transitional areas. Finally, a narrower vegetation transition baseline increases the possibility for a wetland community shift to a wetter wetland community.

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Chapter 1
Introduction

Great Lakes coastal wetlands are complex and dynamic environments which have high environmental, social, and economic importance. A coastal wetland is a land that is periodically or permanently inundated by shallow water and provides a habitat for vegetation and animals (Keddy et al., 1986; Keough et al., 1999). Coastal wetlands are highly influenced by water level fluctuations, and changes in climate (e.g. alterations in air temperature, regional precipitation, evapotranspiration, snow cover, and surface runoff), which influence wetland water levels (Herdendorf, 1987; GLIN, 1998; Mortsch, 1998). With accelerated climate change and global warming, it is necessary to map and model dynamic coastal wetlands (Hebb, 2003).

Mapping the topography of coastal wetland areas provides valuable data for managing wetlands (Eakins and Grothe, 2014; Hochberg, et al., 2003; Medeiros et al., 2015; NOAA, 2015). Digital mapping of the coastal terrain surface has many challenges including difficulty in obtaining high accuracy and high density topographic data in both the upland terrain and aquatic environment, and difficulty in filling the shallow water gap in the land-water transition area. A coastal topographic model is a digital model that can provide height information for both the terrain surface and aquatic environment, including the land-water transition area (Hogrefe et al., 2008). Integrating multiple topographic data sources in a coastal topographic model is necessary, because a single topographic data source cannot provide high accuracy and high density elevation information for both the terrain surface and aquatic environment.

Topographic data can be collected by several approaches, including traditional surveying methods, remote sensing technologies, and multi-beam swath sonar bathymetry. Remote sensing technology, such as Light Detection and Ranging (LiDAR), is considered to be a useful approach for obtaining high accuracy and high density elevation data in coastal areas, while bathymetry data provide elevation data in aquatic environment where water is present (Lyzenga, 1985; Eakins and Taylor, 2010). Based on a coastal topographic model, the land-water transition area can be filled by performing an edge matching algorithm or extracting depth estimations from remote sensing images (Hogrefe et al., 2008; Xi et al., 2010; Medeiros et al., 2015).

Wetland ecosystem simulation models simplify the components of and structures in a wetland system to model relationships and ecological processes in that ecosystem. Such models can assist resource managers to better understand and model ecosystem functioning and processes (Odgen et al., 2005; Wang et al., 2009). In general, a wetland simulation model simplifies a wetland ecological process in three stages: 1) a driving factor (e.g. human activities or natural forces) outside the wetland ecosystem causes physical or chemical changes (e.g. water level declines) within the ecosystem; 2) physical or chemical changes (stressors) cause changes in biological components and patterns (ecological effects) within the ecosystem (e.g. soil moisture content); 3) attributes, such as species or processes are selected to represent hypothesized effects of stressors (e.g. wetland vegetation species) within the ecosystem (Odgen et al., 2005).

A coastal wetland ecosystem is highly influenced by water level fluctuations. Such changes in water levels have significant effects on the type, quantity, and quality of wetland vegetation. Such ecological processes can be simplified by a wetland simulation models (Hebb et al., 2013; Hudon, 1997; Hudon et al., 2006; Morris et al., 2002; Poiani et al., 1993; Narumalani et al., 1997; Van Horssen et al., 1999; Visser et al. 2013). For example, Hebb (2013) developed a spatial wetland simulation model to simulate the response of the wetland vegetation community to water level fluctuations in Long Point, Ontario, Canada. According to Hebb's (2013) model, the driving factor was climate change causing a decline or increase in water levels within the Long Point wetland complex on Lake Erie. Water level fluctuations change the growing environment for wetland vegetation; resulting in changes in wetland vegetation communities' quantity and distribution.

Long Point wetland was selected as the primary study area, as one of the most important inland coastal wetland systems in the Great Lakes and one of the largest national wildlife areas in Ontario. The sediment from Big Creek and the water level changes in Lake Erie make Long Point a dynamic environment, where the water level fluctuations have significant and observable effects on coastal wetland vegetation communities (Bayly, 1979; Catling et al., 1981; Rubec et al., 2009). Hence, mapping and modeling the dynamic coastal wetland environment in Long Point is important for resource management and planning.

A pre-existing wetland simulation model was developed for Long Point and the model was used to simulate the response of wetland vegetation communities to water level fluctuations (Hebb et al., 2013). Hebb's (2013) wetland simulation model uses wetland classification maps and a coastal topographic model as inputs to simulate future wetland communities' cover. It assesses the likelihood of certain wetland communities occurring after a water level change, and the likelihood of wetland vegetation communities changing to another vegetation community (Hebb et al., 2013). Hebb's research indicated that "the model could be improved with more accurate elevation and bathymetry data" and more broadly, "the model could be improved by enhancing the decision rules and vegetation tolerance ranges with the field work" (Hebb et al., 2013, p.198). This study addresses the limitations of Hebbs' model and applies remote sensing and GIS technologies for improving mapping coastal topography and modeling wetland ecosystem communities in Long Point.

1.1 Thesis Goals and Objectives

This study was conducted to address four key research questions: (1) How can remote sensing and GIS technologies improve mapping of coastal topography? (2) Do different coastal topographic models affect the simulation of wetland vegetation communities in Long Point, Ontario? (3) What are the changes in the type and spatial distribution of wetland vegetation communities in response to different water levels in 2001 and 2015 in the study area? (4) How do changes in model parameters affect the simulation results?

The goal of this research was to apply remote sensing and GIS technologies to improve mapping coastal topography and modeling of wetland vegetation community responses to water level fluctuations at Long Point, Ontario. More specifically, the steps to achieve the objectives of this study were:

1) To generate a coastal topographic model for Long Point based on LiDAR data and bathymetry data, and to assess different Long Point coastal topographic models, especially along the land-water transitional area;
2) To update the existing wetland simulation model by Hebb (2003) and to perform a sensitivity analysis of the updated wetland simulation model;
3) To conduct a field survey in Long Point and to compare ground truth data with simulated results;
4) To simulate future Long Point wetland vegetation community types using the updated wetland simulation model.

1.2 Thesis Structure

This thesis consists of seven chapters as follows:

Chapter 1: Introduction: Provides a brief introduction to the importance of remote sensing and GIS applications in wetland ecosystem studies.

Chapter 2: Literature Review: Reviews current coastal topographic model generation techniques and wetland simulation models.

Chapter 3: Study Area: Provides background about the geography of the Long Point wetland study area.

Chapter 4: Data: Provides a description of available datasets used in this study.

Chapter 5: Methodology: Details a coastal topographic model generation approach and an updated wetland vegetation simulation model.

Chapter 6: Results: Outlines the main results of this study, including a new coastal topographic model, the updated wetland simulation model, changes in wetland communities' response to different water levels in 2001 and 2015, and model sensitivity analysis results.

Chapter 7: Discussion and conclusion: Analyzes and interprets the key findings of this study. Advantages and limitations of the methods in this research are discussed. Recommendations and future applications are also addressed.

Chapter 2
Literature Review

2.1 Wetlands and Wetland Classification

A wetland is a land that is seasonally or permanently covered by "water long enough to promote wetland or aquatic processes as indicated by poorly drained soils, hydrophytic vegetation, and various kinds of biological activity that are adapted to a wet environment" (National Wetlands Working Group, 1987; Sather and Smith, 1984). Wetlands have several valuable functions, such as providing habitat for plants and wildlife (e.g., birds, fish, mammals, and reptiles); filtering pollutants and improving water quality; controlling flooding by storing and slowly releasing rain, snowmelt, and flood waters; protecting the shoreline and stream banks from erosion; providing economic benefits (e.g., tourism, fishing opportunities and commercial fur-trapping); and providing recreation, education and research opportunities (EPA, 2016; Hebb, 2003; Keddy, 2010; Sather and Smith, 1984).

Depending on the hydrology, vegetation type, soil type, and the presence or absence of peat, wetlands are classified into five basic types: bogs, fens, swamps, marshes, open water wetlands (National Wetlands Working Group, 1997). Marshes and open water wetlands are the most common wetland types in the Great Lakes region. A marsh is a wetland which is dominated by herbaceous plants, and it is usually found at the edge of lakes and rivers (Cowardin et al., 1979). Water levels in marshes are daily, seasonally or annually fluctuating due storms, winds, evapotranspiration, surface runoff and snow melt (National Wetlands Working Group, 1997; Mortsch, 1998). Marshes are diverse and dominated by submergent and emergent vegetation (e.g., cattails, reeds, and coontails), and the vegetation occurs related to water depth gradients (National Wetlands Working Group, 1997). Vegetation in marsh is sensitive to water level fluctuations. An open water wetland is the transitional wetland between seasonally occurring wetland (i.e., bog, fen, swamp or marsh) (Hebb, 2003). Open water wetlands generally occur in a water depth of less than 2 m (National Wetlands Working Group, 1997). The dominant vegetation types in open water wetlands are floating emergent and submergent (e.g., water-lily, pondweed, duckweed, and coontail).

In Great Lakes areas, bogs are usually found in the upper Great Lakes (GLIN, 1998). A bog is a wetland whose substrate is an accumulation of peat (Keddy, 2010; National Wetlands Working Group, 1997). Water input in bogs primarily comes from rainfall, and snowmelt (National Wetlands Working Group, 1997). The primary vegetation types in bogs are Sphagnum mosses with tree, shrub, or treeless vegetation (National Wetlands Working Group, 1997). A fen is also dominated by grasses and is fed by mineral-rich surface water or ground water (Cowardin et al., 1979). It is characterized by its water chemistry, and it is common in the Great Lakes area. A swamp is a forested or wooded wetland, and it is not as wet as marshes, fens and open bogs (National Wetlands Working Group, 1997). Swamps are located along the landward margin and are isolated from the lake (GLIN, 1998; Hebb, 2003). A wetland complex ecosystem may contain several these types of wetlands.

A coastal wetland is a type of wetland which is located in the transitional area between the land and the shore of a lake or ocean, and is highly influenced by lake processes (e.g., lake waves and water level fluctuations). Long Point coastal wetland opens to Lake Erie, and the barrier Long Point peninsula provides a relative stable environment for vegetation. Driving factors, which are outside the wetland ecosystem that causes physical or chemical changes within the Long Point wetland complex, include lake processes, evapotranspiration, surface runoff and snow melts. The Long Point wetland complex is dominated by marsh and open water wetland. The wetland vegetation in Long Point wetland complex consists of several vegetation communities. Like a typical marsh wetland, the distribution of Long Point wetland vegetation communities occurs in different moisture conditions along an elevation gradient (or water depth gradient). As shown in Figure 2.1, from a high water level tolerance to a low water level tolerance, the gradient of wetland vegetation communities are submergent, floating emergent, emergent, wetland meadow, wetland shrubs, and wetland trees (Bolsenga, et al., 1993). For example, as moisture conditions become wetter (water level increases), the wetland vegetation communities generally shift to wetter vegetation communities (e.g. emergent and floating emergent). The tolerance ranges of Long Point wetland vegetation communities will be summarized in Section 2.3.3. A coastal wetland is a dynamic environment.

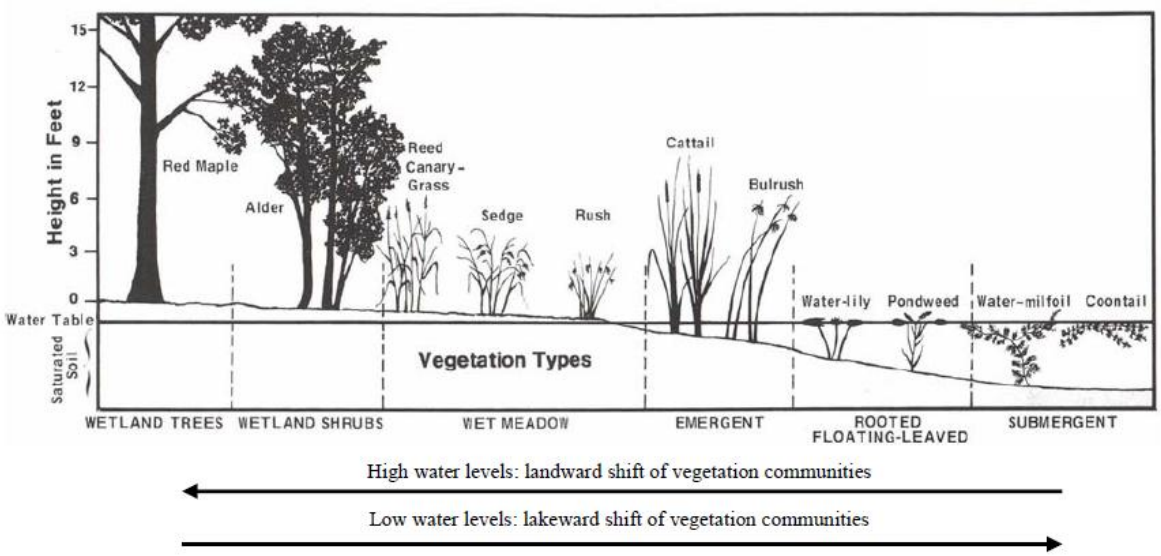

Figure 2.1: Cross section of a typical marsh (Bolsenga et al., 1993)

2.2 Wetland Ecosystem Simulation Model

A wetland ecosystem simulation model is a model that simplifies the components, structures and procedures of wetland systems to model relationships and ecological processes (Odgen et al., 2005; Wang et al., 2009). In general, a wetland ecosystem simulation model includes four components: driver, stressor, ecological effect and attribute (see Figure 2.2) (Odgen et al., 2005). Drivers are driving factors that occur outside the ecosystem, such as human activities, climate changes, or natural forces; stressors represent chemical or physical changes within the ecosystem that are caused by drivers, such as water level decline in the wetland or polluted water; ecological effects include biological, physical, and chemical response within the ecosystem caused by stressors; and attributes contain biological components of the natural system (Odgen et al., 2005). For example, humans managing wetland water (driver) could lower water levels within a wetland (stressor); the decline in water level in a wetland results in a decrease of soil moisture content (ecological effect), while a lower soil moisture content would lead to changes in the distribution and quantity of wetland vegetation within the wetland ecosystem. A wetland simulation model is built on the recognition of wetland ecosystem “driver- stressors-effect-attribute” components and the understanding of relationships within the wetland ecosystem (Odgen et al., 2005; Wang et al., 2009)

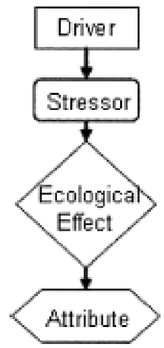

Figure 2.2: Simplified diagram of a conceptual ecological model (Odgen et al., 2005)

2.2.1 Non-spatial Simulation Model

Non-spatial wetland ecosystem simulation model is a model that aggregates changes in wetland ecosystems, while changes in other locations within a wetland ecosystem are not predicted (Hebb, et al., 2013). Hudon (1997) applied a linear regression approach to model the changes of wetland biomass related to water level fluctuations in St. Lawrence River. Driving factors such as anthropic and climate effects cause changes in water level and vertical depth in the St. Lawrence River (Hudon, 1997). Various water level conditions are considered in the model, such as seasonal timing of flood and low water levels and average yearly water level (Hudon, 1997). The changes in water level cause changes in biomass and species composition of emergent and submergent macrophytes. Hudon (1997) successfully modeled the relationship between the water level and area of biomass and species of macrophyes in a local scale. Morris et al. (2002) developed an equation-based model to simulate the changes of marsh vegetation productivity to the increase in water level on Goat Island, U.S. The model successfully theoretically simulates the response of marsh vegetation productivity to changes in lake level. However, these models can only model aggregated changes in the wetland ecosystems, and spatial simulation models, which can model the wetland ecosystem in a regional scale, are discussed in the following section.

2.2.2 Spatial Simulation Model

A spatial simulation model is a model that predicts relationships or ecological processes in wetland ecosystems and spatially distributes modeling results (Poiani et al, 1993; Narumalani et al., 1997; Van Horssen et al., 1999; Hebb et al., 2013; Visser et al., 2013). GIS technology is usually used for spatially explicit modeling results. Geographic Information System (GIS) is “an information system that is designed to work with data referenced by spatial or geographic coordinates; it is both a database system with specific capabilities for spatially referenced data as well as a set of operations for working with the data” (Star et al., 1990, p.14). With the application of GIS, data in simulation models are stored and processed in spatially referenced formats. Several researchers have applied GIS for wetland simulation modeling (Poiani et al, 1993; Narumalani et al., 1997; Van Horssen et al., 1999; Hebb et al., 2013; Visser et al., 2013). The model components and approaches to describe ecological processes in the existing spatial simulation models are summarized in Table 2.1. The comparison of different spatial simulation models is discussed in the following section.

Poani and Johnson (1993) developed a spatial wetland simulation model to simulate the response of wetland vegetation (emergent and meadow) to water level changes. All data in the simulation model were stored and processed in 2-dimensional grid with 9.3 m spatial resolution (Poiani et al., 1993). Poiani (1993) described ecological processes in a semi-permanent marsh ecosystem in three stages: 1) natural forces such as precipitation, runoff, and potential evapotranspiration (driver) cause changes in wetland water levels (stressor); 2) wetland water level fluctuations further change seed bank composition and plant survivorship status (ecological effect); and 3) change in seed bank composition and plant survivorship status finally change the distribution and amount of emergent and meadow community within the wetland ecosystem (attribute). In Poiani’s (1993) model, water depth is the key variable to determine the fate of wetland vegetation, and the relationship between water depth and the fate of wetland vegetation was described by a series of rules; the water depth for each cell was calculated based on cell elevation and the estimated whole wetland basin water level, which was estimated from air temperature, snowmelt runoff, precipitation, and potential evaporation. Poiani’s (1993) model has successfully modeled the relationship between wetland vegetation and water level with a rule-based approach. However, there are several limitations in Poiani's (1993) model: 1) only two types of wetland vegetation communities (meadow and emergent) were considered, 2) the key factor (water depth) was not accurate for each cell, since cell elevation was derived from limited field survey locations, and 3) the water depth tolerance ranges for each wetland vegetation were not considered. Hence, more wetland vegetation communities' types could be involved in the simulation model and the accuracy of elevation information should be improved.

Narumalani (1997) developed a spatial wetland simulation model to simulate the response of aquatic macrophytes to water level fluctuations. All processes were completed in raster file with 5 m spatial resolution. In Narumalani's (1997) model, the fate of aquatic macrophytes is determined by water depth, slope, and the probability of the plant exposure to wind. The relationship among variables was described by a logistic multiple regression approach. A Digital Elevation Model (DEM) generated from lake contours, was used to obtain water depth information (Narumalani et al., 1997). As mentioned previously, cell elevation in Pioani's research was derived from limited field survey locations. The application of a DEM produces a higher accuracy cell elevation in Narumalani's (1997) research. However, wetland vegetation communities are still over-simplified, and only one wetland vegetation (cattails) is considered in Narumalani's (1997) model.

Visser et al. (2013) developed a spatial wetland simulation model to simulate the area of emergent and submergent vegetation to changes in water conditions, including water depth, water salinity and water temperature. The study area was divided into 500 m by 500 m cells, and all the simulations were performed within each cell (Visser et al., 2013). For each cell, the percentages of the area occupied by different wetland vegetation types were recorded, and the vegetation composition of each cell was simulated (Visser et al., 2013). This simulation model took into account several environment variables, and a large amount of wetland vegetation types were considered. However, only the area of vegetation communities were displayed in the model and the model was not able to show the distribution of wetland vegetation within the study area.

Hebb et al. (2013) developed a spatial wetland simulation model to simulate the response of eight wetland vegetation communities to water level fluctuations. The model simplifies the wetland ecosystem processes as three steps: 1) drivers outside a wetland ecosystem (e.g., climate change) cause long-term water level fluctuations in the ecosystem; 2) water level fluctuations (stressor) influence the physical (e.g., water level depth and duration) conditions within the wetland (ecological effect); 3) the ecological effects result in the changes of wetland vegetation type (attribute) and quantity (area) (see Table 2.1). A coastal DEM generated based on bathymetry data and land elevation points, was applied to provide cell elevation information in both terrain and aquatic environments (Hebb et al., 2013). In Hebb et al.'s (2013) model, the response of eight wetland vegetation communities was determined by pre-existing vegetation types and its water depth tolerance range; the relationships between wetland vegetation and its water depth tolerance range were described by a series of rules; all processes were completed in a 2-dimensional grid with a high spatial resolution (12 m).

In conclusion, water level is recognized as the key factor to influence the type and spatial distribution of wetland vegetation. Overall, the aforementioned wetland spatial simulation models have successfully simulated wetland vegetation with satisfactory results. Compared to other wetland spatial simulation models (see Table 2.1), Hebb et al.'s (2013) simulation model has several advantages: 1) the model successfully simulated considerable wetland vegetation communities at a relatively high spatial resolution in an inland coastal wetland; 2) the key factor water level, which is a primary influence on changes in wetland vegetation, is considered; 3) the rule-based approach is considered to be a simple and effective approach to model the relationship between wetland vegetation and water level fluctuations. Hence, Hebb et al.'s (2013) model is selected as a basis for further study and will be introduced in the following section.

Table 2.1: A summary table of wetland ecosystem simulation models and their characteristics

<table>
<tr><th rowspan="2">Type</th><th rowspan="2">Model</th><th rowspan="2">Study Area</th><th colspan="4">Model Components</th><th rowspan="2">Model Resolution</th><th rowspan="2" colspan="2">Advantages</th><th rowspan="2">Limitations</th><th rowspan="2">Reference</th></tr>
<tr><th>Driver</th><th>Stressor</th><th>Ecological Effect</th><th>Attribute</th></tr>
<tr><td rowspan="2">Non-spatial simulation model</td><td>Linear regression</td><td>St. Lawrence River</td><td>Anthropic and climatic forces</td><td>The changes of seasonal or yearly average water level and vertical depth</td><td>N/A</td><td>Biomass and species composition of emergent and sub-emergent macrophytes</td><td>N/A</td><td colspan="2">Various seasonal and yearly water level conditions are considered;</td><td>Only in local scale; limited wetland vegetation types</td><td>Hudon, 1997</td></tr>
<tr><td>Equation-based</td><td>Goat Island</td><td>Sea level rise</td><td>Water depth increase</td><td>The changes of wetland environment</td><td>Productivity of marsh vegetation</td><td>N/A</td><td colspan="2">Successfully predict vegetation productivity in theory</td><td>Only in local scale; required huge filed works</td><td>Morris et al., 2002</td></tr>
<tr><td rowspan="4">Spatial wetland simulation model</td><td>Rule-based</td><td>The Cottonwood Lake</td><td>Precipitation, runoff, potential evapotranspiration</td><td>The changes of Water level</td><td>Seed bank composition, seeding recruitment, and plant survivorship</td><td>The amount and distribution of meadow, shallow marsh emergent, upland and open water</td><td>9.3 m</td><td rowspan="4">Simulated the spatial distribution and amount of wetland vegetation</td><td>Simple and effective approach to simulate wetland vegetation</td><td>Model contains two sub-models, errors in one led to additional errors in other sub-model; wetland processes are oversimplified</td><td>Poiani et al., 1993</td></tr>
<tr><td>Logistic multiple regression</td><td>The Savannah River</td><td>Natural forces, human activities</td><td>The changes of Water level</td><td>slope condition, exposure to wind</td><td>The distribution of aquatic macrophytes</td><td>5m</td><td>Several environmental factors are considered in the model</td><td>Wetland processes are oversimplified; limited wetland vegetation types</td><td>Narumalani et al., 1997</td></tr>
<tr><td>Logistic multiple regression</td><td>Central part Netherlands</td><td>Water management plans</td><td>The change of chemical and hydro-biological factors</td><td>Hydrological conditions and ground water quality variables</td><td>The spatial patterns of 78 wetland plants species</td><td>1km</td><td>Several ecological factors are considered in the model</td><td>Low resolution; the regression model itself is not spatially different in this research</td><td>Van Horssen et al., 1999</td></tr>
<tr><td>Rule-based</td><td>Lake Ontario-St. Lawrence River basin</td><td>Anthropic and climatic forces</td><td>The changes of hydrologic conditions (e.g., average water depth, the numbers of days flooded)</td><td>N/A</td><td>The area and distribution of four wetland communities</td><td>30m</td><td>Several hydrologic variables are considered</td><td>Limited wetland vegetation types</td><td>Hudon et al., 2006</td></tr>
</table>

Table 2.1: A summary table of wetland ecosystem simulation models and their characteristics

Types	Model	Study Area	Model Components				Model Resolution	Advantages		Limitations	Reference
			Driver	Stressor	Ecological Effect	Attribute					
Spatial wetland simulation model	Rule-based	Long Point coastal wetland	Climate change	The changes of water depth	N/A	The amount and distribution of ten wetland communities	12m	Simulated the spatial distribution and amount of wetland vegetation	simulate in a relative high resolution; effective and simple; the states of neighbor are considered in simulation	Model input is low accuracy; limited factors are considered in simulation model	Hebb et al., 2013
	Niche-based	Louisiana coastal wetland	Coastal restoration and protection plans, time	The change of water depth, salinity, and water temperature	Vegetation death probability; fraction of area occupied by emergent, sub-emergent, and open water	The amount of emergent and sub emergent vegetation	500m		Not restricted to plant species	Required a large amount of input data; low resolution	Visser et al. 2013

2.2.3 Wetland Simulation Model at Long Point: A Case Study

Hebb (2003) developed a wetland simulation model to predict the response of wetland communities to water level fluctuations. The simulation model contains ten wetland communities: lake, open water, floating emergent, emergent, tall dense dry emergent, tall wet emergent, short wet meadow, meadow, treed, and upland (Hebb, 2003). The simulation model "adheres to the tolerance ranges of each wetland community and assumes that a wetland community can only tend to the community immediately above or below that community's specific tolerance range" (Hebb, 2003, p.64). For example, the floating emergent community can only shift to open water or emergent when water depth exceeds its tolerance range. All the wetland community tolerance ranges were summarized from the literature (Dane, 1959; Geis, 1985; Kadlec and Wentz, 1974; Newmaster et al., 1997; Ould and Holbrow, 1987; United States Environmental Protection Agency, 2000). The tolerance ranges of each wetland community are listed in Table 2.2.

