REMOTE SENSING AND GIS

FOR WETLAND MONITORING

USE OF REMOTE SENSING AND GIS FOR WETLAND MONITORING AND ASSESSMENT

By

DANIEL ROKITNICKI-WOJCIK, B.Sc.

A Thesis
Submitted to the School of Graduate Studies
in Partial Fulfillment of the Requirements
for the Degree
Master of Science

McMaster University

Master of Science (2009) McMaster University

(Biology) Hamilton, Ontario

TITLE: Use of Remote Sensing and GIS for Wetland Monitoring and Assessment

AUTHOR: Daniel Rokitnicki-Wojcik, B.Sc. (McMaster University)

SUPERVISOR: Professor Patricia Chow-Fraser

NUMBER OF PAGES: xvi, 156

GENERAL ABSTRACT

The goals of this thesis are to assess the use of remote sensing and Geographic Information Systems (GIS) to map and classify coastal wetland habitat along the entire coast of eastern Georgian Bay, Lake Huron. Little mapping has been completed in this region where there is potentially the largest concentration of coastal wetlands in the Great Lakes.

In chapter 1, we developed a method that uses high-resolution IKONOS imagery (1-m resolution) with an object-based approach to classify wet meadow vegetation in these coastal wetlands, and assessed the transferability of classification rulesets developed independently for 3 different satellite scenes. We showed that 4 different classes (meadow/shrub, emergent, senescent vegetation, and rock) can be mapped with an overall accuracy of 76%. When classification rulesets developed for individual scenes were transferred to other scenes without gathering additional field information for those scenes, we found a difference in accuracy of about 5%. This difference in accuracy is acceptable considering the trade-off in costs associated with field surveys. We recommend that managers use IKONOS in fine-scale habitat mapping and that rulesets only be developed for geographically distinct areas.

In Chapter 2, we conducted a study to test the feasibility of using this mapping approach to complete the field surveys required in Ontario Wetland Evaluation System (OWES). In addition, we determined empirically how inclusion of vegetated deep-water habitat below 2 m can affect relevant OWES

component scores, because the current system does not consider any vegetated habitat below 2 m, even though this portion of coastal wetlands is known to provide critical habitat for many Great Lakes fishes. We sampled 16 wetlands that varied in size and inundation characteristics and grouped them into 4 categories: small aquatic, small terrestrial, large aquatic, and large terrestrial. When the vegetated deep-water habitat was included, total wetland area and the overall score for all assessed criteria assessed increased significantly; however, this increase was not sufficiently large to make any practical difference in the overall score using existing the point-scale. This is largely because submerged aquatic habitat is not adequately represented in current evaluation protocols and is severely undervalued.

In chapter 3 we developed a method to quantify and monitor change in coastal marsh habitat in southeastern Georgian Bay using multi-temporal IKONOS imagery. We detected a significant increase in the proportion of terrestrial habitat (high marsh) at the expense of the aquatic habitat (low marsh) over six years from 2002 to 2008. There did not appear to be any effect of human activities (indicated by the number of buildings within 500 m of wetlands) on habitat changes. We conclude that water levels may currently exert greater pressure on these systems than does cottage density in the region. We recommend that the approaches developed in this study be applied as quickly as possible to comprehensively map existing wetland habitat in eastern Georgian Bay to monitor responses to further water-level and human-induced disturbance.

ACKNOWLEDGMENTS

I would like to thank Pat for asking me to do this work and for all her support from the beginning to the completion of this project. I have learned a tremendous amount about science and inquiry and I thank you for taking me on and shaping my future career in science.

I would like to thank my supervisory committee of Mike Waddington and Jonathan Stone for their comments and suggestions. I would also like to thank Mike for introducing me to adventure running as it has kept me sane during the writing process.

My labmates have made all the field sampling and lab work a blast. Thank you Jon for all your input and help with the GIS and remote sensing aspect of the project, as I'd still be at the computer without your help. Thank you Rachel for all your support and for help with field sampling and editing my writing. Thank you to everyone who has helped me in some shape or form including: Anhua Wei, Kristina Cimaroli, Maja Cvetkovic, Brandon Gidley, Tim Hurley, Lyndsay Smith, Stephanie Yantsis, and April Stevens. I would like to thank all the cottagers and Mary Muter for all their logistical support and allowing us to have such great field experiences in one of the most beautiful landscapes in Canada.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

GENERAL INTRODUCTION

In Canada, wetlands are defined as those lands that are "saturated with water long enough to promote wetland or aquatic processes as indicated by poorly drained soils, hydrophytic vegetation and various kinds of biological activity which are adapted to a wet environment" (National Wetlands Working Group, 1988). Wetlands at the highest level are classified as either organic or mineral, where organic simply refers to the organic substrate found in peatlands and mineral to the remainder that are influenced by mineral, non-organic substrates. Peatlands are wetlands that have accumulated a minimum of 40cm of peat or partially decomposed vegetation. Wetlands are further subdivided into 4 types that are indicative of their respective biology, hydrology, geomorphology, and ecology. These 4 classes include marsh, swamp, fen, bog, and shallow water (Warner and Rubec, 1997).

Wetland Classes

A bog is a wetland that is ombrotrophic in nature, where the main or sole source of water is precipitation and not runoff or groundflow. They are nutrient poor and acidic, with mosses as the dominant vegetation consisting mainly of the *Sphagnum* genus. Bogs can also have significant shrub and conifer cover. Bogs are peatlands with the water table at or near the surface and can have a raised surface. Fens are also peatlands; however, that are predominantly groundwater fed with the water table at the surface in channels or pools. They are less acidic than bogs and vary in nutrient content that is indicative of their water source. Mosses and emergent vegetation dominate with many being indicators of this wetland type (Warner and Rubec 1997).