Table 2.2: Wetland community tolerance ranges in theory (Hebb, 2003, p.19)

Wetland Community	Water depth range (cm)
Lake	>200
Open Water/ Submergent	60 to 200
Floating Emergent	30 to 60
Emergent	-30 to 30
Tall Emergent	-30 to -50
Meadow	-50 to -80
Treed	-80 to -100
Upland	<- 100

Note. Negative "water depth" values indicate height above lake level in centimeters (cm)

In Hebb's (2003) wetland spatial simulation model, the predicted wetland community is determined by water depth, its surrounding wetland community, and pre-existing wetland community type (Hebb, 2003). Figure 2.3 shows the overall structure of Hebb's (2003) spatial simulation model at Long Point, Ontario. First, in Hebbs' (2003) wetland simulation model, a base year (used to initiate the model) and a hypothetical lake level are selected by users. Seven base years (i.e., 1945, 1955, 1964, 1978, 1985, 1995, and 1999) are available for selection and each base year corresponds to a pre-existing wetland classification map developed from air photo interpretation.

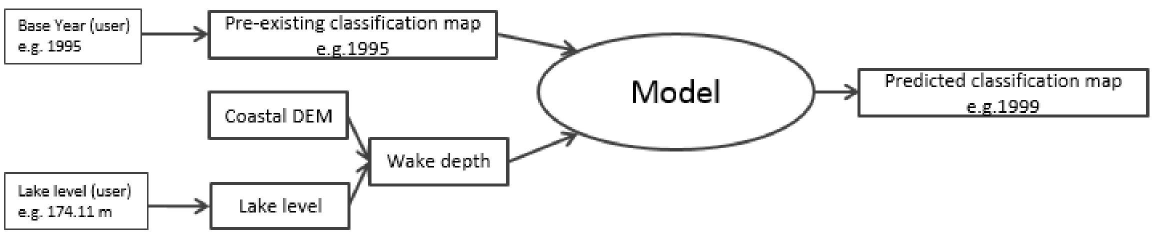

Figure 2.3: Conceptual model of the spatial wetland simulation model at Long Point, Ontario

The pre-existing classification map and water depth information are used in the simulation processes. The pre-existing classification map contains ten wetland communities in the base year, and water depth represents the distance from water surface to the lake floor or land surface. Water depth is determined by the coastal topographic model and the hypothetical lake level. Elevation values in a coastal topographic model represent height above the mean sea level. In general, the elevation values are stored in a 2-dimensional grid raster file with a high spatial resolution (e.g. 12 m). Water depth of each cell is calculated by subtracting the coastal topographic model from the hypothetical lake level (see Figure 2.4). It should be noted that only seasonal or annual mean water level changes are used in Hebb's (2003) simulation model.

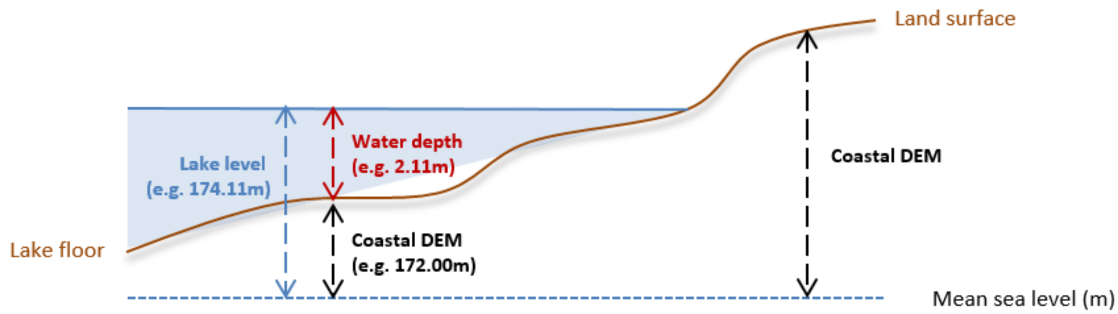

Figure 2.4: Diagram of water depth, lake level, and coastal topographic model. The coastal DEM represents a coastal topographic model. Water depth is calculated by subtracting the coastal DEM elevation from the lake level.

In Hebb's (2003) wetland simulation model, a series of if-else statements (see Table 5.2) were written in ARC Macro Language (AML) to simulate the response of ten wetland communities to water level changes. Water depth is the key factor in determining the change in the pre-existing wetland community (Hebb, 2003). All the input data and processes in the simulation model are completed in a 2-dimensional grid raster file with a 12 m spatial resolution.

Hebb's (2003) model successfully simulated the response of many wetland community types to water level fluctuations at a relatively high spatial resolution (12 m); a rule-based approach that was applied in the simulation model, is considered to be a simple, effective and successful way to model wetland vegetation. However, there were limitations identified in Hebb's (2003) wetland spatial simulation model. First, the model interface was not user-friendly. For example, the units of input parameters were not indicated. Second, the model was not considered to be easy to use, since several codes were required to be written by users in order to run the model. Third, the model was written in AML programming language and can only be run on an ArcInfo workstation, which is now obsolete. A popular and flexible programming language should be used to update the model. Also, the coastal topographic model that is used in the simulation model is considered to be low in accuracy and has noticeable errors, especially in the transition area between water and land. A high accuracy coastal topographic model is required. Finally, tolerance ranges of each wetland community are summarized in theory and they may not really fit in this study area. A model sensitivity analysis could be conducted to adjust the tolerance range in the study area.

2.3 Coastal Topographic Model

A high accuracy coastal topographic model is important in a spatial wetland simulation model, as a high accuracy coastal topographic model can provide high accuracy water depth information which is a key determinant of the wetland vegetation response. A coastal topographic model is a digital model that can provide cell elevation values in both terrain surfaces and aquatic environments (Hogrefe et al., 2008). Achieving digital representations of terrain surface is a significant challenge, especially in coastal environments where land meets the water interface (Hochberg, at al., 2003; Eakins and Grothe, 2014). Coastal topographic models can be used for modeling coastal inundation or flooding, and they also can be applied in ecosystem management (Hochberg, et al., 2003). In general, a coastal topographic model is created by integrating topographic data and bathymetric data (Gesch et al., 2002; Eakins and Grothe, 2014). This section summarizes some common challenges and methods in creating a coastal topographic model, including data source, data processing, and model development.

2.3.1 Topographic Data Sources

Topographic and bathymetric data can be measured by different approaches. Topographic data collection methods include traditional land surveying, elevations estimated from satellite imagery or air photo, airborne Light Detection and Ranging (LiDAR) data, and the Synthetic Aperture Radar (SAR) data while bathymetric data are collected using multi-beam swath sonar bathymetry, digitized bathymetric charts, and hydrographic soundings. Considering the limitations of surveying, a single data source might fail to provide high accuracy elevation values both in terrain surface and aquatic environment (Gesch et al., 2002). Hence, a coastal topographic model is usually created by integrating terrain topographic data and bathymetric data (Eakins and Grothe, 2014). The integration of multiple topographic data in a coastal topographic model takes advantage of each data source. Common methods used for obtaining topographic and bathymetric data are introduced in the following section.

Interferometric Synthetic Aperture Radar (InSAR), an active remote sensing technique, measures distance by calculating the travel path variations of the radiation signal (Rosen et al., 2000; Geymen, 2014). The InSAR system is primarily operated on a satellite and it can collect data in nearly all atmospheric conditions over large areas (Zebker et al., 1986; Rosen et al., 2000). The applications of InSAR include monitoring natural hazards (e.g. earthquakes and landslides) and generating elevation products (e.g. DEM). InSAR is a geodetic surveying method which uses two or more SAR images to create elevation products (Zebker et al., 1986). The advantages of using InSAR images to generate elevation products include 1) providing spatially "continuous" data; 2) collecting data for large areas (e.g. thousands of square kilometers) at low cost (Geymen, 2014). InSAR techniques now can generate up to 10 m accuracy in a DEM.

Light Detection and Ranging (LiDAR), an active form of remote sensing techniques, measures distance using near-infrared light (Lyzenga, 1985). LiDAR is primarily operated on two platforms: airborne and mobile. The principle of airborne LiDAR is shown in Figure 2.5. Three technologies are integrated in the LiDAR system: the laser scanner to measure accurate distance; the Global Positioning System (GPS) to determine geographic position; and an Inertial Measurement Unit (IMU) to record the orientation of the sensor (Hollaus et al., 2010). Airborne LiDAR is an efficient technology for deriving elevation products of the earth's surface (e.g. DEM and Digital Terrain Model (DTM)), because it can obtain elevation data for a large area in a very short time (e.g. 20-50 km^2 per hour) and it can provide high resolution and high accuracy elevation data (e.g. horizontal accuracy 30-50 cm) (Gesch, et al., 2009). Other advantages of LiDAR include minimum human dependence, weather independence and low operation cost (Gesch, et al., 2009). Airborne LiDAR is often applied in coastal areas due to its ability to rapidly obtain data for large areas (Lyzenga, 1985; Brock et al., 2009). The raw LiDAR data contain several returns, and a coastal topographic model requires bare-earth LiDAR data which represents a surface free of trees and buildings (Eakins and Taylor, 2010). However, LiDAR technology is limited to shallow water areas because the LiDAR laser signal cannot penetrate dense grasses and turbid water (Medeiros et al., 2015). Hence, the integration of multiple topographic data is necessary when generating a coastal topographic model in coastal area.

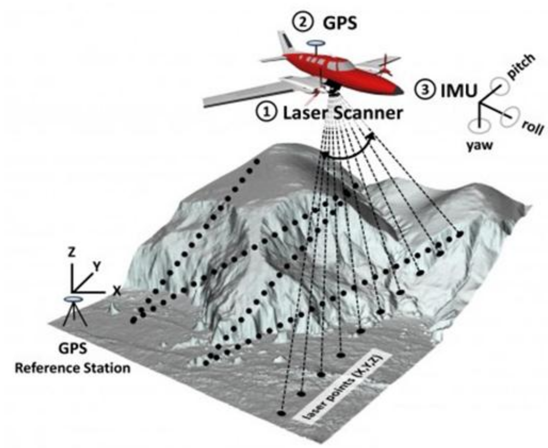

Figure 2.5: LiDAR principle (Hollaus, et al., 2010)

Bathymetric data are collected by a sounding survey which measures the vertical distance from the sea surface to sea floor or the lake surface to the bottom of the lake. Bathymetric data are usually represented by points or contours, and digital bathymetric data can be generated by vectoring paper sheet bathymetric data. Sounding surveying (e.g. NOAA bathymetric contours) provides lake-floor or sea-floor geological and geophysical data, but it lacks details in shallow water (Gesch et al., 2002). Bathymetry datasets in the Great Lakes include National Oceanic and Atmospheric Administration (NOAA) and Canadian Hydrographic Service (CHS) bathymetric datasets. CHS provides depth in meters in Great Lakes, while NOAA offers digital bathymetric data by totaling a hundred thousand soundings data and vectoring paper bathymetric contours (CHS, 2016; NOAA 2016).

In conclusion, LiDAR data can provide high accuracy and high density elevation value in upland areas, and bathymetry data can represent topography in the aquatic environment. However, a single topographic or bathymetric dataset cannot provide high accuracy and high density elevation information in both terrain surface and aquatic environments. A data gap often occurs in the land-water transitional zone, because surveying ships cannot access shallow waters (Gesch et al., 2002; Eakins and Grothe, 2014). Hence, integrating multi-source topographic data, which can take advantage of each topographic dataset, is necessary in coastal areas.

2.3.2 Data Integration Issues

Several problems exist when dealing with multiple topographic data sets in coastal topographic models. One main issue is that different topographic data may be measured in different vertical datums (Gesch et al., 2002; Hogrefe et al., 2008; Eakins and Grothe, 2014). Bathymetric data are often referenced to a tidal datum, while land topographic data are usually referenced to an orthometric datum (Zhou, 2005; Eakins and Grothe, 2014). Hence, unifying the vertical datum is the central step in the integration process. A vertical datum is a zero elevation surface system to which the elevation of a specific point on the Earth is referred (NOAA, 2016). Vertical datums include two categories: orthometric datums (e.g. NAVD 88 and CGVD 28) and tidal datums (e.g. Mean Lower Low Water and Mean High Water). Orthometric datums are referenced to mean sea level, while tidal datums are referenced to stages of tide at a particular location (NOAA, 2016).

The Great Lakes-St. Lawrence River system is the area shared by the United States and Canada, and a common tidal datum is required in this area for coordinated management. The International Great Lake Datum of 1985 (IGLD 85), one of the common tidal datums in the Great Lake-St. Lawrence River basin, was established by the National Oceanic and Atmospheric Administration’s National Ocean Service Center, the Canadian Hydrographic Service, and the Geodetic Survey of Canada and to provide a common datum between the United States and Canada (NOAA, 2016). The zero point for IGLD 85 is located at Rimouski, Quebec, and all water levels which refer to this datum represent feet or meters above this point (Fisheries and Oceans Canada, 2016). In addition, the IGLD 85 is a dynamic height system, and tidal datums for each of the Great lakes are different (e.g. low water datum for Lake Erie is 173.5 m).

The transformations between two vertical datums can be easily accomplished by conversion software. VDatum was a tool developed by NOAA's National Ocean Service Center to perform transformations among ellipsoidal datums, American vertical datum, and tidal datums (e.g. NAVD 88 to IGLD 85) (NOAA, 2016). GPS•H, a tool to perform transformations between ellipsoidal datums and Canadian geodetic vertical datums (e.g. CGVD 28 to NAD 83), is provided by Natural Resources Canada's Canadian Geodetic Survey (NRC, 2016). It should be noted that VDatum is the only free tool to perform transformations between the IGLD 85 and other datums. Hence, other country's vertical datums (e.g. CGVD 28) cannot be directly converted to the IGLD 85 using one conversion tool. Zhou (2005) developed a vertical datum conversion routine in the Great Lakes areas (see Figure 2.6). The transformation between the IGLD 85 and other datums can be completed by intermediate datums (NAD83 and NAVD88) which connect all datums together (Zhou, 2005). For example, the transformation between CGVD28 and IGLD 85 can be achieved by converting CGVD 28 to NAD83 using GPS•H, and then converting NAD 83 to NAVD88 using VDatum, and finally converting NAVD88 to IGLD 85 using VDatum.

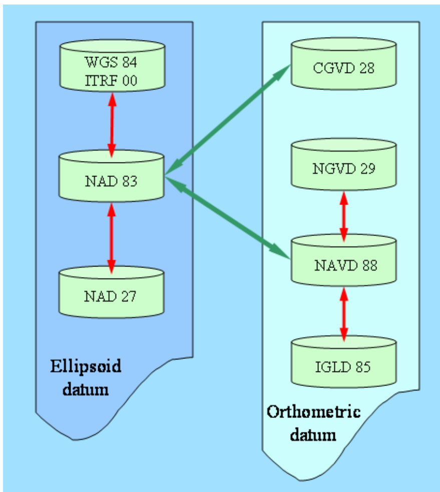

Figure 2.6: The Vertical Datum conversion routine (Zhou, 2005)

Another problem is that terrain topographic data are usually measured with positive values upward, while bathymetric data are positive values downward (Gesch et al., 2002;

Zhou, 2005). For example, in LiDAR data, 173 m represents 173 m above the mean sea level. In bathymetry data, 2 feet represents 2 feet under the shoreline (0 feet). Hence, changing the sign of elevation value is necessary. Furthermore, differences in topographic data may result in a mix of measurements in different units (e.g., meter and feet); suggesting that universal unification of measurement units is necessary.

2.3.3 Coastal Topographic Model Generation

A coastal topographic model is a digital model that typically is represented as a 2-dimensional grid raster file. Elevation values in this model are derived from topographic data and bathymetric data. The most significant challenge of this process is integrating multiple elevation models in land-water transitional zones. A data gap often occurs in the land-water transitional zone, because surveying ships cannot access shallow waters and remote sensing signal cannot penetrate dense grasses and turbid water (Gesch et al., 2002; Eakins and Grothe, 2014; Medeiros et al., 2015).

A coastal topographic model can be built by performing interpolation algorithms on all of the elevation data if the raw topographic data are available. Interpolation is a method that creates a continuous surface based on sampled point values (Watson and Philip, 1985). There are several interpolation algorithms often applied, such as Inverse Distance Weighted (IDW), Kriging, natural neighbor, spline, and Topo to raster. Each interpolation method has its strengths and weaknesses. **IDW** is an interpolation algorithm that interpolates a raster surface from points using an inverse distance weighted approach (ESRI, 2016). The closer the point is to the cell; the more influence it has on the output cell value. IDW is useful when the input sample points are dense and cover the entire surface (Watson and Philip, 1985). Since IDW interpolates cell values using a weighted distance average, the output cell value is between the highest input value and the lowest input value and cannot exceed this range. Hence, IDW is not suitable for a surface which contains ridges or valleys if extreme values have not been measured (Watson and Philip, 1985). **Spline** interpolation minimizes the curvature of the surfaces, and generates a smooth surface that passes through the input points (ESRI, 2016).

The predicted surface passes exactly through the input points. This interpolation algorithm is usually applied for generating surfaces from water table heights or pollutant concentrations. **Topo to Raster** is an interpolation tool provided by ESRI that allows users to generate a hydrologically prediction surface using a point, line, or polygon feature class (ESRI, 2016). This method first interpolates a raster surface using the Distance Transform algorithm, and then the Iterative Finite Difference algorithm is applied to smooth the raster surface (Hutchinson, 2000; ESRI, 2016). When generating a surface based on contours, this algorithm first builds a generalized morphology based on the curvature of the contours, and then interpolates output values based on elevation information in contours (ESRI, 2016). Interpolating all elevation data (e.g. LiDAR and bathymetric in this application) may generate a deep trough if there is an escarpment between land elevation data and bathymetric data. In conclusion, Spine is the most suitable method to interpolate a predicted surface based water table heights point dataset, and TopoToRaster is the most suitable method to interpolate a predicted hydrological surface based on polyline or polygon dataset.

Another approach is building a coastal topographic model based on multiple level-2 elevation products, such as the elevation model generated from raw elevation data. This situation is quite common, because raw elevation data are not always available and there is a large amount of level-2 elevation products (e.g. LiDAR-derived DEM and USGS DEM). This approach merges two or more level-2 elevation products and uses the shoreline to determine the selection of bathymetric data or topographic data for merging (Gesch et al., 2002; Eakins and Taylor, 2010; Eakins and Grothe, 2014). This approach can minimize the deep trough in the land-water transitional zone, and it assumes that the lake bottom in the coast is relatively smooth (Eakins and Grothe, 2014). This approach estimates the coast elevation based only on bathymetric data using an interpolation algorithm. In general, this approach consists of six steps: 1) collecting elevation data from multiple sources; 2) unifying data file format, horizontal datums and vertical datums; 3) evaluating and edit the elevation data; 4) generating a bathymetric surface based on bathymetric data and coastline; 5) clipping the bathymetric surface to the coastline; 6) merging bathymetric surface and land topographic surface (Eakins and Taylor, 2010; Eakins and Grothe, 2014). In addition, there are issues along the edges of datasets when merging two or more level-2 elevation models. These may arise from differences in spatial resolution, datum conversion, or datasets spatial extent and overlay.

2.4 Chapter Summary

Hebb's (2003) spatial wetland simulation model has successfully modeled the response of wetland communities to water level fluctuations in Long Point, Ontario. The model simulates a high spatial resolution raster data and contains many wetland vegetation classes. A rule-based approach, which is used in Hebb's (2003) model, has been proven to be an effective and simple way to model the relationship between wetland vegetation and water depth. However, there are several limitations of Hebb's (2003) model: 1) the coastal topographic model is low in accuracy and contains several errors; 2) the simulation model is not easy to use as several codes are required and can only be run on an ArcInfo workstation; 3) tolerance ranges of each wetland community may not be suitable in the study area; 4) model sensitivity of wetland communities' tolerance ranges was not tested. Hence, this thesis addresses the issues related to Hebb's (2003) model and applies remote sensing and GIS to improve wetland vegetation modeling.

Chapter 3
Study Area

The Long Point wetland complex, located on the northern shore of Lake Erie in Southern Ontario, Canada, is one of the most important wetland complexes in Canada. It is about 40 km long and one kilometer across at its widest point. Long Point provides an area favorable to wetland development and has diverse vegetation and wildlife species. Otherwise, it is an important location for bird migration. The climate in Long Point is highly influenced by Lake Erie.

As shown in Figure 3.1, the study area contains the whole Long Point wetland complex, part of the town of Port Rowan, part of Lake Erie, Long Point Inner Bay and a small part of Long Point Bay. The boundary of the study area is determined by the availability of LiDAR data and bathymetric data. The Long Point coastal wetland can be divided into three sub-sections: a western section (including Big Creek National Wildlife Area and part of Long Point Inner Bay), a middle section (including Long Point Provincial Park), and an eastern section (including the tip of the peninsula that extends into Lake Erie).

Figure 3.1: Study area: Long Point wetland

The Long Point coastal wetland is dominated by shallow open water and marsh. The wetland vegetation of Long Point is quite diverse. In this study, wetland vegetation and land cover are grouped into ten wetland communities: lake, open water, floating emergent, emergent, tall wet emergent, tall dense dry emergent, short wet meadow, meadow, treed, and upland. As mentioned in Chapter 2.2.3, all the wetland classification and wetland simulation were based on these ten wetland communities.