Swamps are peatlands or non-peatlands with characteristic dominance of tall woody vegetation. Swamps can take the form of a flooded forest, shrub thicket, or peat-laden conifer stand. pH can vary greatly, reflecting the diverse conditions giving rise to these wetlands. Water is seasonally intermittent or permanent with the water table lying at or below the surface. Marshes are non-peatlands with characteristically shallow water that is dynamic in nature, from daily to seasonal variation that is reflected in the variety of emergent vegetation present. Water can come from any source, such as precipitation, runoff, groundwater, and waterbodies. Nutrients in marshes are higher than in bogs and fens and conditions are less acidic, which is reflected in the diversity of vegetation types from shrubs and sedges, to floating and submergent. Wetlands categorized as shallow water are the transition between other wetland classes that exhibit seasonal inundation and deep permanently inundated waterbodies. The boundary is at 2m for this class and include ponds, shallow lakes, and oxbows (Cowardin et al., 1979; OMNR, 1993; Zoltai and Vitt, 1995; Warner and Rubec, 1997; Mitsch and Gosselink, 2000).

Ecology of Wetlands

Wetlands provide numerous goods and services that are directly beneficial to humans and, for that reason, hold strong value for conservation. These include and are not exclusive to water purification, pollution assimilation, flood retention, erosion control and groundwater recharge (Mitsch and Gooselink, 2000). Wetlands also hold great utility value to human activities that prove to be contributing factors to their degradation, disturbance, and destruction. These include resource extraction (peat, wood, and game) and drainage and infilling for agriculture and infrastructural development. Wetlands also play an important role in the proper natural functioning of ecosystems irrespective of human-derived benefit, as they provide critical habitat for wildlife, nutrient cycling, significant contributions to aquatic and terrestrial food webs, and comprise a significant portion of the landscape mosaic. Wetlands are dynamic systems exposed to both aquatic and terrestrial processes, each with a suite of species in addition to those adapted solely to wetlands resulting in highly diverse and productive communities (Maynard and Wilcox, 1997).

Canada is a wetland-rich nation; Environment Canada's Atlas of Canada estimates that Canada contains roughly 14% of global wetlands (127 million ha) of which 23% are within Ontario (29 million ha). This equates to roughly a third of Ontario's landmass. The majority of wetlands in Ontario are northern boreal peatlands. In the south, there is a shift towards a higher composition of mineral substrates and, therefore, mineral type wetlands of swamp and marsh.

Coastal Wetlands

Wetlands exist in a variety of forms, from isolated forested peatlands to open coastal marine marshes. Coastal wetlands are those that occur at the transition between dry uplands and water bodies (OMNR; 1993). In the Laurentian Great Lakes, coastal wetlands are those that are hydrologically connected to the Great Lakes; however, herein we will be considering only those that are within the historical 100-year high water mark or approximately 2km from the shoreline (OMNR, 1993). Wetland inventory is a sought after tool in wetland conservation as wetland area has been identified as a key monitoring indicator (Maynard and Wilcox, 1997). An accurate estimate of the areal extent of Great Lakes coastal wetlands has yet to be determined with several incomplete inventories in existence providing low-end conservative estimates. The Great Lakes Coastal Wetland Consortium has provided an estimate for the Canadian shores of Lake Huron at around 16,000 ha (Ingram et al., 2004). The American shoreline of the Great Lakes is well covered from a cohesive national inventory effort in the National Wetland Inventory (NWI; Wilen and Bates, 1995). In Canada, a national-specific inventory effort is currently lacking; however, a Canadian Wetland Inventory (CWI) is in its infancy and methods have been proposed for nation-wide wetland mapping (Fournier et al., 2007). Current work in our lab is addressing this issue for the eastern shoreline of the Georgian Bay coast (McMaster Coastal Wetland Inventory; Chow-Fraser, unpub. data) with aspects of this thesis being intimately involved in its development.

Threats to Coastal Wetlands

Many coastal wetlands form in protected embayments where exposure to wind and wave action is minimal and where extensive colonization by aquatic vegetation is possible. Unfortunately, protected embayments also provide conditions that are conducive to human development such as housing and marinas. Terrestrial portions of coastal wetlands can have very nutrient-rich mineral substrates, which have historically been exploited for conversion to agriculture. Dredging and infilling of wetlands is a threat to coastal wetlands where human activities can result in either the creation of new land for development or destruction of aquatic habitat for boat traffic. Coastal wetlands of the southern Great Lakes have seen substantial loss (on the order of 80%) post-European settlement through destruction and/or conversion to other landuses (Smith, 1991). Current threats include shoreline development in the form of urban expansion of coastal communities or recreational development for cottages and satellite communities.

The other main threat to coastal wetlands is continual degradation from human-induced activities such as cultural eutrophication and facilitation of invasive species introduction. The remainder of high quality wetlands that reflect true natural conditions tend to be found further from human settlement, in more remote locations. The few coastal wetlands that remain in the Southern Great Lakes tend to be of poor quality, while wetland quality is higher in northern regions such as Georgian Bay (Chow-Fraser, 2006), where permanent human settlements are small and sparse. Continual expansion from the heavily populated southern cities will increasingly become a greater threat to low-impacted northerly sites and steps should be taken to ensure that they too do not undergo human-induced degradation.