Several views of Long Point and Long Point Inner were captured during a field visit to the study area on July 23nd, 2015 (see Figure 3.2). The wetland vegetation communities are distributed along water depth gradients and elevation gradient (Grosshans and Kenkel, 1997). In general, the gradation of wetland vegetation communities from lake to land is floating emergent, emergent, tall wet/ dense dry emergent, meadow, and treed (see Figure 3.2 No.1, No.2, and No.6). Treed communities always grow in dry and high elevation upland areas (see Figure 3.2 No.1, No.6 and No.9). Due to strong lake waves and lake winds, it is difficult for wetland vegetation to grow in areas that are exposed to Lake Erie (see Figure 3.2 No.9).

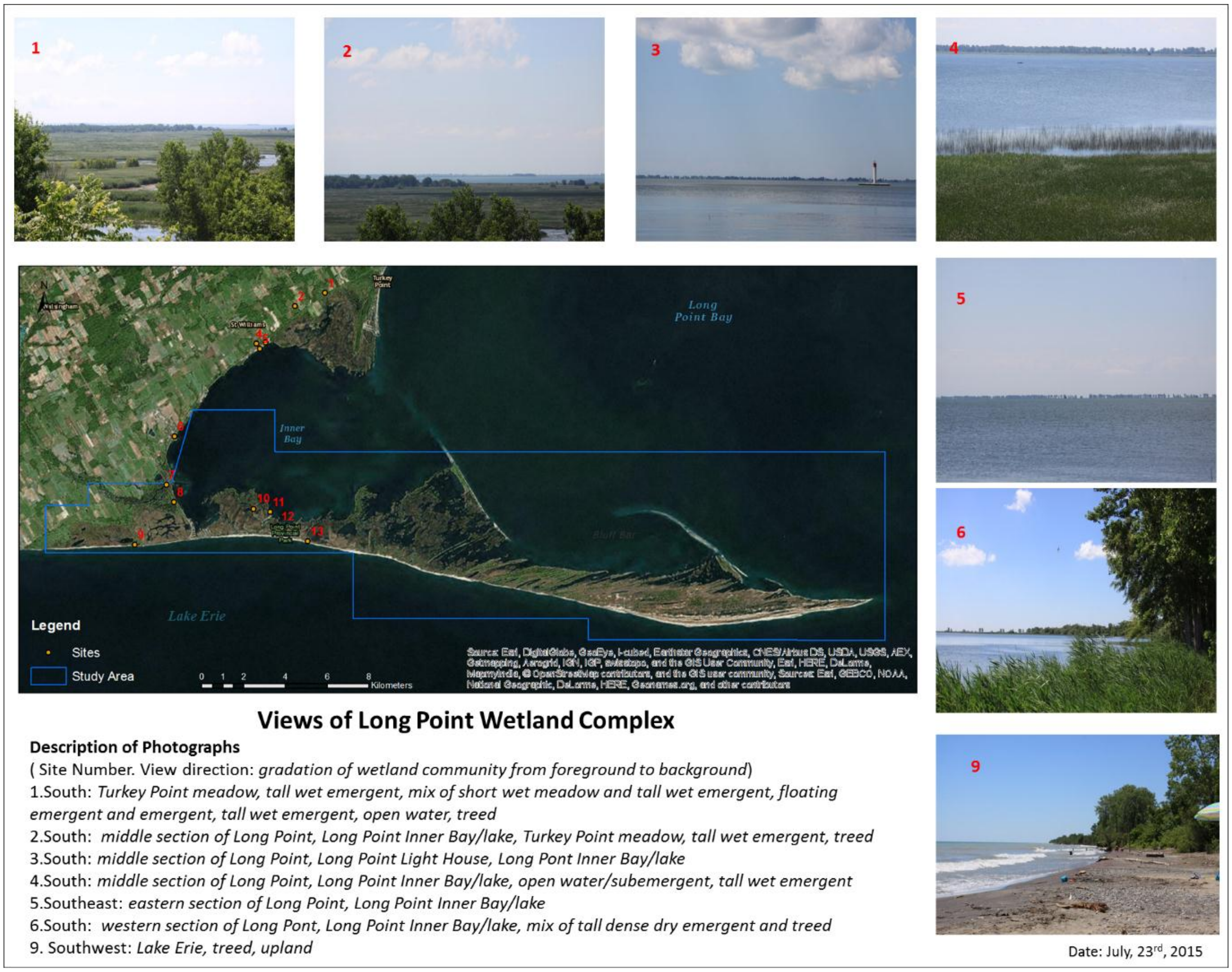

Figure 3.2: Views of the Long Point wetland complex

Figure 3.3 provides images of each wetland community in the Long Point wetland complex. The lake class identifies water areas where wetland vegetation cannot grow. These areas are usually located in Lake Erie and deep within Long Point Bay (see Figure 3.3 a). Open water class is water areas where there is a possibility of wetland vegetation occurring (see Figure 3.3 b, c, and d). Floating emergent and emergent communities usually grow in open water areas (see Figure 3.3 b, c, and d). Tall wet/dense dry emergent is the main wetland vegetation class in Long Point. Some man-made structures in Big Creek National Wild Area, such as channels and dikes (see Figure 3.3 i), are easily misclassified as rivers.

Description of Photographs
(Number, Gradiation of wetland community foreground to background)
a) Lake, treed, upland
b) Mix of emergent, tall wet emergent and tall dense dry emergent, mix of open water and floating emergent
c) Open water, emergent
d) Mix of floating emergent and sub-emergent
d) Mix of floating emergent and sub-emergent
e) Tall wet emergent
f) Tall dense dry emergent
g) Mix of treed and meadow
h) Treed, upland
I) man-made dike (Upland)

Figure 3.3: Long Point wetland vegetation community identification

Qualitative field observations of the response of Long Point wetland vegetation communities to water level fluctuations were collected on September 8th, 2001 and in July 23rd 2015. The two field trips were completed in the same sample sites around Turkey Point and Long Point. The field trip in 2001 was conducted by Hebb (2003), while the field trip in 2015 was completed by Jingwen Huang in similar locations. Thirteen sample sites were included in Huang's field survey (see Figure 3.4). Long Point wetland communities were observed and noted as shown in Figure 2.1. The daily water level in September 8th, 2001 was 174.37 m, while the average water level in July 23rd , 2015 was 174.75 m. With average daily water levels rising 38 cm from Sep. 8th 2001 to July 23rd 2015, the responses of wetland communities to increasing water levels were similar in both the simulation map results and field observations. For example, with rising water levels, areas of floating emergent and emergent communities are observed to be decreasing.

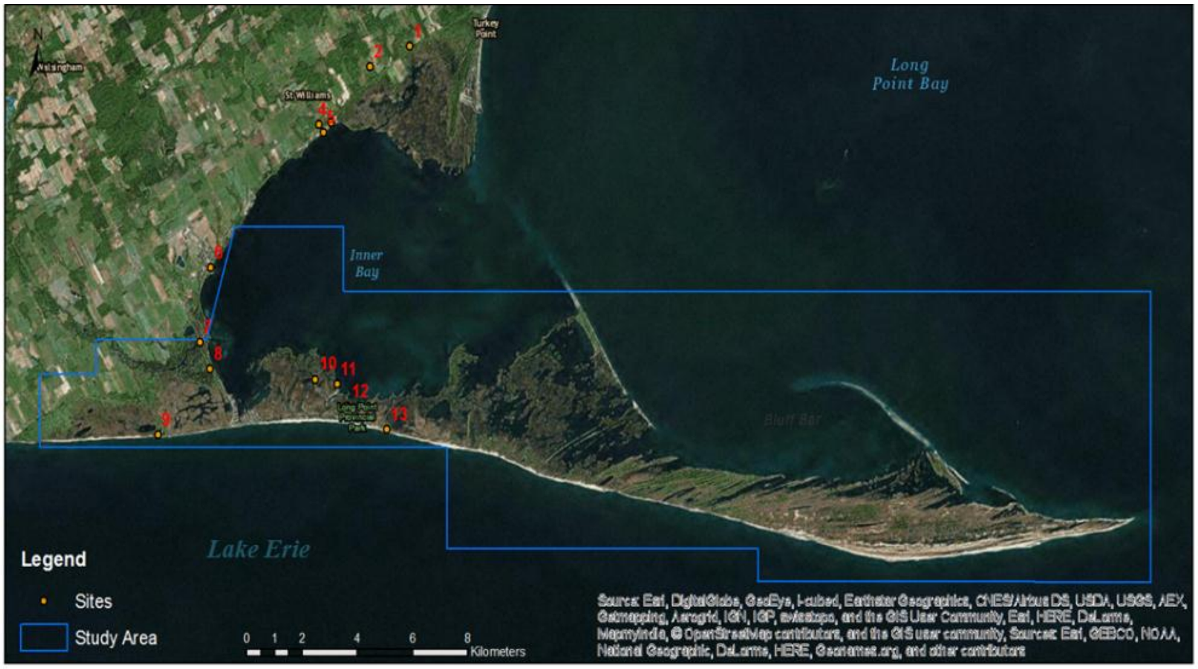

Figure 3.4 : Field survey sample sites

Sample site 2 is located at Turkey Point Lookout. Figure 3.5 shows the comparison of pictures collected of the wetland vegetation communities occurring at this site for the 2001 and 2015 field trips. In 2001, from foreground to background, the gradation of wetland communities contains lake, mix of tall dense dry emergent and tall wet emergent, open water, mix of emergent and floating emergent, mix of tall dense dry and tall wet emergent, meadow, and treed community. In 2015, the gradation of wetland community includes lake, treed, mix of tall dense dry emergent and tall wet emergent, open water, and mix of tall dense dry emergent and tall wet emergent and treed community. With the 38 cm water level increase, there are less floating emergent and emergent communities, and there was notably taller emergent community growth. Similar to the simulated classification maps from 2001 to 2015, the proportions of floating emergent and emergent communities decreased, while the proportion of tall dense dry emergent increased.

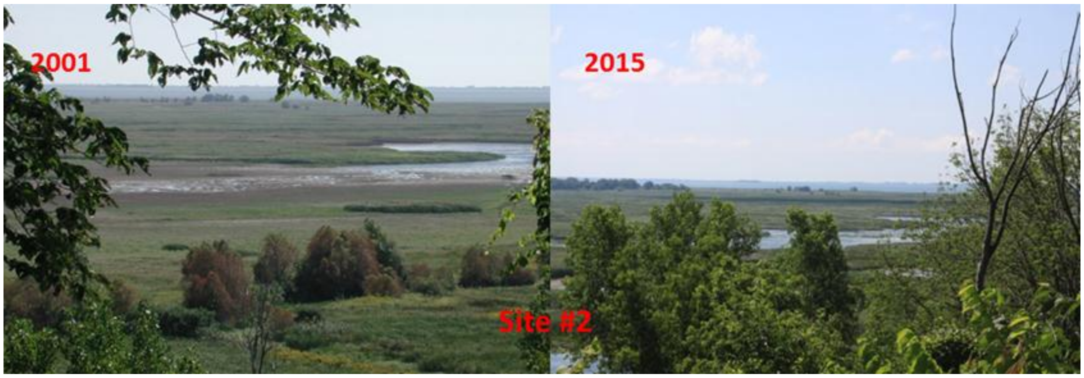

Figure 3.5: Qualitative ground truth observations collected in 2001 and 2015 at field survey sample site # 2. Site # 2 is located at the Turkey Point Lookout. Ground truth observations in September, 2001 were completed by Andrea Hebb; ground truth observations in July, 2015 were completed by Jingwen Huang.

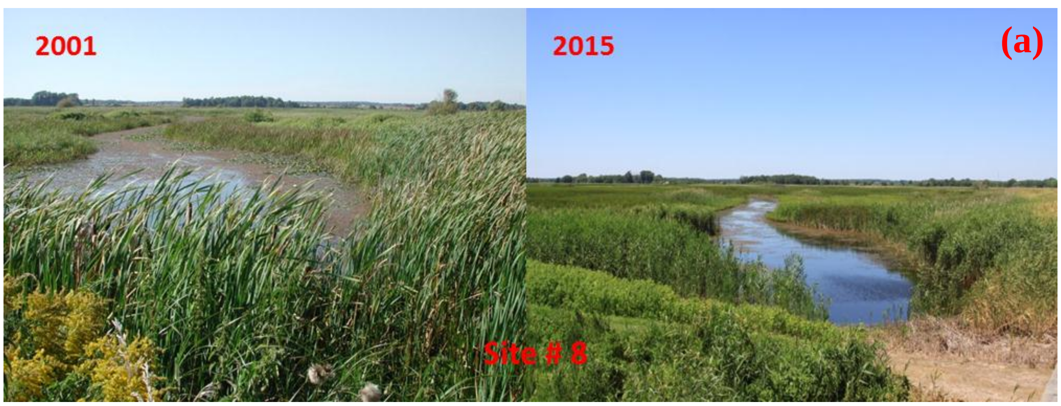

Figure 3.6 (a): Qualitative ground truth observations collected in 2001 and 2015 at field survey sample site # 8. Site # 8 is located in Big Creek National Wild Area (North of Entrance). Ground truth observations in September, 2001 were completed by Andrea Hebb; ground truth observations in July, 2015 were completed by Jingwen Huang.

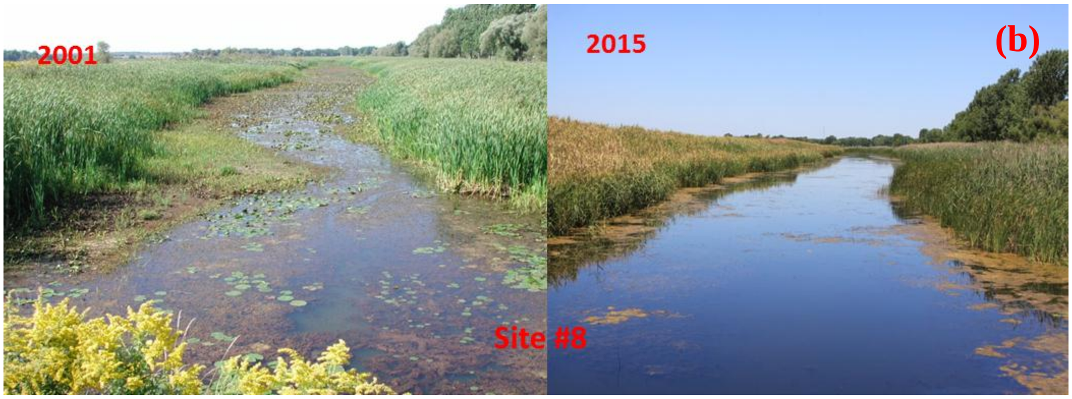

Figure 3.6 (b): Qualitative ground truth observations collected in 2001 and 2015 at field survey sample site # 8. Site # 8 is located in Big Creek National Wild Area (North of Entrance). Ground truth observations in September, 2001 were completed by Andrea Hebb; ground truth observations in July, 2015 were completed by Jingwen Huang.

Sample site no. 8 is located in the north entrance of Big Creek National Wild Area and several man-made channels are located in this sample site (see Figure 3.4). Figure 3.6 compares pictures of the wetland vegetation communities at this site for the 2001 and 2015 field visits. For the ground truth observation in 2001, from foreground to background, the gradation of wetland communities contains treed, tall dense dry emergent, open water, floating emergent and emergent, and tall dense dry emergent. For the ground truth observation in 2015, from foreground to background, the gradation of wetland communities contains treed, tall dense dry emergent, open water, and upland. With 38 cm water level increase, there are less floating emergent and emergent communities in the channels; tall dense dry emergent occupy most of the area (see Figure 3.6 a and b). The diversity of wetland vegetation has declined with the rise in water level from 2001 to 2015.

Sample site no. 9 is located at the end of Hasting Drive and is adjacent to Lake Erie (see Figure 3.4). Figure 3.7 compares pictures of the wetland vegetation communities at this site for the 2001 and 2015 field visits. In 2001, the transition of wetland communities consisting of lake, upland, treed community types was observed (see Figure 3.7). As shown in Figure 3.7, the rising water level resulted in eroded beaches and the shoreline was observed to gradually move upslope to the upland regions. It is noted that the water level rose 38 cm from 2001 to 2015 (Fisher**ie**s and Oceans Canada, 2015).

Figure 3.7: Qualitative observation of ground truth in 2001 and 2015 at field survey sample site # 9. Site # 9 is located at the end of Hasting Dr. Ground truth observations in September, 2001 were completed by Andrea Hebb, and ground truth observations in July, 2015 were completed by Jingwen Huang.

Chapter 4
Data

Datasets used and collected in this study are introduced in this chapter. There are three types of datasets: wetland communities' classification maps, topographic data and ancillary data. Table 4.1 summaries the properties of each dataset.

Table 4.1: Summary of datasets used in this study

Name	Date	Data Type	Resolution	Horizontal Reference	Vertical Reference	Provider
Long Point wetland community classification map	1945,1955, 1964,1978, 1985,1995, 1999	GRID	12 m	NAD 1927 UTM Zone 17N	N/A	Hebb, 2003
Long Point LiDAR-derived bare earth DEM	April, 2010	raster	1 m	NAD 1983 UTM Zone 17N	CGVD28	Canadian Wildlife Service, Canada, Environment Canada
Hebb's coastal topographic model	N/A	GRID	12 m	NAD 1927 UTM Zone 17N	IGLD 85	Hebb, 2003
Bathymetric contours	N/A	shapefile	125 to 500 m contour spacing	NAD 1983 UTM Zone 17N	IGLD 85	Adaptation and Impacts Research Group (AIRG), Environment Canada
RTK ground truth point	May, 2010	shapefile	N/A	NAD 1983 UTM Zone 17N	CGVD28	Hebb, 2003
Boundary	2015	shapefile	N/A	NAD 1983 UTM Zone 17N	N/A	Huang, 2016
SWOOP air photo	April, 2010	raster	20 cm	NAD 1983 UTM Zone 17N	N/A	Ontario Ministry of Natural Resources

4.1 Wetland Communities Classification Maps

Seven years (1945, 1955, 1964, 1978, 1985, 1995, and 1999) of Long Point wetland classification maps were included in this study, and the classification maps were vectorized from aerial photographs and survey data provided by Hebb (2003). Wetland vegetation was grouped into ten communities: lake, open water, floating emergent, emergent, tall wet emergent, tall dense dry emergent, short wet meadow, meadow, treed, and upland. The seven years of wetland classification maps were in GRID format with 12 m spatial resolution and in shapefile format based on the coordinate system NAD 1927 UTM Zone 17N. The seven years of wetland classification data represent different water levels for which wetland classification maps are available (see Figure 4.1). The 1964 represents the lowest water level period; 1985 represents the highest water level period; 1945, 1968, and 1978 reflect a medium water level period where the water level is rising; and 1955, 1978, and 1999 represents a medium water level period where the water level is declining.

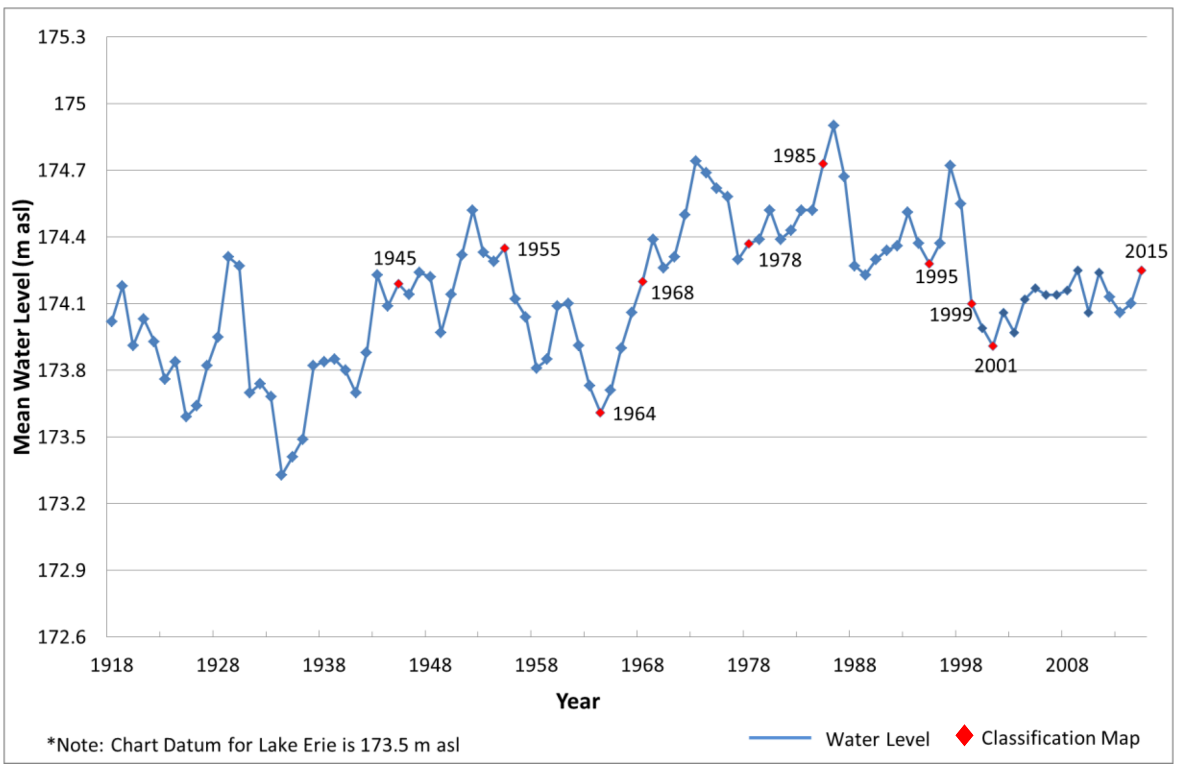

Figure 4.1: Lake Erie Mean Annual Water levels (m IGLD 85) from 1918 to 2015 with years of wetland classification maps and field visit years. The first field survey was completed in 2001 and the second field visit was completed in 2015

4.2 Topographic Data

Three kinds of topographic data are used to generate a new coastal topographic model in this study, including upland topographic, topographic bathymetric and coastal topographic data. Upland topographic data were derived from LiDAR data. The raw Long Point LiDAR data were acquired by an Optech ALTM 3000 airborne Light Detection and Ranging (LiDAR) system on April 2010 by the Canadian Wildlife Service. The laser wavelength of ALTM LiDAR sensor is 1,064 nm, which cannot measure distance under water (Optech, Inc.2016; Medeiros et al., 2015). The Long Point bare earth DEM, which represents the Earth's surface without all vegetation and man-made structures, was interpolated from raw Long Point LiDAR data using an Inverse Distance Weighting (IDW) algorithm. Long Point bare earth DEM is in raster format with a 1 m spatial resolution, the coordinate system is NAD 1983 UTM Zone 17N, and the vertical datum is CGVD 28.

Hebb's coastal topographic model was generated from multi-source data: a bathymetry point, a digital land elevation and a spot point. The Hebb's coastal topographic model, which contains upland topographic surface and the bathymetry of Lake Erie, represents elevation values above mean sea level (Hebb, et al., 2013). Hebb's coastal topographic model is in GRID format with 12 m spatial resolution, the coordinate system is NAD 1927 UTM Zone 17N, and the vertical datum is IGLD 85. Bathymetry data are represented in contours. Bathymetric contours, provided by AIRG, map the underwater depth of Lake Erie. The bathymetric contours cover the entire bottom of Lake Erie and represents elevation values in contours with 125 to 500 meters contour spacing. They are in shapefile polyline format, and the coordinate system is NAD 1983 UTM Zone 17N.