There are natural threats to habitat types within coastal wetlands. Water levels have decreased in recent years on the order of 1m in 10yrs and it is thought that Lake Huron may have reached a new lower mean. Although a decrease in lake level has been shown to increase terrestrial portions of wetlands (Wiliams and Lyons, 1997; Mortsch et al 2008) the impact on lakeward shifts has yet to be examined. We may observe a concomitant decrease in aquatic habitat to terrestrial gains in coastal marshes, which has serious implications for fisheries habitat.

Coastal Wetland Conservation

Conservation of coastal areas is important because they are sensitive areas that have been drastically reduced in populated areas. Since coastal wetlands provide large benefits to humans and ecosystems, it has become critical to identify and create sound conservation strategies for the remainder of coastal wetlands in Canada. Canada has shown its commitment to wetland conservation as a signatory to the RAMSAR convention. Furthermore, there is law and protocol in Canada to indirectly protect wetland habitat and to identify unique wetland habitat for conservation. Under the Fisheries Act, fish habitat is protected from alteration, destruction, and conversion. This includes wetland habitat, as many fish use wetlands for spawning, nursery, and foraging. This is especially true for Great Lakes coastal wetlands, which provide critical habitat to over 80 fish species (Jude and Pappas, 1992) and support a large sport fish industry.

The Ontario Wetland Evaluation System (OWES; OMNR, 1993) is used to rank the relative value of wetlands based on biological, hydrological, human utility, and special habitat feature values and is the basis on which provincial significance and protection under the Planning Act are conferred. Because few wetlands remain in the southern Great Lakes, the majority have been evaluated; however, there has not been an emphasis to catalogue and evaluate coastal wetlands in the northern portion of the Great Lakes, where many remain in a natural state. The OWES currently uses the formal definition in the opening of this introduction; however, submerged habitat deeper than 2m is considered non-wetland because plants do not typically colonize beyond this depth. This is true for impacted wetlands that have altered water chemistry, where turbidity or suspended materials may attenuate light near the surface and therefore limit the depth to which plants can establish. Wetlands that are less impacted, with lower turbidity and suspended solids often have plants at depths of up to 6m due to deeper light penetration in the water column. This is reason to suspect that submergent habitat that is critical for fish species is undervalued in the system put in place to identify significant wetland habitats. No study to date has quantitatively studied measures in conservation protocol to question its validity.

Georgian Bay Coastal Wetlands

Georgian Bay is the 13,000km^2 eastern arm of Lake Huron, connected via the North Channel. It contains one of the longest freshwater shorelines in the world from extensive shoreline convolutions and islands, which have created one of the highest densities of coastal wetlands in the Great Lakes basin (McMaster

Coastal Wetland Inventory; Chow-Fraser, unpub. data). The wetlands are quite unique, as Georgian Bay is split latitudinally by the division of the Precambrian shield to the north and limestone bedrock to the south. These different substrates have shaped the wetland plant communities, water chemistry, and surrounding upland forest habitats (Herdendorf, 2004). In a survey of coastal wetlands of the Great Lakes, Chow-Fraser (2006) found that good to excellent wetlands in terms of water quality predominantly cluster in Georgian Bay. Given that the region is not yet heavily populated and that recreational impacts are the main threats, these wetlands are of high priority for conservation and there is strong need for a Bay-wide management plan. The eastern shoreline has already been listed as a UNESCO world biosphere reserve in recognition of it being a unique landscape with relatively high diversity for a temperate zone. The relatively low levels of development along the coastline can be attributed to its remote location and lack of road access. The large number of wetlands and the widespread extent of the shoreline coupled with the difficulties of sampling in remote locations have directed us to the use of landscape tools to identify and catalogue these wetlands so that we can create a sound strategy to conserve them.

Remote Sensing for Ecological Applications

The ability to obtain information while being remote to the Earth's surface is a great advantage in the pursuit of understanding the natural order of our landscapes and ecosystems. Remote sensing has become an invaluable tool in landscape ecology for identifying, assessing, and monitoring large spatially distinct areas (Kerr and Ostrovsky, 2003; Turner et al., 2003). Regardless of the scale of target variables to be extracted, there now exist a variety of platforms and technologies for ecological applications. Land cover data can be produced using coarse-resolution platforms such as LANDSAT and SPOT; and fine detail vegetation classification can be produced using high-resolution platforms such as IKONOS and Quickbird (Kerr and Ostrovsky, 2003; Jones et al. 2008). Topographical data can enhance any mapping project to aid in discerning features that vary vertically with the addition of a Digital Elevation Model (DEM), as platforms exist as both coarse (RADARSAT) or high-resolution (LIDAR) sources.

The smallest unit of measure in remote sensing imagery is the pixel. The resolution of a sensor or image is dependent upon the size of each pixel for example, 1m IKONOS imagery is composed of 1mx1m pixels. The visualization of each pixel is the result of the reflectance of electromagnetic energy from an Earth surface feature that a sensor can detect. The reflectance of a pixel is manifested in a digital reflectance number, where lower values indicate absorption of energy and higher values indicate reflectance of energy. Images are produced for Red, Green, Blue, and Near Infrared wavelengths of light in the visible band and combined into colour composites of each of the bands (Lillesand and Kiefer, 2000).

Image classification traditionally involves applying a class to each individual pixel in an image based on some predetermined rules. This approach can lead to miss-classification from spectral confusion and does not make full use of existing spatial, contextual, and textural information (Blachke et al., 2000; Chubey et al., 2006; Navulur, 2007). The approach we take is using an image object-based classification where pixels are initially grouped based in similarity in spectral and spatial properties defined by the producer (Navulur, 2007). Image object classification uses spectral and, more importantly, relational and textural information to produce a highly accurate and consistent end product.

Classifying vegetation is a means to identify wetland type, infer potential habitat at the species level, and detect changes in response to natural (declining water levels) and anthropogenic (development) stressors. Remote sensing technology has not yet been used to identify vegetation at the species level due to constraints in spatial resolution, however this may become a possibility in the near future.

Remote Sensing of Wetlands

Remote sensing of wetlands has progressed in concert with technological advancements in sensors. Wetlands are inherently complex systems that are difficult to map because they have diverse vegetation types that do not occur in spatially distinct clusters and they have varying levels of inundation (Ozesmi and Bauer, 2002; Sawaya et al., 2004). Traditional monitoring of wetlands involved image interpretation of aerial photography for broad wetland identification (Fournier et al., 2007). This is still the best option if the finest resolution is needed; however, it is the most costly approach (Wei and Chow-Fraser, 2007).

Coarser platforms, such as 15m and 30m resolution LANDSAT and SPOT, have successfully been used to quantify wetland density, identify wetland habitat from other landuses, and map wetland type for inventories (Jensen et al, 1993; Töyrä et al, 2001; Leahy et al., 2005; Baker et al., 2006; Grenier et al., 2007; Grenier et al., 2008). More recent high-resolution platforms such as 1-m IKONOS and Quickbird have allowed mapping to occur within wetlands to track changes within and among wetlands (Dechka et al., 2002; Mumby and Edwards, 2002; Wolter et al., 2005; Belluco et al., 2006; Fuller et al., 2006; Lawrence et al., 2006; Wei and Chow-Fraser, 2007; Dillabaugh and King, 2008; Ghioca-Robrech et al., 2008). The ability to map wetland vegetation with high-resolution platforms also present challenges, as the great complexity of vegetation and transitions among heterogeneous vegetation types are not easily discernable. It is argued that using object-based approaches will aid in spatial organization of vegetation to increase the accuracy of mapping complex habitat types (Dillabaugh and King, 2008).

Little mapping has been completed in the Georgian Bay region. Wei and Chow-Fraser (2007), evaluated the use of IKONOS imagery to map coastal wetlands of Georgian Bay with focus on the aquatic habitat. To date; however, no one has focused on fine-scale wet meadow habitat mapping in the Great Lakes basin. Furthermore, the use of an object-based approach has not yet been evaluated in coastal wetland mapping in the Great Lakes.

Rationale and Thesis Objectives

Great Lakes coastal wetlands in southern Ontario have all been mapped and evaluated according to the Ontario Wetland Evaluation System (OWES) as part of a concerted effort to conserve these valuable habitats. Unfortunately, there are many coastal wetlands in central and northern Ontario, particularly in eastern and northern Georgian Bay, that have yet to be either mapped or evaluated. In the absence of a comprehensive inventory and an appropriate method to map and quantify different types of aquatic and terrestrial habitat in these wetlands, many of these pristine wetlands could be lost or degraded by human development, in the same way that unprotected wetlands have been destroyed in southern Ontario. This thesis has three separate but related goals to aid conservation of coastal wetland habitats in Georgian Bay.

1) To develop an approach to conduct regional mapping of different types of terrestrial habitat in coastal wetlands of eastern and northern Georgian Bay
2) To quantify deep-water habitat (> 2m) in coastal wetlands and determine their importance in the Ontario Wetland Evaluation System (OWES) relative to shallow aquatic and meadow habitat
3) To quantify changes in aquatic and wet-meadow habitat between 2002 and 2008 in two shoreline segments of Georgian Bay with contrasting human impact

An over-arching goal of my thesis is to determine the feasibility of using IKONOS satellite imagery to track temporal and spatial changes in the amount and type of wetland habitats in Georgian Bay, and to predict the impacts of these changes on fish and wildlife that depend on them.

The thesis is organized into 3 chapters that incorporate different aspects of the abovementioned objectives. The first chapter outlines a mapping approach for coastal wet meadow vegetation using high-resolution IKONOS imagery and image objects. The second chapter determines the valuation of submerged aquatic vegetation deeper than 2m (vegetated deepwater habitat) in the Ontario Wetland Evaluation System. The third chapter outlines a simple approach to quantifying broad wetland habitat change over a 6-year period for two regions with contrasting human impacts.

LITERATURE CITED

Baker, C., Lawrence, R., Montagne, C., Patten, D., 2006. Mapping wetlands and riparian areas using LANDSAT ETM imagery and decision-tree-based models. *Wetlands*. 26: 465-474.

Belluco, E., Camuffo, M., Ferrari, S., Modenese, L., Silvestri, S., Marani, A., Marani, M. 2006. Mapping salt-marsh vegetation by multispectral and hyperspectral remote sensing. *Remote Sensing of Environment*. 105: 54-67.

Blaschke, T., Lang, S., Lorup, E., Strobl, J., and Zeil, P. 2000. Object oriented image processing in a GIS/remote sensing environment and perspectives for environmental applications. In *Environmental information for planning, politics, and the public*. Metropolis-Verlag, Marburg, Germany. p555–570.