4.3 Ancillary Data

Ancillary data are also required in this study, including the study area boundary and SWOOP ortho image. The boundary of study area was determined based on available LiDAR data and bathymetric data. The boundary file is in shapefile format, and the coordinate system is NAD 1983 UTM Zone 17N. The Southwestern Ontario Orthophotography Project (SWOOP) covering Southwestern Ontario has a 20 cm spatial resolution and the coordinate system of the air photos is NAD 1983 UTM Zone 17N. The air photos were acquired in April 2010 and were used for digitizing the shoreline in the study area.

Chapter 5
Methodology

In this research, the methodology includes three parts: 1) coastal topographic model generation and assessment; 2) simulation model update and simulation; 3) model sensitivity analysis of the vegetation transition baseline. The research work flow is shown in Figure 5.1. This chapter describes the coastal topographic model generation, methodology for updating the wetland simulation model, and model sensitivity analysis. Finally, field observation data from a ground truth visit is described.

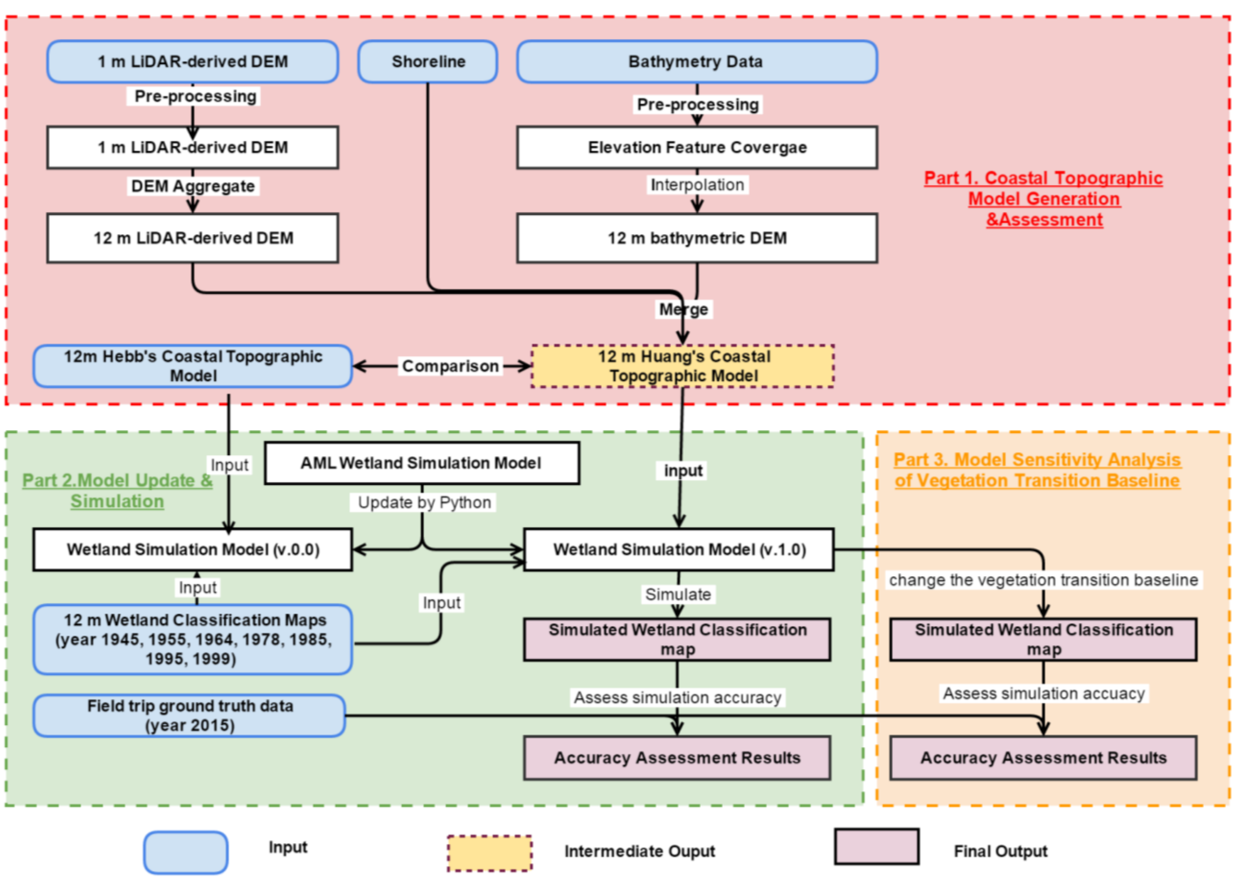

Figure 5.1: Research workflow. Part 1: Coastal topographic model generation and assessment. Part 2: Model update and simulation. Part 3: Model sensitivity analysis of vegetation transition baseline.

5.1 Coastal Topographic Model Generation

This section describes methods used to generate a coastal topographic model for Long Point by integrating multiple topographic and bathymetric datasets. The workflow of coastal topographic model generation is shown in Figure 5.2. The coastal topographic model contains elevation information both in the terrestrial surface and the bathymetry of Lake Erie/Long Point Inner Bay. The generation method is developed to improve the Hebb's coastal topographic model. Improving upon the Hebb's (2003) coastal topographic model for Long Point, LiDAR data were incorporated in developing the new coastal topographic model (Huang's coastal topographic model) to provide higher accuracy and higher density elevation information in upland areas. Furthermore, an edge matching algorithm was performed to smooth elevation values in the land-water transitional zones.

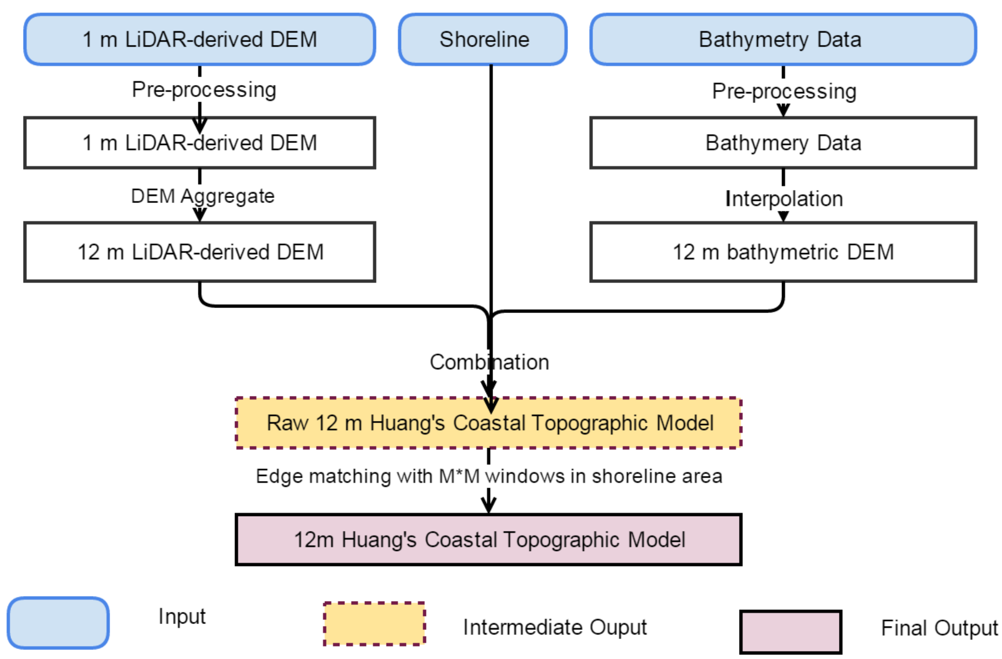

Figure 5.2: Workflow of coastal topographic model generation

5.1.1 Pre-processing

LiDAR data, bathymetry data and shoreline data are integrated to generate a coastal topographic model for the Long Point study area (see Figure 5.2). Pre-processing of these topographic datasets was required to produce compatible products.

Pre-processing of LiDAR data involved three steps: DEM merging, vertical datum conversion and DEM aggregation. First, the original LiDAR-derived bare earth DEMs were stored in separate tiles, which required the separate DEMs to be merged into a single DEM file using the Mosaic tool in ArcGIS.

Second, LiDAR data and bathymetry data were measured referring to different vertical datums (e.g. CGVD 28 and IGLD 85). Hence, vertical datum conversion is necessary to enable both datasets to be comparable. The elevation values in the LiDAR data were referenced to the Canadian Geodetic Vertical Datum of 1928 (CGVD 28) vertical datum, while elevation values in Lake Erie bathymetric contours were referenced to the International Great Lakes Datum (IGLD) of 1985. The CGVD 28, a vertical datum for Canada, is usually used in land geodetic levelling measurements (NRC, 2015), whereas the IGLD 85, a vertical datum in the Great Lakes-St. Lawrence River System, is usually used in hydrologic measurements. The IGLD 85 in Lake Erie is a chart datum of 173.5 m above sea level (NOAA, 2015). Since the coastal topographic model in this study is used for representing water fluctuations and the vertical datum of the Hebb's coastal topographic model is the IGLD 85, the IGLD 85 is chosen as the uniform vertical datum.

The vertical datum conversion of the LiDAR-derived DEM consisted of three steps: 1) converting the LiDAR-derived DEM into an ASCII file; 2) vertical datum conversion from CGVD 28 to NAD 83 using the GPS.H tool provided by the Geodetic Survey Division of Natural Resources Canada; 3) vertical datum conversion from NAD 83 to NAVD 88 using the VDatum tool provided by the National Geodetic Survey of NOAA; 4) vertical datum conversion from NAVD 88 to IGLD of 85 using the VDatum tool; 5) converting the ASCII file to a raster file using the Python command <ASCIIToRaster_conversion> in ArcGIS.

Finally, the 1m LiDAR-derived DEM was aggregated or resampled to a 12 m DEM using the Aggregate tool in ArcGIS. The aggregate method used in this study calculates the mean value for the input pixels (Kambhammettu et al., 2011). This resampling procedure was necessary to ensure compatibility between datasets for further analysis.

Pre-processing of Lake Erie bathymetric data included multiple steps. Lake Erie bathymetric data are represented by depth values from zero to six feet in contours with 125 to 500 m contour spacing. First, the bathymetric values were converted from feet to metres and then subtracted from the chart datum (e.g. IGLD 85). In this study, the Lake Erie contours were interpolated to a 12 m bathymetric DEM using the TopoToRaster interpolation tool in ArcGIS. Since the bathymetric DEM covers the entire Lake Erie, the DEM was then clipped to the study area boundaries.

The final stage of pre-processing was shoreline vectorization. In this study, shoreline data were required to define the transitional zones between terrain surface and submerged water areas. Since the shoreline changes through time, optimally, shoreline data should be acquired at the same time as the topographic dataset (e.g. LiDAR). As previously mentioned, the high resolution SWOOP image was acquired in the same month as the LiDAR data. Hence, a new shoreline was digitized in reference to the SWOOP image. The vectorizing process was performed using the Edit tool in ArcGIS, and the projection coordinate system of the shoreline data was defined as NAD 1983 UTM Zone 17N. In addition, the projected coordinate system of Hebb's coastal topographic model (NAD 1927 UTM Zone 17) was converted to NAD 1983 UTM Zone 17N in order to be comparable.

5.1.2 Coastal Topographic Model Generation

The LiDAR system provides high accuracy and high density elevation data of the terrain surface. However, elevation under water is not possible, since the LiDAR laser signal cannot penetrate dense vegetation and turbid waters (Medeiros et al., 2015). Underwater elevation information can be extracted from bathymetric data instead. Hence, the combination of LiDAR data and bathymetric data can potentially provide complete elevation information in coastal areas. In this study, the coastal topographic model was generated in two processes: topographic data combination and edge matching. It should be noted that the pre-processed LiDAR DEM only partially covered the upland area and some of the land-water transitional area, while the bathymetry DEM covered the entire study area.

The first step combined different sources of topographic data (e.g. LiDAR-derived DEM, and bathymetric topographic model). The combination procedure was performed on the topographic datasets which have the same spatial resolution. For example, the LiDAR-derived DEM with 12 m spatial resolution was combined with the 12 m bathymetric topographic model. The spatial resolution of the new coastal topographic model output was the same resolution as the input topographic data.

A Python script was developed to combine the different topographic data products of the LiDAR-derived DEM, bathymetric topographic model, shoreline data, and study area boundary files as input raster sources. The digital shoreline was used to determine the selection of bathymetric data or topographic data for merging both datasets. For example, within the study area, the script filled in a pixel with an elevation value given decision rules based on the spatial relationship or coincidence between the pixel location and the shoreline. These decision rules specified in the combination Python script are detailed in Table 5.1. For example, for a given pixel in the shoreline area, if the pixel has values available in both the LiDAR-derived DEM and bathymetric topographic model, the pixel value is computed as the average of both elevation values from the two topographic models. The generated coastal topographic model will be subsequently identified as Huang's coastal topographic model, while the original coastal topographic model which was developed by Hebb (2003) is identified as Hebb's coastal topographic model.

Table 5.1: Decision rules of coastal topographic model combination

Spatial relationship between a pixel and the shoreline	**Availability of pixel value in bathy topo and LiDAR**	**New pixel value**
If a pixel locates in the upland area	NC	Pixel value = LiDAR
If a pixel locates in the lake area	NC	Pixel value = Bathy Topo
If a pixel locates in the shoreline area	a. If the pixel has value in Bathy Topo & has no value in LiDAR	Pixel value = Bathy Topo
	b. If the pixel has no value in Bathy Topo & has value in LiDAR	Pixel Value = LiDAR
	c. If the pixel has value in both Bathy Topo & LiDAR	Pixel value = $\frac{(\text{LiDAR}+\text{Bathy Topo})}{2}$
	d. If the pixel has no value in either Bathy Topo or LiDAR	Not happen in this study area

Note. NC represents "do not need to check". LiDAR represents LiDAR-derived bare earth DEM. Bathy Topo represents the bathymetric topographic model.

After combining or selecting from the different topographic data sources, an edge matching algorithm was performed on the combined topographic model. The edge matching algorithm, which was developed as a Python script was used to filter and smooth the elevation values in the transitional zones between the terrain surface and water area in order to reduce abrupt changes in output data values. For a given pixel in the shoreline area, the pixel value was replaced with the mean of neighboring pixels, similar to a mean filter. The transitional zones were defined by the 2011 Long Point shoreline data. The neighbors are defined by an M*M square "windows". In this study, M is assigned as a value of 1 in order to signify single order neighbor pixels. In this study, several M values were tested in order to determine the optimal window size and the procedure is detailed in the following subsection. The two Long Point coastal topographic models could then be subsequently combined with the Long Point wetland classification maps in the wetland simulation model in order to predict the overall response of the wetland community to water level changes.

5.1.3 Coastal Topographic Model Assessment

The coastal topographic model was assessed by comparing elevation values in the coastal topographic model with ground truth elevation points that were collected by the Canadian Wildlife Service, Canada in May 2010. In total, 196 ground truth points were located in the western section of the study area with each point containing ground truth elevation values from surveyed data. The Root Mean Squared Error (RMSE) was computed to assess the differences between estimated values estimated by the coastal topographic model and actual elevation points from ground truth data. In general, higher RMSE values indicate a low level of accuracy for coastal topographic model estimates. The Root Mean Squared Error (RMSE) is calculated using the following equation:

$$\text{RMSE} = \text{sqrt}\ [\sum(Z_{\text{observe I}} - Z_{\text{predict I}})^2/n] \qquad \text{Eq.5.1}$$

where $Z_{\text{observe I}}$ is the ground truth elevation value at I point, $Z_{\text{predict I}}$ is the predicted elevation value at I point, and n is the total number of points.

5.2 Wetland Simulation Model

A wetland model that simulates the response of wetland communities to water level fluctuations was developed by Hebb (2003) and formed the basis for this study. The Hebb's model was updated and coded in a flexible language (Python Script), a user-friendly interface in ArcGIS was developed, and a revised coastal topographic model was produced. A model sensitivity analysis was conducted to evaluate the model simulation results and to explore how simulation accuracy performed with the testing of different model parameters. In addition, a case study of Hebb's (2003) wetland simulation model is described in Section 2.2.3.

5.2.1 Model Update

Python Scripts were used to update Hebb's (2003) wetland simulation model, which was originally developed by Hebb (2003) using AML programming language in an Arc/Info environment. Since Arc/Info has gradually been replaced by ArcGIS, the updated model was developed to run in both ArcGIS and Python IDLE. The steps involved in running the wetland simulation model were structured as follows.

First, users were required to enter a lake level and a base year to initialize the model (see Figure 5.3). The lake level must be higher than the minimum elevation value in the coastal topographic model and less than 180 meters, which was arbitrarily determined by Hebb et al. (2003). Water level fluctuations were then calculated from the lake level and elevation values in the coastal topographic model. Seven base years (i.e., 1945, 1955, 1964, 1978, 1985, 1995, and 1999) are available for selection, and each base year corresponds to a pre-existing wetland community classification map. The input data were stored in 2-D raster files with a 12 m spatial resolution.

Second, the coastal topographic model and the selected wetland classification map were converted to 2-D arrays, and a new array was created in which all array values were equal to the user entered hypothetical lake level. Subsequent simulation and data processing steps were then completed based on 2-D arrays. A value in an array represents a pixel value (e.g. elevation value) in a raster file, while a column and a row of the array represents the pixel location in a raster. Water depth represents depth in meters below or above the hypothetical lake level. Mathematically, water level fluctuation is calculated by subtracting the hypothetical lake level array from the coastal topographic model. A negative value means that water level rises in a particular location, while a positive value means that water level declines. The calculation results were also stored in a 2-D array

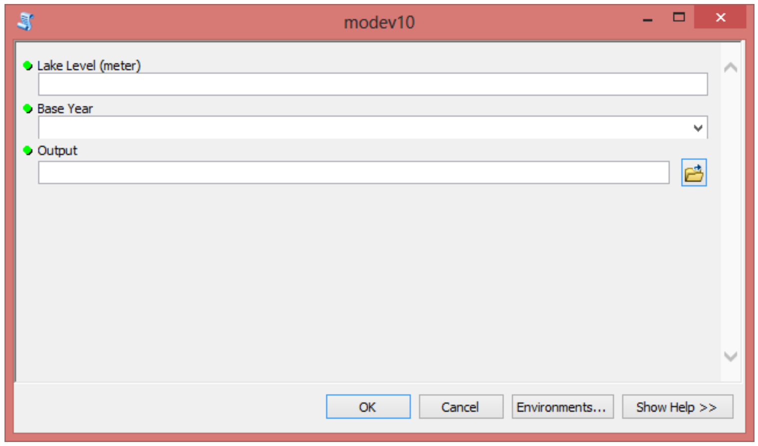

Figure 5.3: Wetland simulation model interface

Next, the response of each wetland vegetation community is determined by the water depth and base year wetland community. The model assumes that a wetland vegetation community can only transform to a community below or above the community's tolerance range (Hebb, 2003). The tolerance ranges of each wetland community were determined from a literature review that was summarized by Hebb (United States Environmental Protection Agency, 2000; Newmaster et al., 1997; Ould and Holbrow, 1987; Geis, 1985; Kadlec and Wentz, 1974; Dane, 1959). For example, a pixel with floating emergent community in the base year will be transformed to an emergent community if the water level decreases 0.3 m. The simulations were completed by a series of if-else statements (see Table 5.2). The decision rules in the wetland simulation model were alternative from the theoretical wetland communities' tolerance ranges (see Table 2.2). The conceptual models of the theoretical wetland communities' tolerance ranges and decision rules of the wetland simulation model v.1.0 are shown in Figure 5.4. The simulated wetland community results were then stored in a new array.

Table 5.2: Decision rules for the wetland simulation model v1.0

Veg=**Lake**: If water level rises >0.3 m, then Veg=L; If water level rises ≤ 0.3 m & ADJ=U, then Veg=U If water level rises ≤0.3 m, then Veg= OW	Veg= **Open Water**: If water level declines ≥0.3 m, then Veg=OW; If water level declines ≤0.3 m, then WVC= FE; If water level rise >2 m, then Veg= L
Veg= **Floating Emergent**: If water level rises <0.3 m & declines > 0.3 m, then Veg=FE If water level declines ≤ 0.3 m, then Veg= E If water level rises >0.3 m, then Veg=OW	Veg=**Emergent**: If water level rises ≤0.3 m & declines <0.5 m, then Veg=E If water level declines ≥0.5 m, then Veg=DE If water level rises >0.3 m, then Veg= FE
Veg=**Tall Emergent**: If water level rises ≥0.3 m & declines ≤0.6 m, then Veg= WE If water level rises ≤0.3 m & declines <0.5 m, then Veg= DE If water level declines ≥0.5 m, then Veg= M Else, Veg= E	Veg=**Meadow:** If water level rises ≥0.3 m & rises ≤0.6 m, then Veg=SM If water level rises ≥0.3 m & declines ≤0.8 m, then Veg= M If water level declines ≥0.8 m, then Veg= T Else, Veg= TE
Veg=**Treed**: If water level rises ≤0.3 m & declines ≤1 m, then Veg=T If water level declines ≥1 m, then Veg=U If water level rises <0.3 m, then Veg=M	Veg=**Upland**: If water level rises ≥ 0.6 m, then Veg=L; If water level no change & ADJ =L, then Veg=L If water level rises ≤ 0.6 m & declines ≤ 0.3 m, then Veg=T; Else, Veg= U

Note. WVG= wetland vegetation community; ADJ= Adjacent to n*n cells; L=Lake; OW= Open Water; FE= Floating Emergent; E=Emergent; TE= Tall Emergent (include tall dense emergent (DE) and tall wet emergent (WE)); M= Meadow (include meadow (M) and short wet meadow(SM)); T= Treed Community; U= Upland.

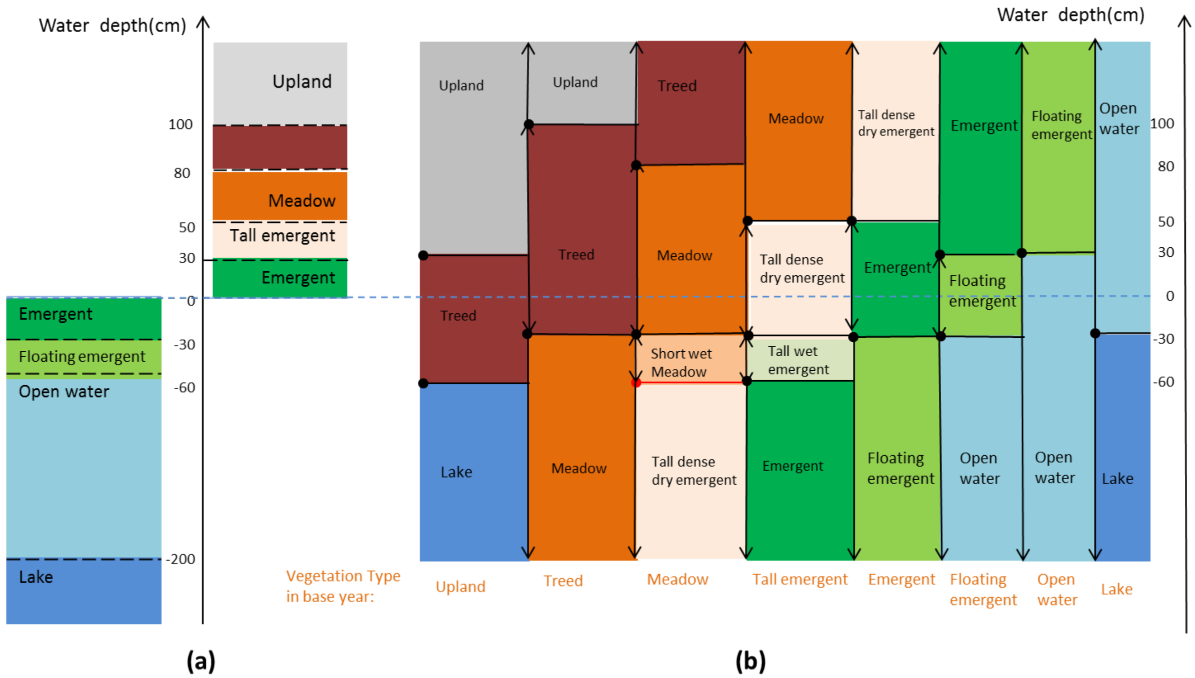

Figure 5.4: Conceptual model of wetland communities' tolerance ranges. (a) Conceptual model of wetland communities' tolerance ranges and the theoretical wetland communities' tolerance ranges were listed in Table 2.2. (b) Conceptual model of wetland communities' decision rules in the wetland simulation model v.1.0, and the decision rules were listed in Table 5.2.