Chow-Fraser, P. 2006. Development of the Water Quality Index (WQI) to assess effects of basin-wide land-use alteration on coastal marshes of the Laurentian Great Lakes. *In: Coastal wetlands of the Laurentian Great Lakes: health, habitat and indicators (Simon, T.P. and Stewart, P.M Eds.)*

Chubey, M., Franklin, S., Wulder, M. 2006. Object-based analysis of IKONOS-2 imagery for exraction of forest inventory parameters. *Photogrammetric Engineering & Remote Sensing*. 72(4): 383-394.

Cowardin, L.M., Carter, V., Golet, F.C., and LaRoe, E.T. 1979. Classification of wetlands and deepwater habitats of the United States. US Dept of Interior

– Fish and Wildlife Service. Washington D.C., 103pp.

Dechka, J.A., Franklin, S.E., Watmough, M., Bennett, R., Ingstrup, D. 2002. Classification of wetland habitat and vegetation communities using multi-temporal IKONOS imagery in southern Saskatchewan. *Canadian Journal of Remote Sensing*. 28(5): 679-685.

Dillabaugh, K.A., King, D.J. 2008. Riparian marshland composition and biomass mapping using Ikonos imagery. *Canadian Journal of Remote Sensing*. 34(2):143-158.

Flanders, D., Hall-Beyer, M., Pereverzoff, J. 2003. Preliminary evaluation of eCognition object-based software for cut block delineation and feature extraction. *Canadian Journal of Remote Sensing*, 29(4): 441-452.

Fournier, R.A., Grenier, M., Lavoie, A., Helie, R. 2007. Towards a strategy to implement the Canadian Wetlands Inventory using satellite remote sensing. *Canadian Journal of Remote Sensing*. 33(S1):1-16.

Fuller, L.M., Morgan, T.R., Aichele, S.S. 2006. Wetland delineation with IKONOS high-resolution satellite imagery, Fort Custer Training Center, Battle Creek, Michigan, 2005: U.S. Geological Survey, Scientific Investigations Report 2006-5051: 8pp.

Ghioca-Robrecht, D.M., Johnston, C.A., Tulbure, M.G. 2008. Assessing the use if multiseason Quickbird imagery for mapping invasive species in a Lake Erie coastal marsh. *Wetlands*. 28(4): 1028-1039.

Grenier, M., Demers, A.M., Labreque, S., Benoit, M., Fournier, R.A., Drolet, B. 2007. An object-based method to map wetland using RADARSAT-1 and Landsat ETM images: test case on two sites in Quebec, Canada. *Canadian Journal of Remote Sensing*. 33(S1): 28-45.

Grenier, M., Labreque, S., Garneau, M., Tremblay, A. 2008. Object-based classification of a SPOT-4 image for mapping wetlands in the context of greenhouse gases emissions: the case of the Eastmain region, Quebec, Canada. *Canadian Journal of Remote Sensing*. 34: (S2): 398-413.

Herdendorf, C.E. 2004. Morphometric factors in the formation of Great Lakes coastal wetlands. *Aquatic Ecosystem Health & Management*. 7(2):179-197.

Ingram, J., Holmes, K., Grabas, G., Watton, P., Potter, B., Gomer, T., Stow, N. 2004. Development of a Coastal Wetlands Database for the Great Lakes Canadian Shoreline, Final Report to the Great Lakes Commission. 18pp.

Jensen, J.R., Cowen, D., Althausen, J., Narumalani, S., Weatherbee, O. 1993. An evaluation of the Coast Watch change detection protocol in South Carolina. *Photogrammetric Engineering & Remote Sensing*. 59: 1039-1046.

Jones, K., Lanthier, Y., van der Voet, P., van Valkengoed, E., Taylor, D., Fernandex-Prieto, D. 2008. Monitoring and assessment of wetlands usuing Earth Observation: The GlobWetland project. *Journal of Environmental Management*. (in press).

Jude, D.J., Pappas, J. 1992. Fish utilization of Great Lakes coastal wetlands. *Journal Great Lakes Research*. 18: 651–672.

Kerr, J., Ostrovsky, M. 2003. From space to species: ecological applications for remote sensing. *TRENDS in Ecology and Evolution*. 18(6): 299-305.

Lawrence, R., Hurst, R., Weaver, T., Aspinall, R. 2006. Mapping prarie pothole communities with multitemporal Ikonos satellite imagery. *Photogrammetric Engineering & Remote Sensing*. 72(2): 169-174.

Leahy, M.G., Jollineau, M.Y., Howarth, P.J., Gillespie, A.R. 2005. The use of Landsat data for investigating the long-term trends in wetland change at Long Point, Ontario. *Canadian Journal of Remote Sensing*. 31(3):240-254.

Lillesand, T., Kiefer, R. 2000. Remote sensing and image interpretation. Fourth Edition. Lehigh Press. New York 724pp.

Maynard, L., Wilcox, D. 1997. Coastal wetlands of the Great Lakes. State of the Lakes Ecosystem Conference 1996. U.S. Environmental Protection Agency. 99 pp.

Mitch, M.J., Gosslink, J.G. 2000. Wetlands. 3rd ed. Wiley. New York. 920pp.

Mortsch, L., Sabila, G., Deadman, P. 2008. Response of vegetation communities in thress Lake Huron fens to historical water level fluctuations. *Aquatic Ecosystem Health and Management*. 11(2):167-181.

Mumby, P., Edwards, A. 2002. Mapping marine environments with IKONOS imagery: enhanced spatial resolution can deliver greater thematic accuracy. *Remote Sensing of Environment* 82: 248-257.

National Wetlands Working Group. 1988. Wetlands of Canada. Ecological Land Classification Series, No. 24. Sustainable Development Branch, Canadian Wildlife Service, Environment Canada.

Navulur, K. 2006. Multispectral image analysis using the object-oriented paradigm. CRC press. New York. 165pp

OMNR 1993. Ontario Wetland Evaluation System. Northern Manual. Ontario Ministry of Natural Resources (OMNR), No.50254.

Ozesmi, S.L., Bauer, M.E., 2002. Satellite remote sensing of wetlands. *Wetlands ecology and management*. 10: 381-402.

Sawaya, K.E., Olmanson, L.G., Hein, N.J., Brezonic, P.L., Bauer, M.E., 2003. Extending satellite remote sensing to local scales: land and water resource monitoring using high-resolution imagery. *Remote Sensing of Environment*. 88: 144-156.

Smith, P.G.R., Glooschenko, V., and Hagen., D.A. 1991. Coastal wetlands of the three Canadian Great Lakes: inventory, current conservation initiatives and patterns of variation. *Canadian Journal of Fisheries and Aquatic Sciences*. 48:1581-1594.

Töyrä, J., Pietroniro, A., Martz, L.W. Multisensor hydrologic assessment of a freshwater wetland. *Remote Sensing of Environment*. 75:162–173.

Turner, W., Spector, S., Gardiner, N., Fladeland, N., Sterling, E., Steininger, M. 2003. Remote Sensing for biodiversity science and conservation. *TRENDS in Ecology and Evolution*. 18(6): 306-314.

Warner, B.G., Rubec, C.D.A. 1997. eds. The Canadian wetlands classification system. 2nd ed. Wetlands Research Centre, University of Waterloo. 95 pp.

Wei, A., Chow-Fraser, P. 2007. Use of IKONOS imagery to map coastal wetlands of Georgian Bay. *Fisheries* 32(4): 167-173.

Wilen, B.O., Bates, M.K. 1995. The US Fish and Wildlife Service's National Wetlands Inventory project. *Vegetation*. 118: 153-169.

Williams, D.C., Lyon, J.G. 1997. Historical aerial photographs and a geographic information system (GIS) to determine effects of long-term water level fluctuations on wetlands along the St. Marys River, Michigan, USA. *Aquatic Botany*. 58:363-378.

Wolter, P.T., Johnston, C.A., Niem, G., J., 2005. Mapping submergent aquatic vegetation in the US Great Lakes using QuickBird data. *International Journal of Remote Sensing*. 26(23): 5255-5274.

Zoltai, S.C., and Vitt, D.H. 1995. Canadian wetlands: Environmental gradients and classification. *Plant Ecology*. 118(1-2):121-137.

Chapter 1

Transferability of an object-based approach to map coastal wet meadow habitat in eastern Georgian Bay using IKONOS imagery

by

Daniel Rokitnicki-Wojcik

and

Patricia Chow-Fraser

Abstract

Coastal wetlands of eastern and northern Georgian Bay provide critical habitat for a number of wildlife and bird species. Unfortunately, only few of these have been delineated and mapped because of their widespread distribution and remoteness, and this is an impediment to conservation efforts aimed at identifying significant habitat. We propose to address this deficiency by developing an approach that relies on use of high-resolution remote sensing technology to map wetland habitat. In this study, we use IKONOS satellite imagery to classify wet meadow vegetation and assess the transferability of classification rulesets to other regions in Georgian Bay. We classified 24 wetlands in three separate satellite scenes and developed an object-based approach to map four habitat classes: emergent, meadow/shrub, senescent vegetation and rock. Independent rulesets were created for each scene and applied to the other images to empirically examine transferability at broad spatial scales. The overall accuracy associated with each scene was 74% for Tadenac, 77% for North Bay, and 76% for Wood's Bay. Wetland mapping accuracy associated with classifying the four habitat classes varied from 54 to 93%, with a mean overall accuracy of 76% across all rulesets. The object-oriented approach used in this study is useful in minimizing misclassification and should be used in future wetland mapping projects. For a given habitat feature, internally derived rulesets based on ground-truth information collected from the same scene provided significantly greater accuracy than those derived from a different scene. Although we present a

significant effect of ruleset origin on accuracy and Kappa coefficient, the difference amounts to about 5% difference in accuracy and we argue that this should not detract from its transferability. We conclude that object-based rulesets derived from IKONOS imagery can successfully classify complex vegetation classes and be applied to imagery taken during the same satellite pass. This indicates that large scale mapping automation may be feasible with images with similar spectral properties.

Introduction

Great Lakes coastal wetlands are highly diverse systems that not only provide critical habitat for a variety of biota but also provide ecological services that benefit humans (Maynard and Wilcox, 1997; Mitsch and Gosselink, 2000). The historic loss of southern Ontario's coastal wetlands post European settlement is conservatively estimated at 80% (Snell, 1987) and this has led to a comprehensive inventory and field verification of remaining coastal wetlands along the shoreline of Lakes Ontario and Erie in Canada (Ingram et al, 2004; Figure 1.1). Despite the large number of coastal wetlands in eastern Georgian Bay (Ingram et al. 2004), however, very little mapping effort and field sampling has been carried out along this shoreline. This is largely because of the predominance of Precambrian shield shoals and the lack of permanent human settlements that make field sampling of this area difficult and costly. Additionally, unlike wetlands of the two lower Great Lakes, few of the Georgian Bay wetlands have been mapped for their habitat types (i.e. aquatic, emergent, meadow, etc.), and this is an impediment to efforts aimed at conserving critical fish and wildlife habitat in coastal wetlands due to the inability to identify significant habitat.