Finally, the new array containing the simulated wetland community is then converted to a raster file. The spatial resolution of the output raster is the same as the input raster. The simulation results can be viewed by importing the raster file into ArcGIS. In the simulated raster file, ten wetland communities were coded numerically (see Appendix B).

5.2.2 Model Sensitivity Analysis

The vegetation transition baseline is an important parameter in the wetland simulation model, because it is the water depth threshold that determines whether the wetland vegetation communities will shift to a wetter wetland community. The default value of the vegetation transition baseline is a water depth of 30 cm, which was determined by literature and Hebb's background knowledge and experience of the study area (2003). However, it is recognized that the value of 30 cm may not necessarily be the optimal value for this study area. Hence, a sensitivity analysis was conducted in this study to test the variation of model simulation results to different vegetation transition baseline values, which was not previously tested by Hebb (2003). Vegetation transition baseline values tested in this study included -40 cm, -35 cm, -30 cm (default value), -25 cm, -20 cm, -15 cm, -10 cm, -5 cm, and 0 cm.

5.2.3 Model Assessment

The accuracy of the Hebb's and Huang's wetland simulation model was assessed by comparing the simulation results with the pre-exiting wetland community classification map. The pre-existing wetland community classification map were digitized and vectorized from aerial photographs and survey data provided by Hebb (2003). The acquisition dates of each pre-existing wetland community classification map are detailed in Tables 4.1 and 4.2, and the mean annual lake level values were determined according to the acquired year of pre-existing classification maps. Simulation result was generated by entering the actual mean lake level and selecting the corresponding base year. The simulated raster was then compared with the pre-existing classification map using the RasterCalculator tool in ArcGIS. An accurately predicted pixel is considered to be a pixel whose value is the same in both the simulated result and the ground truth dataset. The total number of correctly predicted pixels can be determined from the difference raster which was generated by the RasterCalculator tool. The overall accuracy of the simulation model was calculated using the following formula:

$$\text{Overall Accuracy} = \frac{Total\ Number\ of\ correctly\ predicted\ pixels}{Total\ Number\ of\ pixels} \times 100 \qquad \text{Eq.5.2}$$

5.3 Ground Truth Field Survey

A field visit to Long Point and Turkey Point study sites was conducted on July, 23rd, 2015 to collect qualitative observations of wetland communities. The purposes of this field survey were to: 1) collect qualitative observations of ground truth vegetation types and point data; 2) identify Long Point wetland vegetation communities; 3) collect qualitative ground truth observations at selected sample sites. The July 23rd, 2015 field survey results were then compared with similar the ground truth observations collected by Hebb (2003) in the same sampling sites and locations in September 8th, 2001. According to hourly water level records at Port Dover Tidal Observation Station on the day of field trip, the daily average water level in September 8th, 2001 was 174.37 m asl, while in July, 23rd 2015 was 174.75 m asl (Fishers and Oceans Canada, 2015).

Thirteen sampling sites were included in this field survey; six were located in Turkey Point, and the others at Long Point (Figure 6.11). The sampling sites (No.1 to No.5) located at Turkey Point provided a holistic view of Long Point and Long Point Inner Bay, and ground truth data were collected from the sampling sites (No.6 to No.13) located at Long Point (see Appendix A). The sampling sites were determined mainly by site accessibility and the wetland vegetation community typical of the area. Five wetland vegetation communities and three land cover features were identified. The wetland vegetation communities include floating emergent, emergent, tall wet/tall dense dry emergent, short wet meadow/meadow, and treed. Land use and land cover classes contain open water, lake, and upland. Wetland vegetation communities (i.e. floating emergent, emergent, tall wet/tall dense dry emergent, short wet meadow/meadow, and treed) were identified according to the Wetland Plants of Ontario (Newmaster, et al., 1997). Field records included site location and land cover type. Site location coordinates were identified using a Trimble GPS (Figure 5.5 b). In addition, it should be noted that this field survey was limited by site accessibility and time availability for conducting field observations.

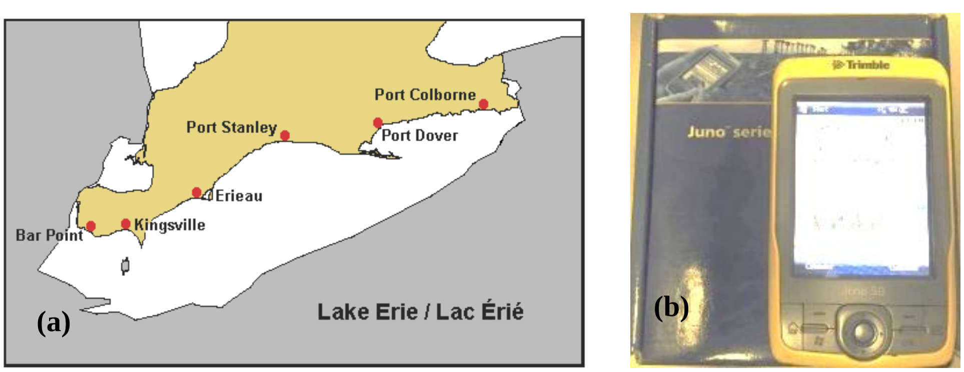

Figure 5.5: (a) Port Dover tidal observation station. (b) Survey tool: Trimble GPS
Image retrieved from: http://www.marees.gc.ca/eng/find/zone/44

Chapter 6
Results

This chapter describes the main results based on the methods shown in Chapter 5. This chapter begins by describing results of generating the coastal topographic model, followed by results of the revised wetland simulation model and simulation output. The simulated wetland communities from 2001 to 2015 will then be discussed to explore the response of wetland communities to water level changes. Finally, results of the model sensitivity analysis of vegetation transition baseline will be described.

6.1 Coastal Topographic Model

In this study, the coastal topographic model is one of the key inputs for the wetland simulation model. This section will first describe the new Long Point coastal topographic model (Huang's coastal topographic model). The second part will expand on the qualitative and quantitative comparison of the two Long Point coastal topographic models (Hebb's coastal topographic model and Huang's coastal topographic model), which were generated by different approaches and using different types of topographic data inputs. It should be noted that Huang's Long Point coastal topographic model was revised from the original Hebb's Long Point coastal topographic model.

Huang's Long Point coastal topographic model was generated by integrating the LiDAR, bathymetry, and shoreline boundary datasets with a spatial resolution of 12 m (see Figure 6.1). Differing from other digital topographic models (e.g. LiDAR-derived DEM), Huang's Long Point coastal topographic model presented in this study provides elevation estimates for both the terrain surface (i.e., above the water surface) and in the aquatic environment (i.e., below the water surface). The elevation values, which refer to the IGLD of 85, represent meters above mean sea level (a chart datum of 173.5 m).

The overall structure of and differentiation between wetland and upland communities in Long Point can be readily recognized from the Huang's Long Point coastal topographic model. Upland areas have relatively high elevation values; while water submerged areas have relatively low elevation values. In the study area, the highest elevation point is located in the town of Port Rowan (west section), while the lowest point is located in Long Point Bay (northeast section). The lands are relative steep in the western section, eastern section, and along the shore near Lake Erie; lands are flats in the middle section of the study area (see Figure 6.1). The resulting Root Mean Square Error (RMSE) of the 12 m Long Point coastal topographic model was 0.445 (see Table 6.1).

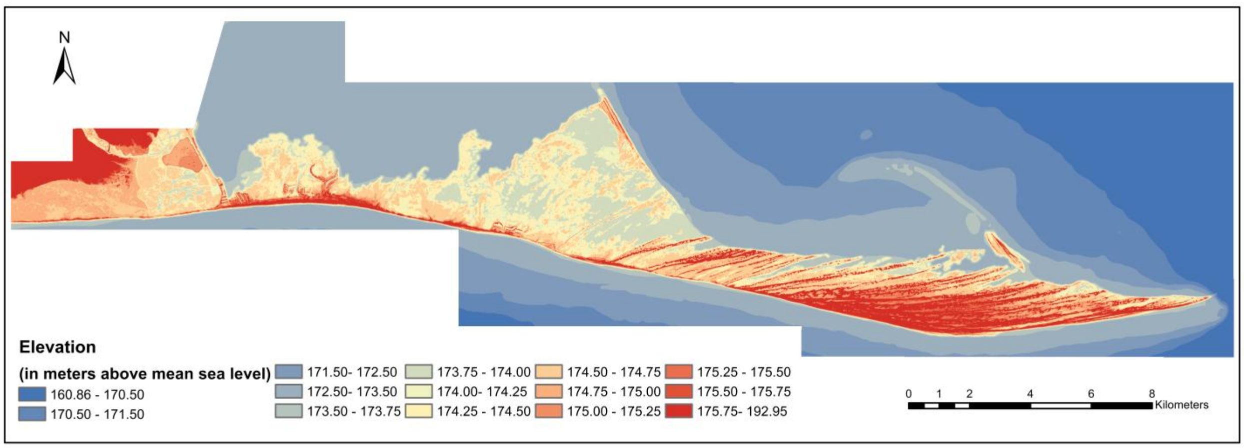

Figure 6.1: Huang's Long Point coastal topographic model with 12 m spatial resolution generated by integrating LiDAR data, bathymetric data, and shoreline data

A coastal topographic model can be generated from different topographic data sources. Hebb's (2003) Long Point coastal topographic model was developed based on bathymetry data and digital terrain modeling points. Hebb's (2003) coastal topographic model, provided by the Adaption and Impacts Research Group (AIRG), also has a 12 m spatial resolution (see Figure 6.2). Similarly with Huang's coastal topographic model, Hebb's model provides elevation information both in the terrain surface and aquatic environment within the study area. The elevation value in the Hebb's Long Point coastal topographic model, which refers to the IGLD 85, also represents heights above mean sea level (a chart datum of 173.5m). The Root Mean Square Error (RMSE) of the Hebb's Long Point coastal topographic model is 1.609 (see Table 6.1).

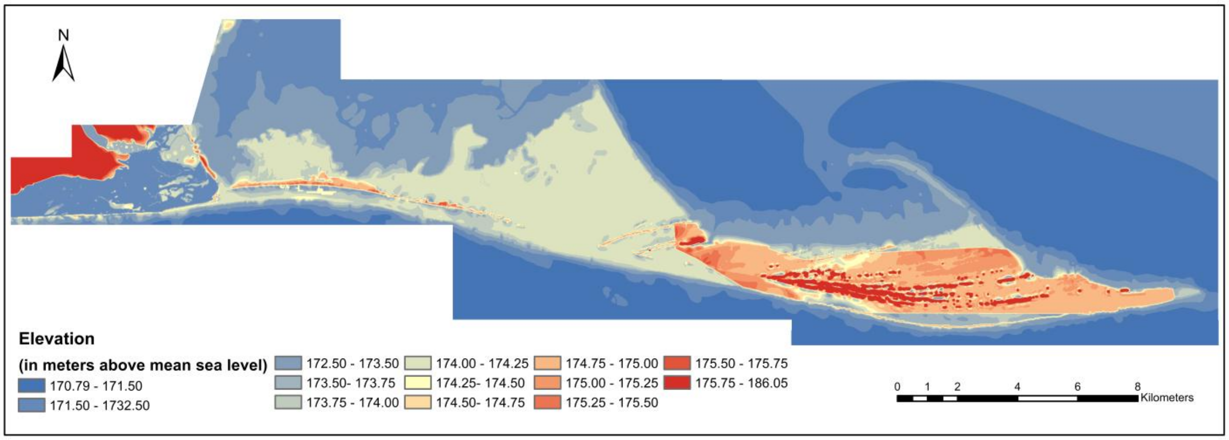

Figure 6.2: Hebb's (2003) Long Point coastal topographic model generated by integrating digital terrain modeling points and bathymetric data. AIRG = the Adaption and Impacts Research Group.

For this study, Huang's Long Point coastal topographic model was generated by integrating the LiDAR-derived DEM, bathymetric data and the shoreline data. Overall, Huang's Long Point coastal topographic model provides more topographic details visually than Hebb's (2003) original Long Point coastal topographic model, especially in upland areas. For example, channels in the Big Creek Area (west section) are easier recognized in Huang's Long Point coastal topographic model, and upland structures are clearer (see Figure 6.1). There is a significant difference between the two models in the Big Creek Area (see Figure 6.1 and Figure 6.2). Both coastal topographic models have similar details in Lake Erie and Long Point Bay areas.

A quantitative comparison of the two Long Point coastal topographic models' performance is shown in Table 6.1. Huang's Long Point coastal topographic model resulted in a wider range of elevation values within the study area. The elevation values range from 160.80m to 192.95m, while the elevation values in the Hebb's original Long Point coastal topographic model range from 170.79 m to 186.05 m. The mean elevation values of both coastal topographic models are similar; the Huang's model value as 172.30 cm and the original Hebb's model is 172.63 cm. The Root Mean Square Error (RMSE) of the 12 m Long Point Coastal Topographic Model is 0.445, while the RMSE of Hebb's original model is 1.609.

Therefore, Huang's Long Point coastal topographic model resulted in higher accuracy than the original Hebb's Long Point coastal topographic model.

Table 6.1: Basic statistical results and RMSE of different coastal topographic models at Long Point

	Mean (m)	Minimum (m)	Maximum (m)	Standard Deviation	RMSE
Huang's coastal topographic model (12 m)	172.30	160.86	192.95	3.10	0.445
Hebb's coastal topographic model(12 m)	172.63	170.79	186.05	1.67	1.609

Note. Huang's Long Point coastal topography model (12 m and 30 m) was generated by integrating LiDAR data, bathymetric data, and shoreline data. The original Hebb's coastal topographic model (12 m) was generated by integrating digital terrain modeling points and bathymetric data. Root Mean Squared Error (RMSE) = sqrt $[\sum(Z_{observe\ I}\text{-}Z_{predit\ I})^2/n]$

The shoreline data was included in coastal topographic model generation for determining whether LiDAR or bathymetric data values would be selected for the integrated elevation product. Elevation values along the shoreline may especially vary among the different topographic datasets considered in this study and the aim was to reduce abrupt differences potentially produced by the integration process. A total of 3,500 sample points were sampled along the shoreline in order to explore the difference in elevation values between the different topographic datasets. Overall, elevation values along the shoreline in the LiDAR-derived bare earth DEM were found to be consistently higher than corresponding elevation values in the bathymetric topographic model (see Figure 6.3). Along the shoreline, the mean elevation value in the LiDAR-derived bare earth DEM was 173.97 m, while the bathymetric topographic model mean elevation value was 173.52 m and the coastal topographic model mean elevation was 173.86m (see Table 6.2). Along the shoreline, there is a mean offset of 46 cm between the LiDAR-derived bare earth DEM and the bathymetric topographic model.

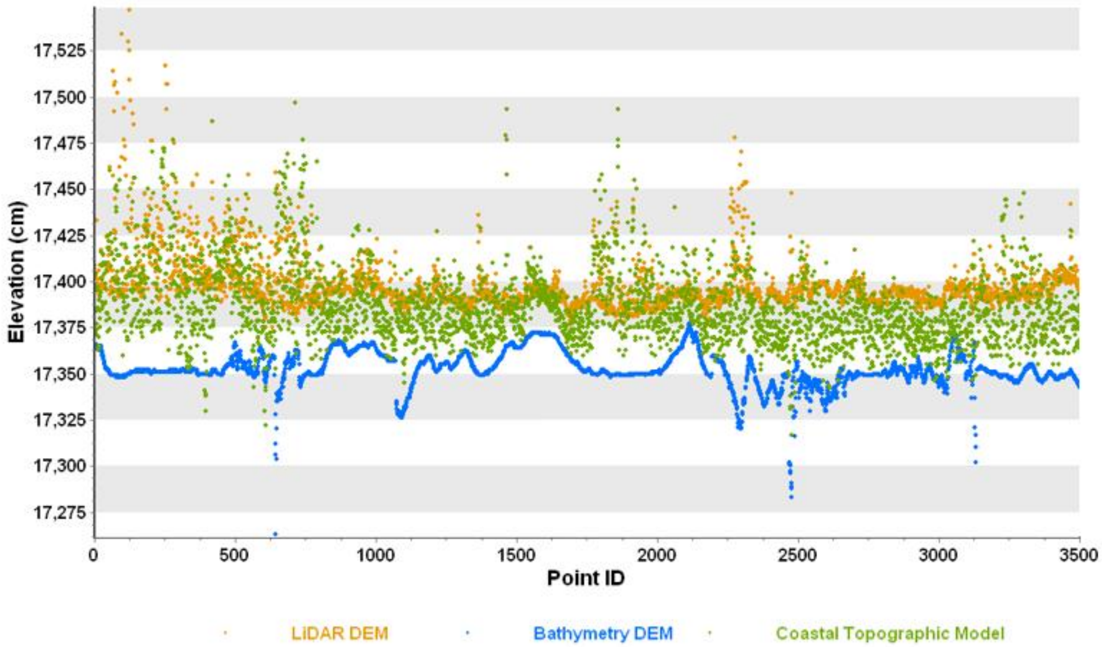

Figure 6.3: Elevation values comparison in different topographic data sources along the shoreline boundary

An edge matching algorithm, similar to a filter, was applied to pixels along the shoreline, resulting in smoothing of elevation values observed along the shoreline. As aforementioned in Chapter 5, for pixels located along the shoreline, attribute values were made equal to the average of elevation values derived from the LiDAR-derived bare earth DEM and the bathymetric topographic model. Then an edge matching algorithm was performed to smooth elevation values based on the neighbors M*M square windows along the shoreline. Different M values generate different coastal topographic models, especially along the shoreline. Several M values (M=1, 2, 3, 4, 10) were tested. Increasing the value of M results in higher elevation values in a coastal topographic model along the shoreline (see Table 7.1). In other words, increasing the value of M results in elevation values converges closer to the LiDAR dataset.

Table 6.2: A comparison of sample elevation points along the shoreline with variable edge matching window sizes

Window size	Sample Points Elevation values (m)			
	Mean	Minimum	Maximum	Standard Deviation
M=1	173.86	173.17	174.97	0.22
M=2	173.93	173.22	175.25	0.26
M=3	173.98	173.18	175.37	0.29
M=4	174.03	173.27	175.79	0.28
M=10	174.11	172.96	176.93	0.30

Note. M is the neighbors M*M square window

6.2 Wetland Simulation Model

In this study, the wetland simulation model predicts the response of wetland communities based on pre-existing wetland vegetation communities and water level changes. This section first briefly introduces the updated simulation model and then describes the simulation results. Finally, the subsequent section expands on the qualitative and quantitative analysis by exploring changes in coastal topographic model parameters that potentially impact the wetland vegetation simulation results.

6.2.1 Updated Wetland Simulation Model

Three versions of the wetland simulation models were developed, named Model v.0.0, v.1.0, and v.2.0. All three models share the same user interface and utilize identical pre-existing wetland classification maps. Users are required to enter three parameters: a lake level in meters, a base year, and the location of the output raster (see Figure 6.4). A base year can be selected from any of the seven base years: 1945, 1955, 1964, 1978, 1985, 1995, and 1999. Model v.0.0 uses Hebb's coastal topographic model as model input data to simulate wetland communities, and Model v.1.0 uses Huang's Long Point coastal topographic model produced in this study as input data. Both Models v.0.0 and v.1.0 use the same vegetation community tolerance ranges, which were derived from the literature (see Table 2.2) with model decision rules of each wetland community summarized in Table 5.2. Model v.2.0 was used for model sensitivity analysis. Both Model v.0.0 and v.1.0 use the same study area boundaries.

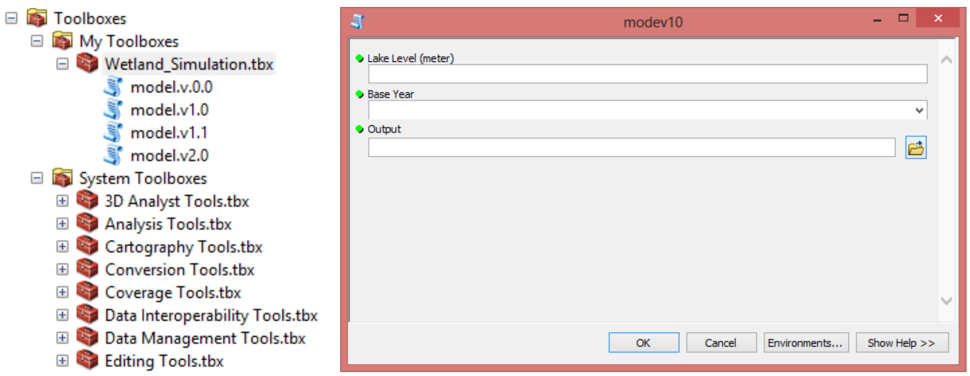

Figure 6.4 : Wetland simulation model interface in ArcGIS

The model simulation output is a raster file and can be displayed in an ArcGIS environment. Figure 6.5 shows an example of wetland simulation model results. The predicted wetland community classification map contains ten wetland communities: lake, open water, floating emergent, emergent, tall wet emergent, tall dense dry emergent, short wet meadow, meadow, treed, and upland (see Figure 6.5).The study area is dominated by meadow and tall dense dry emergent vegetation communities, and floating emergent and emergent vegetation communities are distributed along near the water area.

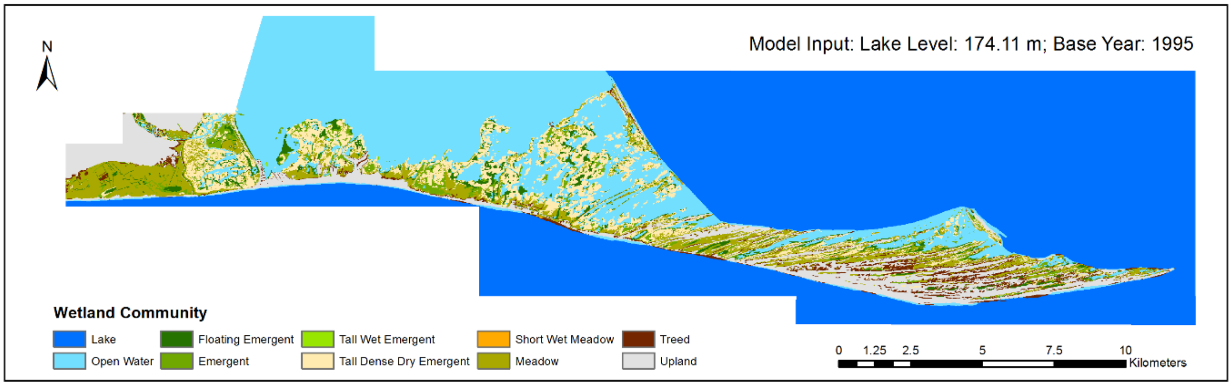

Figure 6.5: Example of wetland simulation model output

6.2.2 Wetland Simulation Model Comparison

Different coastal topographic models considered in the wetland simulation models tested in this study yielded different vegetation community prediction results. As previously mentioned, Model v0.0 uses Hebb's coastal topographic model as input data which was integrated by bathymetry data and digital terrain modeling points (Hebb, 2003); Model v1.0 uses the updated coastal topographic model from this study integrating LiDAR, bathymetry and shoreline data sources. The two coastal topographic models have been assessed and compared in the previous section (see Chapter 6.1). By entering the same model parameters (including base year and lake level), these two simulation models yielded different results. The implications/outcomes of the different topographic models (e.g., v.0.0 and v.1.0 shown in Figures 6.6(a) and 6.7(a), respectively) were assessed by running a simulation for 1999 wetland vegetation communities and compared to the ground truth wetland community classification map in 1999, see Figures 6.6(b) and 6.7(b), respectively).

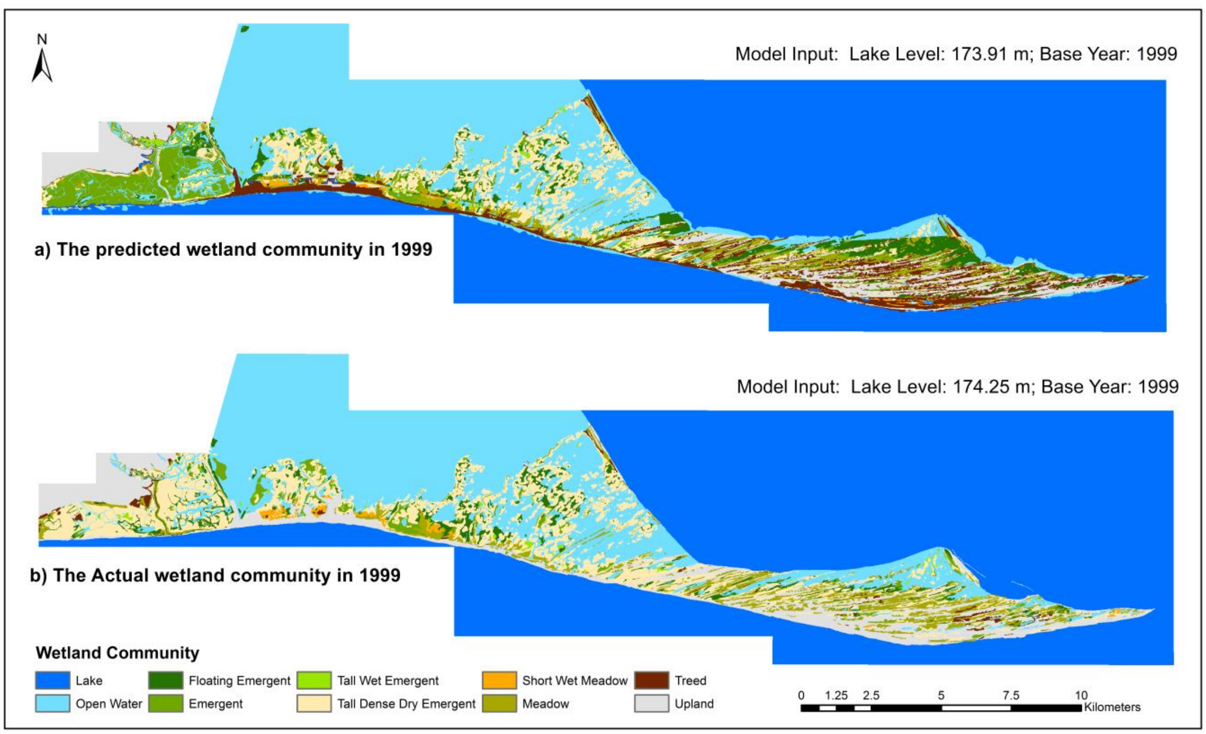

Figure 6.6: Model results: a) predicted wetland community map in 1999 from Model v.0.0; b) actual wetland community map in 1999 interpreted from aerial photograph. The simulation model input: base year: 1995, simulation year 1999, lake level 174.11 m.

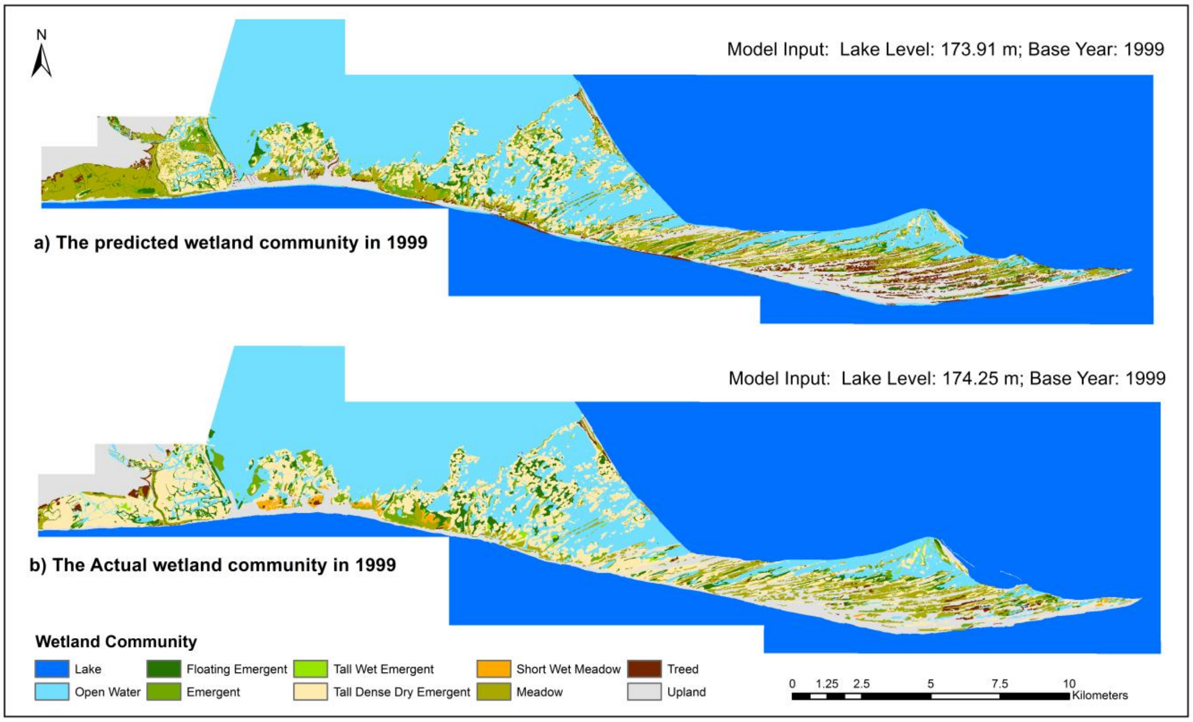

Figure 6.7: Model results: a) predicted wetland community map in 1999 from Model v.1.0; b) actual wetland community map in 1999 interpreted from aerial photograph. The simulation model input: base year: 1995, simulation year 1999, lake level 174.11 m.

The percentage of each wetland community in the simulation results and the ground truth classification map are calculated. The percentages are shown in Table 6.3. For example, in the Model v.0.0 predicted wetland classification map in 1999, 2.68% of pixels were classified as floating emergent and 3.26% of pixels were classified as emergent. As shown in Table 6.3, the percentages of lake and open water in the ground truth classification map, Model v.0.0 predicted classification map, and Model v.1.0 predicted classification map were all visually similar in terms of spatial patterns of vegetation communities. The percentage covers of floating emergent, emergent, treed community and upland in Model v.1.0 predicted result in 1999 were more closely associated with the ground truth classification map of 1999.

Table 6.3: The percentage of each wetland community in different predicted wetland classification map outputs

Wetland classification map	Percentage of wetland community in wetland classification map									
	L	OW	FE	E	WE	DE	SM	M	T	U
Ground truth wetland classification map in 1999	55.88%	21.34%	1.73%	1.06%	0.20%	8.96%	0.27%	3.07%	0.41%	7.07%
Model v.0.0 predicted wetland classification map in 1999	55.11%	21.59%	2.68%	3.26%	0.27%	5.54%	0.26%	2.77%	4.10%	4.42%
Model v.1.0 predicted wetland classification map in 1999	55.47%	21.61%	1.72%	1.51%	0.01%	5.78%	0.01%	5.36%	1.16%	6.87%

Note. L= Lake community; OW= Open water community; FE= Floating emergent community; E= Emergent community; WE= Tall wet emergent community; DE= Tall dense dry emergent; SM= Short wet meadow; M= Meadow; T= Treed; U= Upland. The ground truth wetland classification map in 1999 was derived from air photo interpretation. The simulation model (Models v.0.0 & v.1.0) parameter: base year: 1995, simulation year: 1999, lake level 174.11 m. Model v.0.0 uses Hebb's coastal topographic model, and the Model v.1.0 uses Huang's coastal topographic model.

The simulation accuracy of each model can be assessed by the ability of the model to correctly predict the wetland communities within the study area. The ground truth wetland classification map is 1999 is shown both in Figures 6.6(b) and 6.7(b), and the ground truth map was used to assess the accuracy of model simulation results. Accuracy assessment results for Model v0.0 and Model v1.0 are shown in Tables 6.4 and 6.5, respectively. With a 174.11 m hypothetical lake level and 1995 as the base year, the overall accuracy of the Model v0.0 simulation result was 83.85%, while the overall accuracy was 88.32% for Model v1.0. Overall, Model v1.0 resulted in a superior prediction accuracy of wetland vegetation in response to water level fluctuations than compared to Model v0.0. Therefore, a high accuracy coastal topographic model plays an important role in improving the prediction accuracy of the wetland simulation model.

A high accuracy coastal topographic model not only improved the overall model simulation accuracy, but also the simulation accuracies of most wetland communities, such as floating emergent, emergent, tall dense dry emergent, meadow, and treed community. As shown in Tables 6.4 and 6.5, Model v1.0 improved the simulation accuracies of lake (from 98.05% to 99.14%), open water (from 89.31% to 93.78%), floating emergent (from 30.95% to 36.71%), emergent community (from 39.19% to 44.98%), tall dense dry emergent community (from

47.26% to 51.41%), meadow community (from 33.43% to 46.44%), treed community (from 33.68 to 40.75%) and upland (from 50.42% to 78.99%). For the lake class, Model v0.0 resulted in many pixels being wrongly predicted as open water (20,287 pixels), while Model v1.0 resulted in fewer pixels being inaccurately predicted as open water (8,002 pixels). Model v0.0 also resulted in many pixels being wrongly classified as floating emergent community (29,599 pixels), while Model v1.0 had fewer pixels inaccurately predicted as floating emergent community (10,717 pixels). For floating emergent community, Model v0.0 inaccurately classified 8,114 pixels as open water, while Model v1.0 resulted in fewer wrongly predicted pixels as open water (3,905 pixels). For the upland class, many pixels were wrongly predicted as treed community by Model v0.0 (48,068 pixels), while Model v1.0 had fewer pixels misclassified as treed community (10,892 pixels).

The simulation resulted in low classification accuracy for the short wet meadow vegetation class due to the limitation of decision rules in the simulation model. In the decision rules (see Table 5.2), a pixel with short wet meadow community in the base year may be transformed to a meadow, treed, or a tall dense dry emergent community if the water level changes. However, no rule specifies that a vegetation community may transform into a short wet meadow community. Hence, the percentage of short wet meadow tends to decrease whenever the water level rises or declines. This limitation in decision rules results in low (or close to zero) prediction accuracy of short wet meadow (see Table 6.5).

Table 6.4: Simulation model (v.0.0) accuracy assessment result

		Ground Truth Class										User Accuracy
		L	OW	FE	E	WE	DE	SM	M	T	U	
Model predicted Class	L	1088449	27	54	11	0	468	7	246	77	5489	99.42%
	OW	20287	378668	8114	3394	449	12116	134	1026	143	4421	88.32%
	FE	1	29599	10657	3354	326	6007	180	1360	205	1611	19.99%
	E	0	3404	9105	8227	446	40361	20	1528	283	1295	12.72%
	WE	4	358	262	59	252	4138	14	109	18	227	4.63%
	DE	24	6794	3227	3822	1849	84131	713	6690	546	2311	76.41%
	SM	10	139	59	66	9	764	1462	1591	104	909	28.59%
	M	186	1649	1721	750	504	20404	1800	20376	2351	5255	37.05%
	T	590	1680	705	736	93	6061	845	19926	2759	48068	3.39%
	U	577	1670	525	576	61	3580	248	8102	1705	70779	80.59%
Producer's Accuracy		98.05%	89.31%	30.95%	39.19%	6.32%	47.26%	26.96%	33.43%	33.68%	50.42%	
Overall Accuracy		83.85%		Kappa	Coefficient	0.746						

Note. L= Lake community; OW= Open water community; FE= Floating emergent community; E= Emergent community; WE= Tall wet emergent community; DE= Tall dense dry emergent; SM= Short wet meadow; M= Meadow; T= Treed; U= Upland. The simulation model input: base year: 1995, simulation year 1999, lake level 174.11 m. Model v.0.0 uses Hebb's coastal topographic model.

Table 6.5: Simulation model (v.1.0) accuracy assessment result

		Ground Truth Class										User Accuracy
		L	OW	FE	E	WE	DE	SM	M	T	U	
Model predicted Class	L	1100585	45	0	0	0	13	0	44	0	1369	99.87%
	OW	8002	397598	3905	3499	562	9335	172	1149	43	4829	92.66%
	FE	0	10717	12639	2578	143	5087	76	1266	229	1363	37.07%
	E	0	1943	9492	9444	174	6567	89	1282	123	848	31.52%
	WE	1	82	0	8	65	128	0	0	0	0	22.89%
	DE	42	7429	4487	3132	2149	91531	95	3782	130	2023	79.73%
	SM	13	40	4	0	0	1	0	107	0	24	0.00%
	M	186	3214	2918	1199	773	56114	4377	28310	1273	8138	26.58%
	T	587	678	282	367	64	2590	199	14029	3338	10892	10.11%
	U	712	2242	702	768	59	6664	415	10988	3055	110879	81.24%
Producer's Accuracy		99.14%	93.78%	36.71%	44.98%	1.63%	51.41%	0.00%	46.44%	40.75%	78.99%	
Overall Accuracy		88.32%		Kappa	Coefficient	0.815						

Note. L= Lake community; OW= Open water community; FE= Floating emergent community; E= Emergent community; WE= Tall wet emergent community; DE= Tall dense dry emergent; SM= Short wet meadow; M= Meadow; T= Treed; U= Upland. The simulation model input: base year: 1995, simulation year 1999, lake level 174.11 m. Model v.1.0 uses the updated coastal topographic model from this study.

A difference map was generated to show how the simulation accuracy of two simulation model results differed spatially (see Figure 6.8). In the difference map, the red areas indicate pixels where the wetland simulation model correctly predicted wetland vegetation type in Model v.1.0, but not for Model v.0.0. White areas indicate that both Models v.1.0 and v.0.0 have the same performance and the blue areas indicate that the wetland simulation model correctly predicted the wetland vegetation in Model v.0.0, but not in Model v.1.0. Compared with Model v.0.0, model v.1.0 improved in accuracy prediction for the outer peninsula (see Figure 6.8, zones C7, C8, D7, D8), in the upland area (see Figure 6.8, B2, B3), and the open water area in the outer peninsula (see Figure 6.8, zone C7). However, the simulation accuracy in Lake Erie along the shoreline is quite low for Model v.1.0 (see Figure 6.8, zone D7). There is little wetland vegetation growth along the shoreline area near the Lake Erie side. Hence, there resulted in no significant change in simulation accuracy between the two models (v.1.0 and v.0.0) in the middle section of the study area (see Figure 6.8, zone B4).

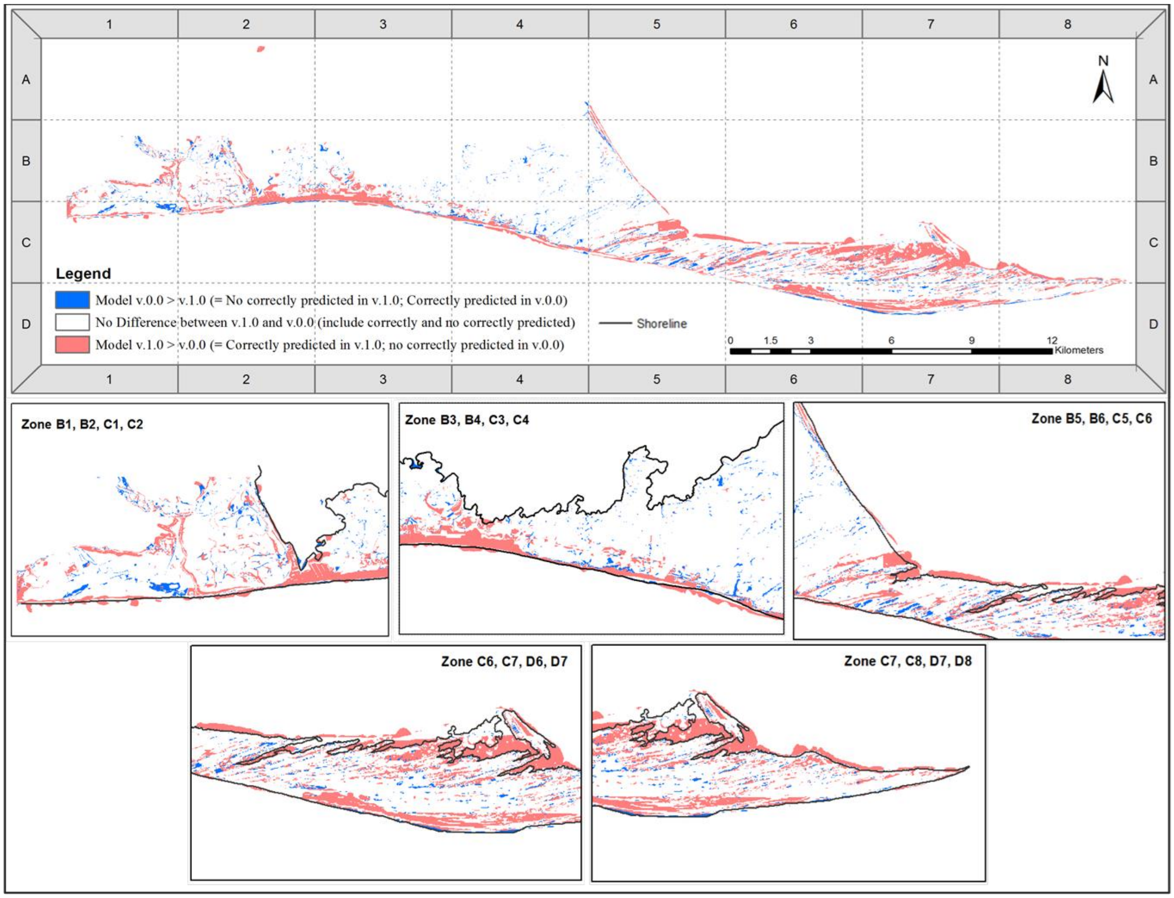

Figure 6.8: Image differencing between predicted results from two simulation models (Models v.0.0 and v.1.0). The simulation model input: base year: 1995, simulation year 1999, lake level 174.11 m

6.3 The Response of Wetland Vegetation Community to Water Level Fluctuations

In this section, the responses of wetland community to different mean annual lake levels and to different daily average lake levels are compared. The response of wetland community to different annual lake levels are compared between the model simulated classification maps, while the responses of wetland community to different daily lake levels are compared by two field surveys which were conducted in September, 2001 and July, 2015. The years of 2001 and 2015 were chosen due to the availability of field survey results.

Lake Erie mean annual lake levels from 1918 to 2015 are shown in Figure 6.9. The lake-wide average water levels were obtained from the Department of Fisheries and Oceans Canada, referring to the IGLD 85. The Lake Erie mean annual water level in 2001 was 173.91m, while in 2015 was 174.25m. Water levels increased about 34 cm from 2001 to 2015. The response of wetland communities (amount and distribution) to different water levels can be simulated using the wetland simulation model by entering different water levels.

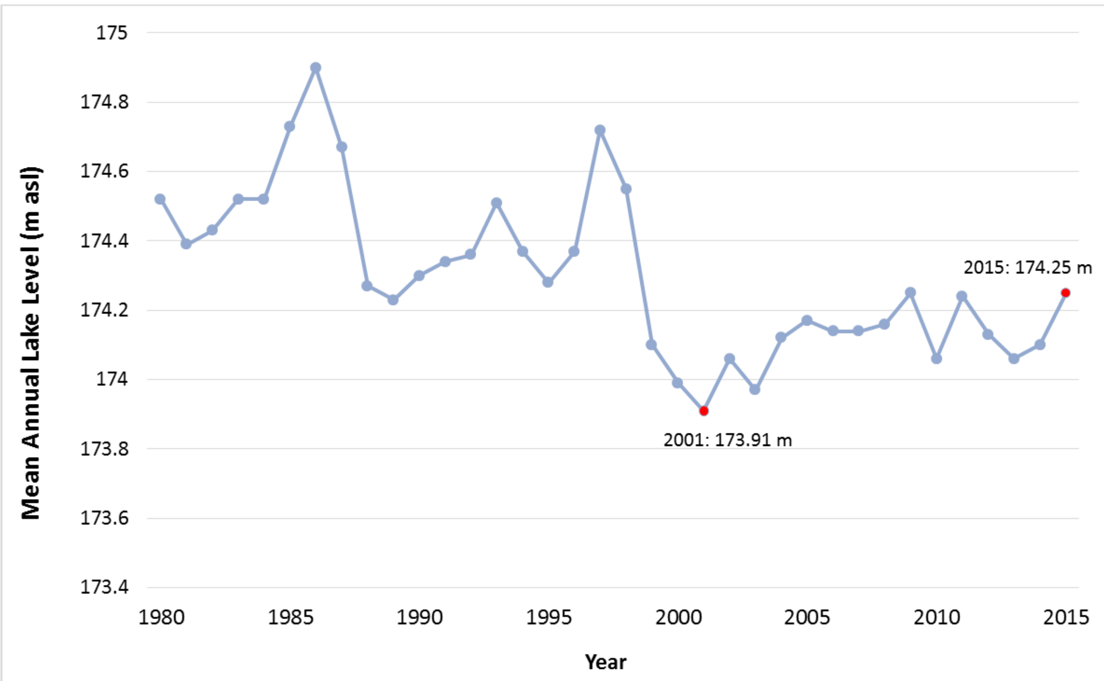

Figure 6.9: Lake Erie mean annual water levels (m asl) from 1980 to 2015. Chart Datum for Lake Erie is 173.5 m asl

The simulated wetland community classification map in 2001 is shown in Figure 6.10(a), and the simulated classification map in 2015 is shown in Figure 6.10(b). These maps were simulated by the wetland simulation model based on the ground truth classification map in 1999 (base year 1999) and different lake level inputs (173.91 m and 174.25 m). Ten wetland communities are included in the simulated classification maps. With the mean annual water level increase of 34 cm from 2001 to 2015, the meadow community in the Big Creek area, and the middle wetland (west and middle section) shifted to a wetter wetland community (tall dense dry emergent), and the changes of other wetland communities (e.g. floating emergent, emergent, tall wet emergent, short wetland meadow) cannot be visually seen from the simulated classification maps (see Figure 6.10).