Wetlands are inherently difficult to map because they are ecotones whose boundaries exist along a wetland/upland continuum, and is subject to regular changes in inundation (Oszemi and Bauer, 2002) that create complex habitats

(Gluck et al, 1996). Remote sensing technology with satellite imagery is currently the only feasible tool for large-scale, landscape-level mapping and classification of wetland habitats. In the past, coarse-resolution (10-30 m) platforms such as LANDSAT (Poulin et al, 2002; Li and Chen, 2005; Baker et al, 2006; Grenier et al, 2007) and SPOT (Jensen et al, 1993; Töyrä et al, 2001, Grenier et al, 2008) were only capable of discriminating among wetland types (marsh, swamp, fen, and bog). The advent of high-resolution satellites has made mapping within-wetland vegetation possible using platforms such as IKONOS (1-m resolution) (Dechka et al, 2002; Fuller et al, 2006; Lawrence et al, 2006; Wei and Chow-Fraser, 2007; Dillabaugh and King, 2008) and now Quickbird (0.60-m resolution) (Wolter et al, 2005; Ghioca-Robrech et al, 2008).

Two classification approaches have been used in the past to map wetlands. In the pixel-based approach, each pixel is assigned a class based on some pre-determined rules and algorthims. This can lead to gross missclassification because it does not account for orientation and context of the pixels in relation to neighbouring pixels. For example, a pixel exhibiting spectral properties consistent with "meadow" would be misclassified as meadow even if it actually occurs in the midst of floating vegetation. By comparison, in the object-based approach, pixels are first grouped, and the resulting objects have spatial, contextual, and relational characteristics that can be manipulated and incorporated into algorithms and rulesets that can create more meaningful and accurate classifications. Hence, missclassifications are reduced when the "floating" pixel with abnormal spectral values are grouped correctly with neighbouring "floating" pixels because of its spatial context; in other words, mean spectral value of neighbouring pixels can effectively dampen the influence of outliers (Flanders et al. 2003; Navulur, 2005). This explains why the object-based classification approach has become the more popular alternative in recent years (Laliberte et al., 2004; Wulder et al., 2004; Chubey et al., 2006; Zhou et al., 2008) and has been used to map tropical mangrove swamps (Wang et al., 2004) and boreal peatlands (Grenier et al., 2007; Grenier et al., 2008).

Although past studies have applied classification techniques to multiple scenes (Grenier et al., 2007; Wei and Chow-Fraser, 2007), these have involved pixel-based approaches that require scene-specific training (i.e. field-truthing in additional scenes to be classified; Lillesand and Kiefer, 2000; Navulur, 2005). No study has yet examined the transferability of rulesets derived from one scene using the object-based approach, to map vegetation in other scenes that were not used in development of the ruleset. Sawaya et al. (2003) have cautioned against applying rulesets to multiple scenes unless they have been acquired during the same satellite pass because time, angle, and atmospheric conditions at acquisition can create considerable inter-scene differences. The feasibility of transferring rulesets derived from a single scene to multiple scenes without the need for additional field-truthing is something worth investigating, especially for mapping habitats at the scale of eastern Georgian Bay.

This study expands on the work of Wei and Chow-Fraser (2007), who successfully classified aquatic coastal wetland vegetation at 11 sites in Lake Huron and Georgian Bay using IKONOS satellite imagery. Here, we focus on the terrestrial component of coastal marshes to map the wet-meadow portion from the water's edge to the upland forests. We will investigate the feasibility of using IKONOS imagery and an object-based classification approach to classify coastal meadow vegetation in three satellite scenes into 4 classes (meadow/shrub, emergent, senescent vegetation, and rock). As a second objective, we test the scene-to-scene transferability of rulesets developed for images taken during the same satellite pass, to assess the feasibility of developing one ruleset to a large collection of single-pass scenes for the entire southeastern shoreline of Georgian Bay. This is the first study that applies an object-based approach to mapping coastal wetlands in one of the largest coastal systems in the world, Lake Huron, and will lay the groundwork for large-scale mapping initiative without the need for expensive field surveys.

Methods

All of the coastal wetlands mapped are situated along the eastern shoreline of Georgian Bay, the eastern arm of Lake Huron, Ontario, Canada (Figure 1.1). Coastal marshes are operationally defined in this study as wetlands that are hydrologically connected to Georgian Bay via surface water within 2km of the shoreline (Ontario Wetland Evaluation System; OMNR, 1993). The 24 wetlands that were classified in this study are located in Wood's Bay (Figure 1.2), Tadenac Bay (Figure 1.3) and North Bay (Figure 1.4) regions.

IKONOS imagery (Geoeye, Dulles, VA, USA) was acquired during the same satellite pass on July 1st, 2002 for all three scenes used in this study. All images are cloud-free, multispectral (Red, Green, Blue, and Near Infrared bands), and were pan-sharpened by the image provider with a resolution of 1m. All imagery was acquired just prior to maximal vegetative growth in midsummer to capture the full extent of the wetlands.

Description of Regional Differences

The Wood's Bay scene is the most northerly, smallest by area, and ranks second in terms of wet-meadow habitat among the three scenes (Figure 1.1). Within the Wood's Bay scene, 6 wetlands were classified covering 38 ha of a possible 147 ha (Figure 1.2). The Tadenac scene is located south of Wood's Bay, is intermediate in area, and has the least wet-meadow habitat. Within the Tadenac scene, 10 wetlands were classified covering 38 ha of a possible 77 (Figure 1.3).