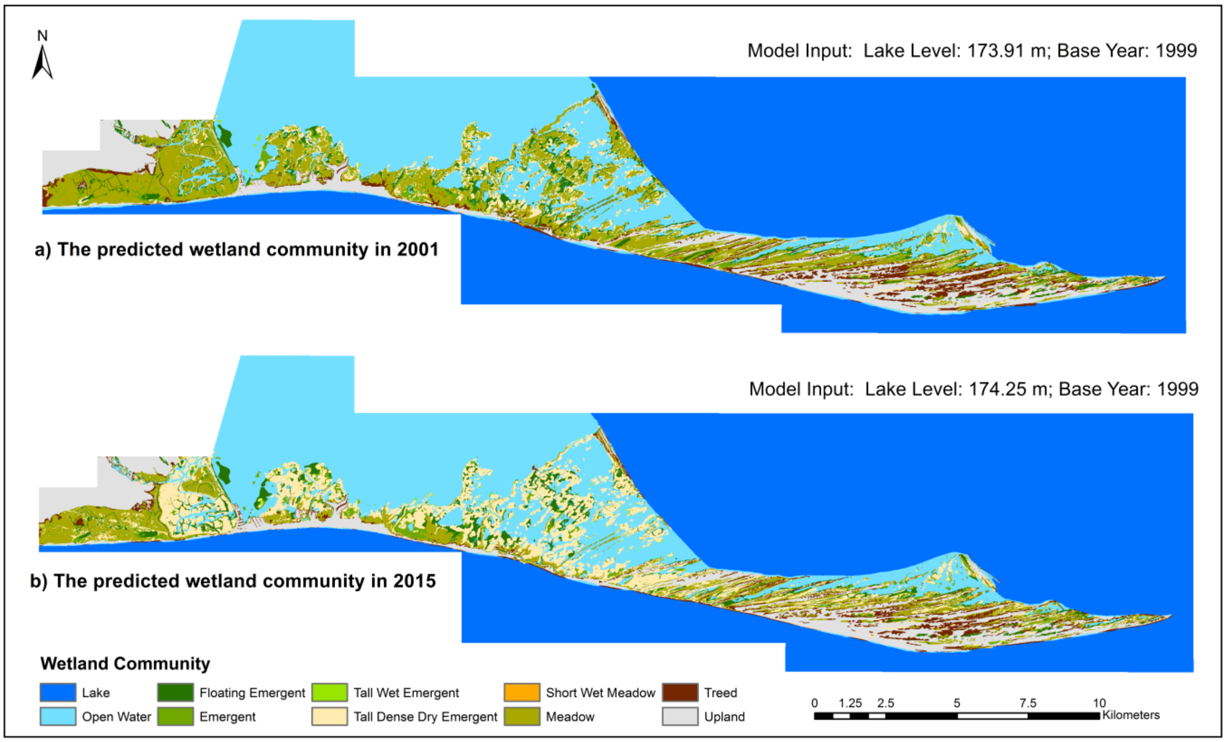

Figure 6.10: Model v.1.0 simulation results in 2001 and 2015. (a) Predicted wetland community in 2001; Model v.1.0 input: base year: 1999, simulation year 2001, lake level 173.91m. (b) Predicted wetland community in 2015; model v.1.0 input: base year: 1999, simulation year 2015, lake level 174.25 m**.**

The distribution of each wetland community in the simulated classification maps is shown in Figure 6.11. With a water level increase of 34 cm, the proportion of some communities increased, including the lake class (from 55.179% to 55.6%), open water (from 20.578% to 21.291%), tall wet emergent (from 0.045% to 0.124%), tall dense dry emergent (from 2.697% to 7.054%), and short wet meadow (from 0.005% to 0.021%); the percentages of some communities decreased, including floating emergent (from 2.220% to 1.942%), emergent (from 1.621% to 1.170%), meadow (from 8.348% to 4.339%), treed (from 2.331% to 1.922%), and upland (from 6.977% to 6.529%). There is a significant increase in the percentage of tall dense dry emergent class. The total amount of vegetation (i.e. floating emergent, emergent, tall wet emergent, tall dense dry emergent, short wet meadow, meadow, and treed) decreased from 17.266% in 2001 to 16.68% in 2015. Similar evidence of changes in wetland communities to water level fluctuation from 2001 to 2015 can be found from qualitative field observations detailed in the following section.

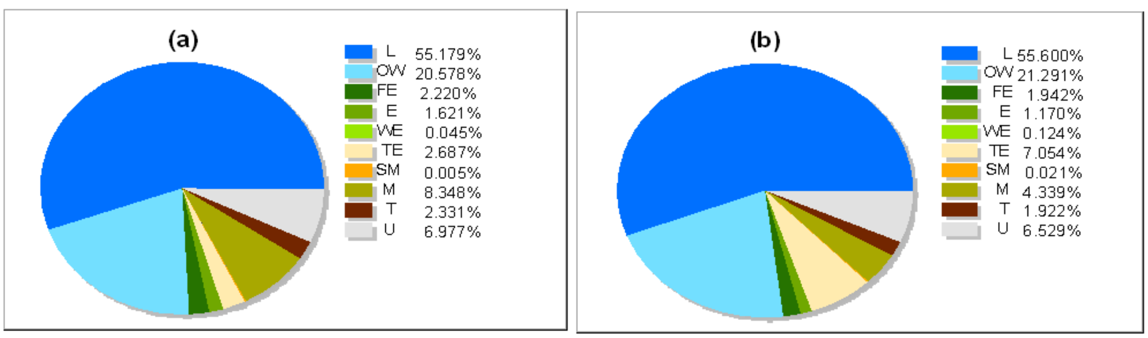

Figure 6.11: Percentage of each wetland community in the wetland community maps predicted by Model v.1.0. (a) Percentage of wetland communities in the predicted wetland community map in 2001; Model v.1.0 input: base year: 1999, simulation year 2001, lake level 173.91 m. (b) Percentage of wetland communities in the predicted wetland community map in 2015; Model v.1.0 input: base year: 1999, simulation year 2001, lake level 173.91 m

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6.4 Model Sensitivity Analysis of Vegetation Transition Baseline

Model sensitivity analysis is a useful tool to calibrate model parameters and to explore the variation in model simulation outputs to different model parameters (Hamby, 1994; Xu et al., 2004). The vegetation transition baseline is considered to be the most important threshold in the wetland simulation model, and it is a parameter tested in the model sensitivity analysis.

The vegetation transition baseline is the minimum value in centimeters above mean sea level for determining when a wetland vegetation community will shift to a wetter wetland community. Rather than using a minimum tolerance of each vegetation community (e.g. minimum tolerance depth of floating emergent: -60 cm) or mean lake level (i.e. water depth: 0 cm) to mark the transition from a wetland vegetation community to a wetter wetland community, a depth of -30 cm was used to determine the transition between communities (Hebb, 2003). For example, the emergent community will shift to floating emergent community when water depth is deeper than 30 cm. Previously, the value of the vegetation transition baseline or threshold was determined by the researcher's experience. This study tests different vegetation transition baseline values and assesses corresponding changes in model simulation accuracy and the simulation accuracy for each type of wetland community.

The overall model simulation accuracy is influenced by changes in the vegetation transition baseline. As shown in Figure 6.12, overall model simulation accuracy (A) changes with testing different vegetation transition baselines (B). In Figure 6.12, negative transition baseline values represent depth under mean water level. The overall model simulation accuracy (A) of the simulated classification map in 1999 was 88.32% when the vegetation transition baseline (B) was equal to the default value of -30cm. As shown in Figure 612, there is a significant increase in A from -40cm to -25cm with reaching a peak of 88.34% when B is equal to -25cm, while falling significantly between -25cm to 0cm. Therefore, this test shows that the simulation model yields the highest overall simulation accuracy when based on a water depth of -25cm to mark the transitions for a wetland vegetation community to a wetter wetland community. This value is remarkably close to the default value of -30 cm that was originally adopted by Hebb (2003).

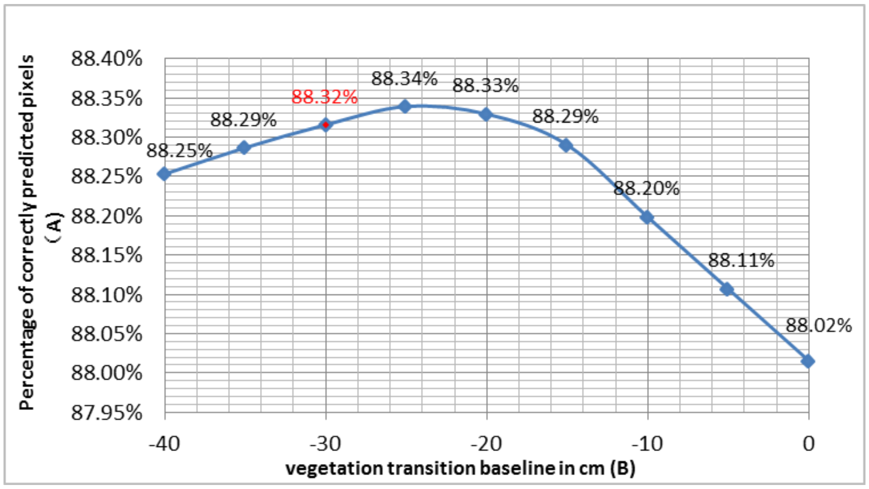

Figure 6.12: The response of overall simulation accuracy of Model v.1.0 to the change of vegetation transition baseline (default value = -30 cm). The simulation model input: base year: 1995, simulation year 1999, lake level 174.11 m. Negative transition baseline value represents depth under mean water level.

The simulation accuracies of each wetland community are also influenced by changes in vegetation transition baseline. Graphical display of changes in prediction accuracy of each wetland community (A) to a different vegetation transition baseline (B) is shown in Figure 6.13; ten wetland community classes are included. The default value of vegetation transition baseline (B) is -30 cm, and the corresponding simulation accuracy of each wetland community is highlighted in red (see Figure 6.13). The simulation accuracies of some wetland communities (i.e. lake, open water, tall wet emergent, and short wet meadow) have positive relationships with the vegetation transition baseline. In other words, the simulation accuracies of those wetland communities are improved with increasing vegetation transition baseline. The simulation accuracies of some wetland communities (i.e. floating emergent, emergent, tall dense dry emergent, meadow, and treed) actually decreased with increasing vegetation transition baseline. In other words, the simulation accuracies of most wetland vegetation communities have a negative relationship with the vegetation transition baseline. Noticeably, the simulation accuracy of the upland class remained the same despite changes in vegetation transition baseline. Moreover, significant changes (increase or decrease) of the simulation accuracy of open water, floating emergent, emergent, and tall dense dry emergent were observed when the vegetation transition baseline (B) was made equal to -25 cm.

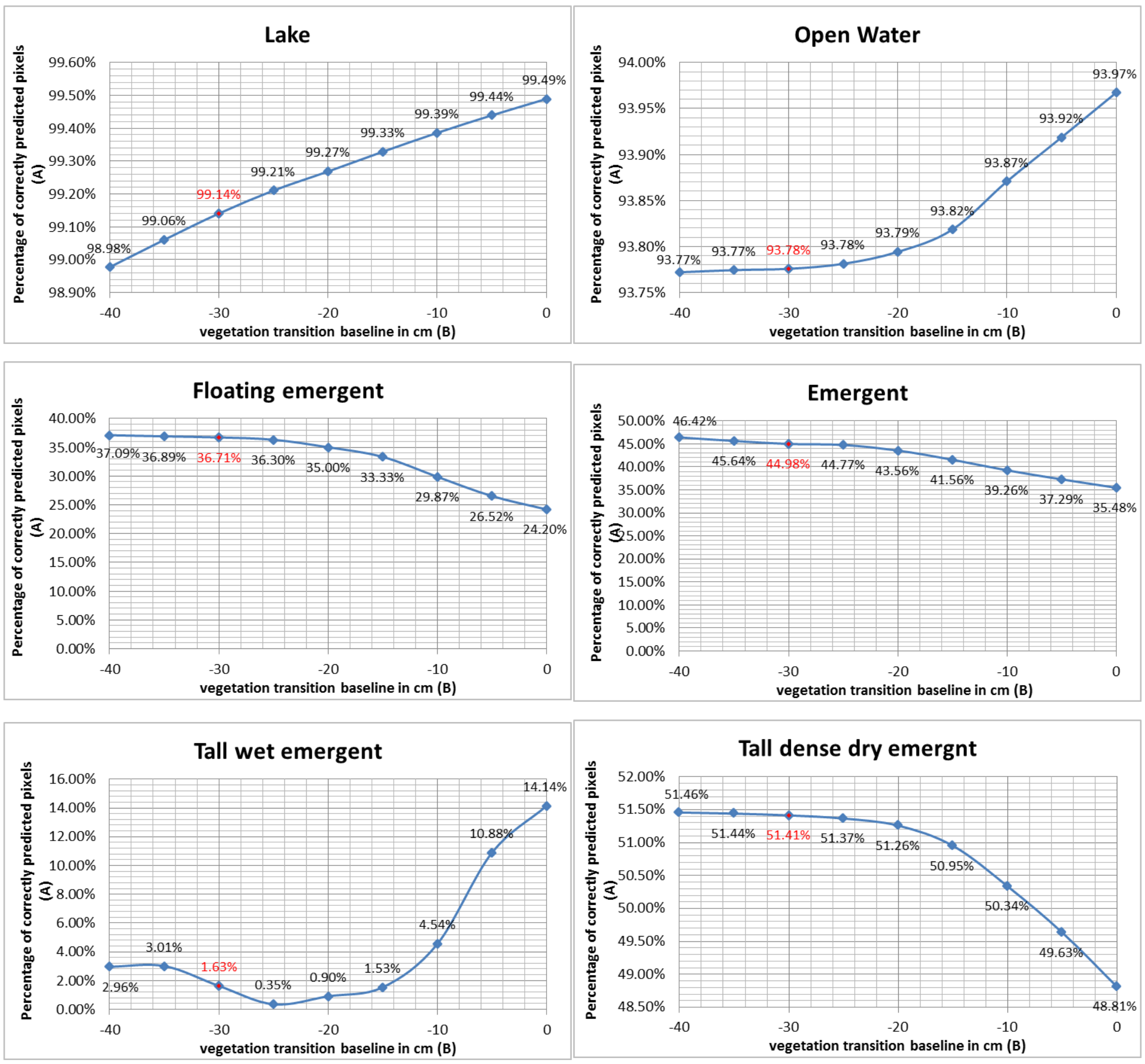

Figure 6.13: The prediction accuracy of wetland community classes based on Model v.1.0 with changes in vegetation transition baseline (default value = -30 cm). The simulation model input: base year: 1995, simulation year 1999, lake level 174.11 m. Negative transition baseline values represent depth under mean water level.

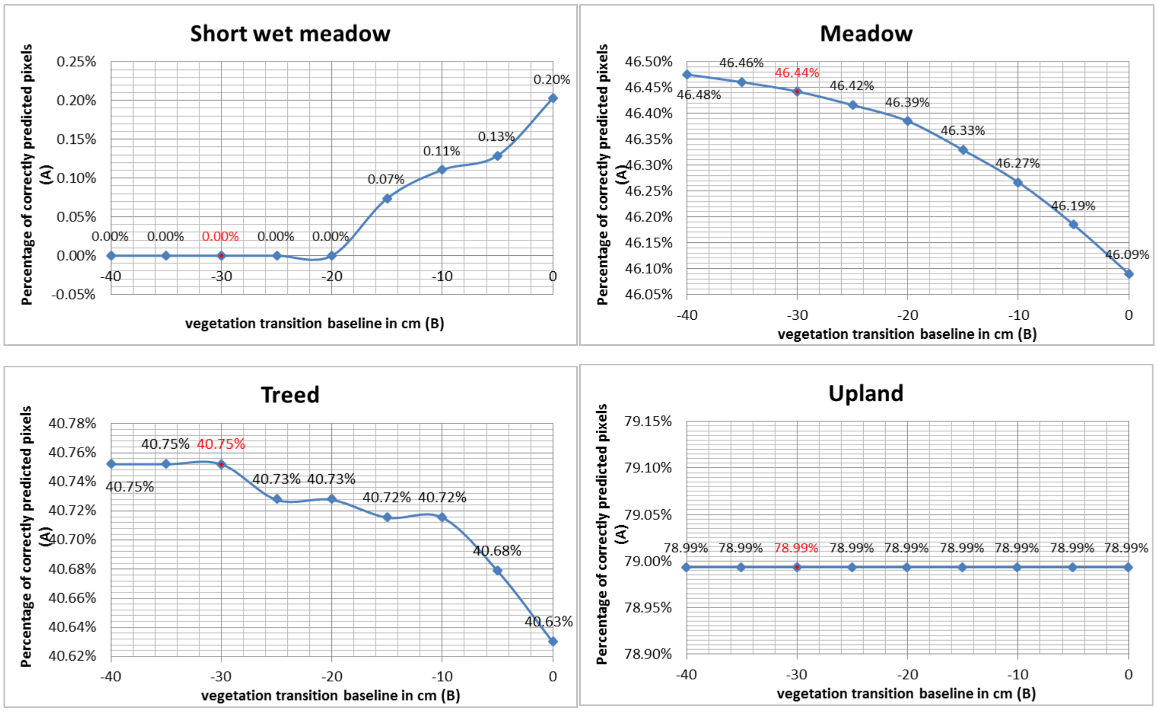

Figure 6.13: The prediction accuracy of wetland community classes based on Model v.1.0 with changes in vegetation transition baseline (default value = -30 cm). The simulation model input: base year: 1995, simulation year 1999, lake level 174.11 m. Negative transition baseline values represent depth under mean water level.

The overall model simulation accuracy reaches a peak value when the vegetation transition baseline is equal to -25cm; there is a significant change (increase or decrease) in prediction accuracy of certain of the simulation accuracy of some wetland communities (e.g., lake, open water, tall wet emergent, and meadow) when the baseline is equal to -25 cm. Hence, a new wetland simulation model (Model v.2.0) with a whose vegetation transition baseline is equal to -25cm was developed and compared constructed to compare with the wetland simulation Model v.1.0 whose, where the vegetation transition baseline is was equal to -30cm30 cm. Figure 6.14 shows the simulation wetland classification maps based on resulting from different vegetation transition baselines. Both simulation wetland classification maps in 1999 contain ten classes, and there is was no significant change of in the spatial distribution of wetland community communities' spatial distribution with the variation of in vegetation transition baseline.

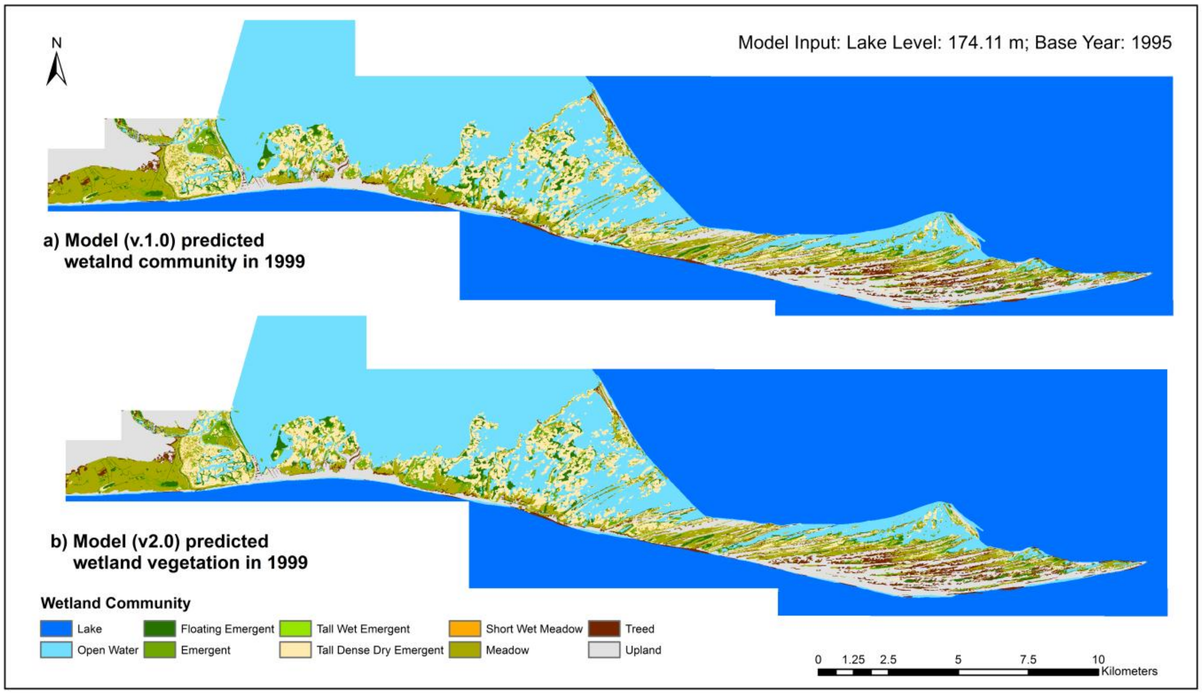

Figure 6.14: Model results: a) predicted wetland community map in 1999 from Model v.1.0 (with vegetation transition baseline = -30 cm); b) predicted wetland community map in 1999 from Model v.2.0 (with vegetation transition baseline = -25 cm). The simulation model input: base year: 1995, simulation year 1999, lake level 174.11 m.

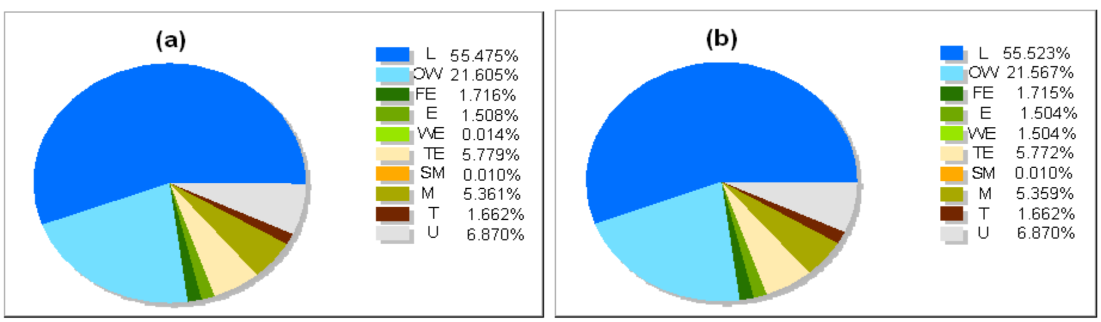

Figure 6.15: Percentage of each wetland community in Model v.1.0 and Model v.2.0 predicted wetland community maps. (a) Percentage of wetland communities in the predicted wetland community map from Model v.1.0 (with vegetation transition baseline = default value = - 30 cm); (b) Percentage of wetland communities in the predicted wetland community map from Model v.2.0 (with vegetation transition baseline = - 25 cm). Simulation model input: base year: 1999, simulation year 1999, lake level 174.11 m.

The proportion of wetland communities in the simulation maps are changed with variable vegetation transition baselines. As shown in Figure 6.15, with a tighter vegetation transition baseline (from -30 cm to -25 cm), there are slight increases of the proportion of lake (from 55.475% to 55.523%) and tall wet emergent (from 0.014% to 1.504%); slight decreases of the proportion of open water (from 21.605% to 21.567%), floating emergent (from 1.716% to 1.715%), emergent (from 1.508% to 1.504%), tall dense dry emergent (from 5.779% to 5.772%), and meadow (from 5.361% to 5.359%); and the short wet meadow, treed and upland classes were unchanged. This supports the notion that wetland communities change with fluctuations in the vegetation transition baseline.

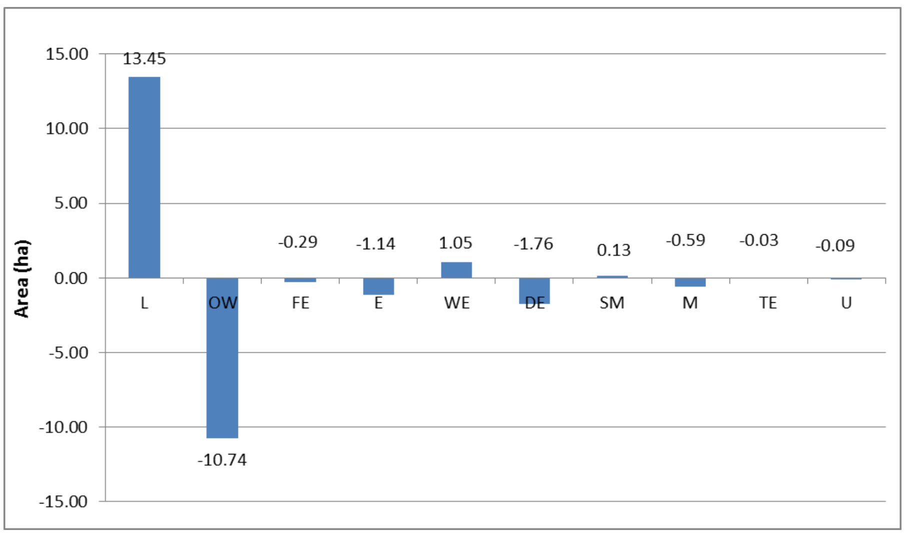

Figure 6.16: The changed area of each wetland community class using Model v.1.0 (with vegetation transition baseline = default value = -30 cm) to the simulation result using Model v.2.0 (with vegetation transition baseline = -25 cm). The simulation model input: base year: 1995, simulation year 1999, lake level 174.11 m. Positive values represent areas that have increased from Model v.1.0 to Model v.2.0, while negative values represent declining area from Model v.1.0 to Model v.2.0. L= Lake community; OW= Open water community; FE= Floating emergent community; E= Emergent community; WE= Tall wet emergent community; DE= Tall dense dry emergent; SM= Short wet meadow; M= Meadow; T= Treed; U= Upland

The area of each wetland community class has also changed with a narrower vegetation transition baseline (from -30 cm to -25 cm). As shown in Figure 6.16, with a narrower vegetation transition baseline, the areas of lake, tall wet emergent and short wet meadow increased. There is a significant increase in the total area of lake (13.45 ha), while the tall wet emergent class increased by 1.05 ha, and short wet meadow increased by 0.13ha. With a narrower vegetation transition baseline, the areas of open water, floating emergent, emergent, tall dense dry emergent, meadow, treed, and upland generally decreased. As shown in Figure 6.16, there is a significant decrease in the area of open water (10.74 ha). The area of floating emergent decreased by 0.29 ha, emergent decreased by 1.14 ha, tall dense dry emergent decreased by 1.76 ha, meadow by 0.59 ha, treed community by 0.03 ha, and upland by 0.09 ha. Therefore, variations in the vegetation transition baseline have significant effects on the area of lake, open water, emergent and tall dense dry emergent.

Table 6.6: Simulation Model v.1.0 (with vegetation transition baseline = default value = -30 cm) accuracy assessment result

		Ground Truth Class										User Accuracy
		L	OW	FE	E	WE	DE	SM	M	T	U	
Model predicted Class	L	1100585	45	0	0	0	13	0	44	0	1369	99.87%
	OW	8002	397598	3905	3499	562	9335	172	1149	43	4829	92.66%
	FE	0	10717	12639	2578	143	5087	76	1266	229	1363	37.07%
	E	0	1943	9492	9444	174	6567	89	1282	123	848	31.52%
	WE	1	82	0	8	65	128	0	0	0	0	22.89%
	DE	42	7429	4487	3132	2149	91531	95	3782	130	2023	79.73%
	SM	13	40	4	0	0	1	0	107	0	24	0.00%
	M	186	3214	2918	1199	773	56114	4377	28310	1273	8138	26.58%
	T	587	678	282	367	64	2590	199	14029	3338	10892	10.11%
	U	712	2242	702	768	59	6664	415	10988	3055	110879	81.24%
Producer's Accuracy		99.14%	93.78%	36.71%	44.98%	1.63%	51.41%	0.00%	46.44%	40.75%	78.99%	
Overall Accuracy		88.32%		Kappa	Coefficient	0.815						

Note. L= Lake community; OW= Open water community; FE= Floating emergent community; E= Emergent community; WE= Tall wet emergent community; DE= Tall dense dry emergent; SM= Short wet meadow; M= Meadow; T= Treed; U= Upland. The simulation model input: base year: 1995, simulation year 1999, lake level 174.11 m.

The simulation accuracies of wetland communities are influenced by the variation in vegetation transition baseline (Model v.1.0 = -30 cm and Model v.2.0 = -25 cm). The simulation accuracies of wetland communities are shown in Table 6.6 and Table 6.7. Overall, with a narrower vegetation transition baseline, the overall simulation accuracy improves from 88.32% (Model v.1.0) to 88.43% (Model v.2.0). Model v2.0 improved the simulation accuracies of the lake class (from 99.14% to 99.21%). The simulation accuracies of some wetland communities are unchanged in model v.1.0 and v.2.0, including open water (93.78%), short wet meadow (0.00%), and upland (99%). The prediction accuracy of some wetland communities slightly decreased, including floating emergent (from 36.71% to 36.30%), emergent (from 44.98% to 44.38%), tall wet meadow (from 1.63% to 0.35%), tall dense dry emergent (from 51.41% to 51.37%), meadow (from 46.44% to 46.42%), and treed community (from 40.75% to 40.73%) classes.

Table 6.7: Simulation Model v. 2.0 (with vegetation transition baseline = -25 cm) accuracy assessment result

		Ground Truth Class										User Accuracy
		L	OW	FE	E	WE	DE	SM	M	T	U	
Model predicted Class	L	1101362	49	0	0	0	17	0	53	0	1503	99.85%
	OW	7225	397621	4054	3502	562	9333	172	1141	43	4695	92.83%
	FE	0	10712	12499	2699	143	5092	76	1265	229	1363	36.68%
	E	1	1930	9483	9320	235	6572	89	1282	123	848	31.19%
	WE	0	125	2	12	14	200	0	4	0	0	3.92%
	DE	44	7377	4485	3132	2139	91447	95	3807	130	2026	79.74%
	SM	17	48	5	0	2	1	0	94	0	31	0.00%
	M	180	3206	2917	1199	771	56114	4377	28294	1275	8128	26.58%
	T	587	678	282	367	64	2590	199	14029	3336	10892	10.10%
	U	712	2242	702	768	59	6664	415	10988	3055	110879	81.24%
Producer's Accuracy		99.21%	93.78%	36.30%	44.38%	0.35%	51.37%	0.00%	46.42%	40.73%	78.99%	
Overall Accuracy		88.42%		Kappa	Coefficient	0.818						

Note. L= Lake community; OW= Open water community; FE= Floating emergent community; E= Emergent community; WE= Tall wet emergent community; DE= Tall dense dry emergent; SM= Short wet meadow; M= Meadow; T= Treed; U= Upland. The simulation model input: base year: 1995, simulation year 1999, lake level 174.11 m.

A difference matrix was generated to examine differences between the two predicted wetland community maps. In Figure 6.17, the white element in the differencing matrix represents pixels with no difference detected between the two predicted results; while the red element in the matrix represents differences between the two predicted results. As shown in Figure 6.17, 928 pixels that were simulated as open water in Model v1.0 were simulated as lake pixels by Model v.2.0. Model v.1.0 predicted 182 pixels as floating emergent that were predicted to be open water by Model 2.0. For the pixels which were simulated as emergent in Model v.1.0, 168 were simulated as floating emergent by Model 2.0. Therefore, a narrower vegetation transition baseline tends to yield more wetland classified pixels, thus shifting to a wetter wetland community.

In the differencing map shown in Figure 6.18, the red area indicates that there are differences between two simulation results, while the white area indicates that there is no differencing between two simulation results. As previously mentioned, the two simulation results were generated based on different vegetation transition baselines (-30cm and -25cm) with 1,590 pixels indicating change. The pixels were spatially located adjacent to the shoreline, coinciding with areas where the water meets the land. Hence, it is concluded that areas directly along the shoreline are much more sensitive to variations in vegetation transition baseline.

Simulation model (v.2.0) predicted class

Simulation model (v.1.0) predicted class	L	OW	FE	E	WE	DE	SM	M	T	U
L	1102103	0	0	0	0	0	0	0	0	0
OW	928	428292	0	0	0	0	0	0	0	0
FE	0	182	33916	0	0	0	0	0	0	0
E	0	0	162	29800	0	0	0	0	0	0
WE	0	0	0	83	201	0	0	0	0	0
DE	0	0	0	0	156	114644	0	0	0	0
SM	0	0	0	0	0	34	155	0	0	0
M	0	0	0	0	0	0	43	106459	0	0
T	0	0	0	0	0	0	0	2	33024	0
U	0	0	0	0	0	0	0	0	0	136484

No difference between predicted results, and no selected for display in the differencing map

Difference between predicted results, and selected for display in the differencing map

Figure 6.17: Differencing matrix of the predicted results from two simulation models (Model v.1.0 and Model v.2.0). Simulation model v.1.0 is a simulation model whose vegetation transition baseline = default value = -30 cm and simulation model v. 2.0 is a model whose vegetation transition baseline = -25 cm. The simulation model input: base year: 1995, simulation year 1999, lake level 174.11 m. L= Lake community; OW= Open water community; FE= Floating emergent community; E= Emergent community; WE= Tall wet emergent community; DE= Tall dense dry emergent; SM= Short wet meadow; M= Meadow; T= Treed; U= Upland

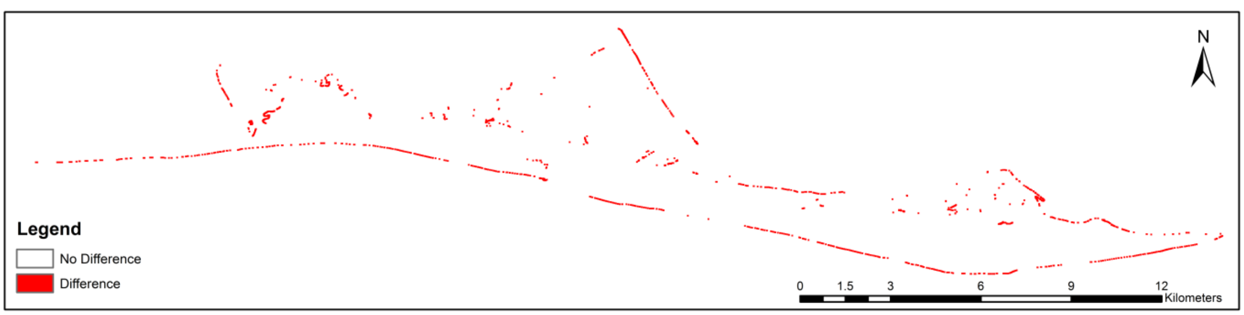

Figure 6.18: Differencing map generated from two simulation models' (v1.0 & v.2.0) predicted results. Model v.1.0 assumes a vegetation transition baseline = default value = -30 cm and Model v. 2.0 has a vegetation transition baseline = -25 cm. The simulation model input: base year: 1995, simulation year 1999, lake level 174.11 m. The display rules of the differencing map can be found in Figure 6.21.

Chapter 7
Discussion and Conclusions

In this study, remote sensing and GIS were applied to improve modeling the response of wetland vegetation communities to water level changes. In this chapter, key findings are discussed by revisiting the three key research questions defined in Chapter 1. First, how can remote sensing and GIS be applied for producing a high accuracy and high density coastal topographic model? Second, how do different topographic models in the wetland simulation model affect model prediction accuracy? Finally, what is the effect of variable model parameters on the model simulation result? Limitations and directions for future work are also discussed.

7.1 Coastal Topographic Model Generation

In order to generate a highly accurate and high density coastal topographic model in the study area, multi-source topographic data (i.e. remote sensing data and bathymetry data) were integrated, and shoreline boundary data was considered when generating the coastal topographic model to determine the selection of topographic data sources.

An integration of multi-source topographic data (i.e. LiDAR data and bathymetry data) in a coastal topographic model successfully provided elevation information for both the terrain surface and aquatic (submerged) environments. The integration of multiple data sources can optimize the advantages of each topographic dataset. This study used the shoreline to determine the selection of topographic data sources in the coastal topographic model. However, in this study, both the LiDAR-derived DEM and the bathymetric topographic datasets covered the shoreline area. In other cases, elevation data may not be available (i.e. a data gap) in the shoreline area, which would then require an interpolated method to be performed. This study shows that the application of remote sensing data (LiDAR) in a coastal topographic model provides higher accuracy and density elevation information in coastal areas. Having a high density and high accuracy elevation information in a wetland simulation model is there essential to improving the model prediction accuracy. This integration approach is also flexible in nature and forms a framework for combining elevation datasets. In the future, it can not only be applied for integrating raw topographic data (e.g. LiDAR points and bathymetry points) but also for level-2 topographic data (e.g. LiDAR-derived DEM).

Vertical datum conversion is one step in the process of coastal topographic model generation. However, this is a time-consuming and difficult process. Since the Great Lakes area is located along the border between Canada and the United States, topographic data are acquired by both countries. On the Canadian side, topographic data are usually referring to the Canadian Geodetic Vertical Datum of 2013 and the Canadian Geodetic Vertical Datum of 1928, while on the US side, topographic data usually refer to the North American Vertical Datum 1988 (NAVD 88) or American Samoa Vertical Datum 2002 (ASVD02). Furthermore, bathymetry data are usually referring to IGLD of 85. Hence, vertical datum conversion between IGLG of 85 to another vertical datum is necessary when integrating multi-source topographic data. However, since no tool exists for conversion between IGLD of 85 to CGVD of 2013, this is a significant gap and weakness Great Lakes research. In this study, multiple topographic datasets were integrated according to the spatial location of the shoreline boundary. However, this was mainly reliant on shoreline boundary data being available and shoreline definition can be difficult or subjective to do.

This study is constrained by the availability of raw topographic data as inputs. Due to the accessibility of raw LiDAR data, all vertical datum conversions were performed in level-2 topographic data (LiDAR-derived DEM). It should be noted that the vertical datum conversion on the level-1 (raw) elevation data may produce a higher accuracy result.

7.2 The Effects of Coastal Topographic Models in Wetland Simulation Models

In this study, a coastal topographic model is a key input in the wetland simulation model, which is similar to other wetland simulation models published in the literature (Hebb et al., 2013; Narumalani et al., 1997; Poiani et al., 1993). A coastal topographic model was used for providing water depth information within the study area, and the predicted vegetation community was subsequently determined by different water depth thresholds. Results described in Chapter 6.2 supports the fact that the coastal topographic model has a significant influence on the model simulation result. Three main conclusions and findings resulted from this study.

First, a high accuracy coastal topographic model yields a high accuracy simulation result. For example, in this study, an overall accuracy of 83.85% was achieved based on a low accuracy coastal topographic model (RMSE = 1.609). The accuracy increased to 88.32% when the simulation was based on a high accuracy coastal topographic model (RMSE = 0.445). In addition, a high accuracy coastal topographic model also improves the prediction of which vegetation communities (e.g. lake, open water, floating emergent, emergent, tall dense dry emergent, meadow, and treed community) a wetland may shift to in the future.

Second, the coastal topographic model was generated by integrating LiDAR and bathymetry data and significantly improved prediction accuracy in the upland (e.g. roads and sandy peninsula) and outer peninsula open water areas. These regions tend to be relatively steep in slope (details shown in Figure 6.7). This is due to the superior performance of LiDAR data upland areas, generating more precise and accurate elevation measurements. Moreover, including shoreline data in the modeling process tends to improve accuracy of elevation readings in the land-water transition area.

Third, the simulation accuracy in wetland areas where meadow and tall emergent community occur was similar while using different coastal topographic models. Such areas tend to be flat (refer to Figure 6.7). This may be due to elevation values in the coastal topographic models being similar in wetland areas where both meadow and tall emergent community occur. Second, in the simulation model parameters, the tolerance ranges of meadow and tall emergent community are wider than the tolerances of floating emergent and emergent. Hence, slightly differences between coastal topographic models may be less sensitive and yield similar simulation results.

7.3 Model Sensitivity Analysis of Vegetation Transition Baseline

Parameters in the wetland simulation model have significant influence on the end simulation results. The vegetation transition baseline is specified as a water depth value in centimeters above mean sea level, and it is the minimum value for a wetland vegetation community to shift to a wetter wetland community. It is the most important parameter in the wetland simulation model. A sensitivity analysis was performed to test the variability in model simulation outputs to the vegetation transition baseline (refer to Section 6.4).

First, the overall model simulation accuracy is influenced by changes in the vegetation transition baseline. Second, the prediction accuracy of each wetland community type was also influenced by changes in the vegetation transition baseline. Third, the proportions of wetland communities in the simulation maps varied with different vegetation transition baseline settings. Subsequently, a narrower vegetation transition baseline increases the probability of a wetland community shifting to a wetter wetland community. Furthermore, areas (e.g. pixels) identified along the shoreline were more sensitive to variations in vegetation transition baseline compared to more upland or submerged areas.

7.4 Constraints and Future Work

The spatial resolution of this research is constrained by the pre-existing wetland classification maps. In this research, the resulting spatial resolution of the coastal topographic data, pre-existing wetland community classification maps, and the predicted wetland community classification map was 12 m. Future work can focus on improving the spatial resolution of the datasets by working with higher resolution pre-existing classification maps up to 1 m.

The pre-existing wetland community classification maps used in this study were interpreted from air photos and only available for seven base years (1945, 1955, 1964, 1978, 1985, 1995, and 1999). It should be noted that an up-to-date pre-existing wetland community classification map will improve the accuracy of the wetland simulation model. Hence, future research can work on producing an up-to-date wetland community classification map with higher resolution and accuracy.

One method of improving the input wetland community classification map is using an unsupervised classification approach. For example, the Iterative Self-Organizing Data Analysis Technique (ISODATA) based on a knowledge-based expert system could be used on the latest Landsat 5 TM imagery to produce a Long Point wetland community classification map that is higher in resolution and with a recent acquisition date, depending on data availability. Future work could also potentially use hyperspectral and high resolution remote sensing image (e.g. HyspIRI, HERO, and Probe-1) for wetland classification and further improvement of the accuracy of data products.

Water level changes were the only factors considered in the simulation model in this study for predicting changes to the wetland ecosystem. However, in reality, several factors (such as slope and water temperature) may have influence on changes in wetland vegetation cover. For future research and applications of these simulation models, obtaining a water temperature raster file may be derived from remote sensing imagery, such as near-infrared remote sensing images.

In this study, the simulation accuracy of the wetland vegetation community model was assessed by using a confusion matrix (see Table 6.4). A confusion matrix is the most common method for a classification map accuracy assessment. However, the confusion matrix results highly depend on the selection of ground truth data. Pontius, et al. (2011) suggest that statistics (e.g. proportion correct and the Kappa index) generated by the confusion matrix may be biased, since results may differ according to changing study area boundaries and how ground truth data are selected.. Pontius and Millones (2011) estimated a population matrix, which can subsequently be used to compute unbiased statistics, including proportion correct, different Kappa indices, user's accuracy, producer's accuracy. In addition, Pontius and Millones (2011) exposed problems with using Kappa indices for accuracy assessment and demonstrated that two components: quantity disagreement and allocation disagreement, which focus on the quantity and spatial allocation disagreement of categories between maps, are more useful and simpler approaches. Future work could explore the utility of this accuracy assessment method.

In conclusion, remote sensing and GIS are applied in this research to improve the wetland simulation model. This approach integrated remote sensing data (LiDAR), bathymetric data, and shoreline data, thus generating an improved coastal topographic model of the Long Point wetland in terms of accuracy and sample point density. Hebb's (2003) original wetland simulation model was updated in this research.

A higher accuracy coastal topographic model can yield a higher accuracy prediction result from wetland simulation models. Model sensitivity analysis was performed and the results show that the overall model simulation accuracy and each wetland communities' simulation accuracies are influenced by changes in the vegetation transition baseline. A narrower vegetation transition baseline tends to yield more wetland classified pixels, thus shifting to a wetter wetland community. Therefore, this study shows that the proposed coastal topographic model generation method can be used effectively to map coastal topography. There is also potential to apply the wetland simulation model to other coastal wetlands and geographic regions, although model parameters and tolerance ranges of wetland vegetation communities would have to be redefined.

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Appendix A

Table A1. Summarized characteristics of sampling sites

Site No.	Name	Easting (m)	Northing (m)	Survey Task
1	Joseph W. Csubak Viewing area	552406	4725826	Full view of Long Point and Turkey Point
2	1420 Front Rd	550979	4725174	Long Point and Long Point Inner Bay Observation
3	Booth's harbor	549575	4723451	Long Point and Long Point Inner Bay Observation
4	Palmer Dr	549135	4723396	Long Point and Long Point Inner Bay Observation
5	Blue Water Ave	549274	4723156	Long Point and Long Point Inner Bay Observation
6	Port Rowan Lookout	545217	4718942	Long Point and Long Point Inner Bay Observation
7	Cronmiller's at the bridge	544807	4716640	Ground Truth Data Collection; Wetland Vegetation Recognition
8	Big Creek National Wildlife Area	545186	4715814	Ground Truth Data Collection; Wetland Vegetation Recognition
9	End of Hasting Dr	543303	4713768	Ground Truth Data Collection; Wetland Vegetation Recognition; Shoreline Observation
10	East Old Cut	548992	4715488	Ground Truth Data Collection; Wetland Vegetation Recognition; Shoreline Observation
11	West Old Cut	549773	4715324	Ground Truth Data Collection; Wetland Vegetation Recognition
12	Long Point Provincial Park Fishing Area	550150	4714655	Ground Truth Data Collection; Wetland Vegetation Recognition; Shoreline Observation
13	Long Point Provincial Park	551569	4713924	Ground Truth Data Collection; Wetland Vegetation Recognition

Appendix B

Table A2. Wetland communities in classification maps

Code	Simplified name	Full name
1	L	Lake
2	OW	Open Water
3	FE	Floating emergent community
4	E	Emergent community
5	WE	Tall wet emergent community
6	TE	Tall dense dry emergent community
7	SM	Short wet meadow community
8	M	Meadow community
9	T	Treed community
10	U	Upland

Appendix C

Table A3. Summary of parameters in the wetland simulation model after a model sensitivity analysis is conducted

Parameter	Symbol	Selected for sensitivity analysis	Default value	New value	Unit
The minimum water depth threshold for **lake, emergent, tall dense dry emergent, meadow, and treed community** shift to a wetter wetland vegetation community	min_L, min_TE, min_M, min_T	Yes	-30	-25	cm
The minimum water depth threshold for **tall wet emergent and short wet emergent** shift to a wetter wetland vegetation community	Min_WE , min_SM	Yes	-60	-55	cm
The minimum water depth threshold for **upland** shift to lake	Min_U	No	-60	-60	cm
The maximum water depth threshold for **open water** shift to a drier community	Max_OW	No	30	30	cm
The minimum water depth threshold for **floating emergent** shift to a wetter community	min_FE	No	-30	-30	cm
The maximum water depth threshold for **floating emergent** shift to a drier community	Max_FE	No	30	30	cm
The minimum water depth threshold for **emergent** shift to a wetter community	min_E	No	-30	-30	cm
The maximum water depth threshold for **emergent** shift to a drier community	Max_E	No	50	50	cm
The maximum water depth threshold for **tall dense dry emergent** shift to a drier community	Max_TE	No	50	50	cm
The maximum water depth threshold for **tall wet emergent** shift to a drier community (=the minimum water depth threshold for tall dense dry emergent shift to a wetter community)	Max_WE (=min_TE)	No	-30	-30	cm
The maximum water depth threshold for **short wet meadow** shift to a drier community (=the minimum water depth threshold for meadow shift to a wetter community)	Max_SM (=min_M)	No	-30	-30	cm
The maximum water depth threshold for **meadow** shift to a drier community	Max_M	No	80	80	cm
The maximum water depth threshold for **treed** shift to a drier community	Max_T	No	100	100	cm
The maximum water depth threshold for **upland** shift to treed	Max_U	No	30	30	cm
Adjacent to n*n cells to upland for **lake** shift to upland	n_L	No	5	5	N/A
Adjacent to n*n cells to lake for **open water** shift to lake	n_OW	No	5	5	N/A
Adjacent to n*n cells to lake for **upland** shift to lake	n_U	No	5	5	N/A