The North Bay scene covers the largest area and has a total meadow habitat of 242 ha, and of this, 37 ha belonging to 8 wetlands were classified (Figure 1.4).

The IKONOS imagery was imported into a GIS and all coastal wetlands within each scene were manually delineated. Binary masks were created in ENVI™ (ITT Visual Informations Solutions, White Plains, New York, United States; v4.1) to isolate the wet meadow habitat for classification from the entire images. Masks excluded upland islands within wetlands but did include solitary rocks. The GIS water layer of the Ontario Base Maps (Ontario Ministry of Natural Resources, Land Information Ontario) was modified to produce a polygon of Georgian Bay waters (exclusive of inland lakes, disconnected waters, or wetlands) and this was used to produce the 2-km buffer of the shoreline to identify coastal wetland complexes for this study.

Wetland Vegetation Classes

Classes that were mapped correspond to major vegetation habitat types found in Georgian Bay coastal wetlands: meadow/shrub (high marsh or swamp), senescent vegetation (low or high marsh), emergent (low marsh) and rock (no equivalent OWES class) (Table 1.1, Figure 1.5). We have indicated in parentheses the corresponding wetland types (marsh [high and low] and swamp) to be consistent with the classification procedures of the Ontario Wetland Evaluation System (OWES; OMNR, 1993), which evaluates wetlands on biological, social, hydrological, and unique habitat features at the provincial level.

Unfortunatley, it was not possible to accurately separate meadow from shrub classes, and therefore meadow and shrub classes were merged into meadow/shrub (Figure 1.5). We have included the emergent vegetation class to reflect the transition from terestrial to aquatic marsh habitat (Wei and Chow-Fraser, 2007), and the latter class, rock, was included due to the predominance of exposed precambrian shield that defines this landscape.

Classification Procedure

The classification approach includes creating a decision tree (Lillesand and Kiefer, 2000) composed of rules at each decision or node. The process tree is a decision tree created in Definiens Developer 7™ (Definiens Imaging GmbH, München, Germany) with image objects. It is non-stepwise but hierarchical in that rules lower on the tree can still affect the classification of classes above. This is the concept of optimization, where subsequent rules are used to optimize or correct missclassification from the initial rule. For example, shrub and floating vegetation have similar spectral values, and to minimize misclassification of shrub pixels, we can apply a rule that forces all vegetation objects occupying an area <15 pixels that are surrounded by shrub pixels to be classified as "shrubs", even if spectral properties are more consistent with "floating". The logic is that foating vegetation is not naturally found in small discrete clumps within shrubs which has been verified from field observations.

In this study, criteria used to create the ruleset were spectral, spatial, relational, and contextual in nature (Table 1.2). We used a multi-resolution segmentation algorithm to create the objects from the intial image of pixels. We found that segmenting for a small object size (scale factor of 7) was most beneficial for idenitifying the desired classes and that spectral properties rather than shape were the most important for grouping the pixels. The layout of the ruleset was dictated by how each class could be separated and the best order was selected from numerous trials. The classification strategy was to first use spectral thresholds to separate a class mainly using a band, band ratio (ie. NIR/R), or a vegetation index (ie. Normailized Difference Vegetation Index – NDVI; Lillesand and Kiefer, 2000). This would produce the base classification with some missclassification. Optimization would then be used to correct for the missclassifications.

A mass exploratory pixel-data-mining exercise was used to extract spectral values for over 10,000 pixels from all sites and scenes. Some of these pixels were selected based on expert knowledge of the sites (from field observations) and were different from pixels used for accuracy testing; the majority, however, were not based on field observations. These pixels were then used to find base thresholds and to determine significant differences between spectral properties of different classes. A portion of ground-truth data were used in conjunction with base thresholds from the data mining exercise to create each scene's ruleset. To determine within-scene rulesets, we chose sites in each scene that were sufficiently large to generate data for both training and testing. These were Black Rock West for Tadenac Bay, North Bay 4 East for North Bay, and Grapps Marsh for Wood's Bay.

Inititially, masks were used to isolate all wetlands and then a multi-resolutional segmentation was used to create objects within each wetland. Rules were then created with the "feature-space optimization view" in Definiens, where value intervals can be selected for a band or a feature, and the analyst is given the opportunity to preview which objects would be classified by the given rules. The final rule-set is then applied to the entire scene or scene subset, and accuracy is assessed on a site-by-site basis. Each class was then exported as a shapefile to be analyzed in a GIS. Area analyses were conducted and maps were created using ArcGIS 9.2 (ESRI™, Redlands, CA, USA).

Ground-truthing

Twenty-four wetlands were visited in the summers of 2007 and 2008 and the locations of at least 4 x 4 m^2 quadrats of homogenous vegetation corresponding to our four classes were recorded with a GPS. Although 5 years is considered the limit in the time difference between image acquisition and in-field data collection (Belluco et al, 2006), we do not attribute large errors to the data collected in 2008. At each location, the dominant species were recorded and any pertinent features were noted. Since the error of the GPS ranged from 2-7m, we only used test pixels that occurred in a very large homogeneous area indicated by the GPS coordinates. The number of testing pixels per class were proportionate to the class in question within the wetland. In some instances, the error of the GPS was too great to be used and the boundary of the class was manually delineated on a printed copy of the IKONOS image while the analyst was in the field. We decided to use pixels in the testing data instead of objects because we could not assume that the shape of objects are accurate representations of the class boundaries. Using pixels over objects also dramatically increased the testing sample size.

Accuracy Assessment

We used error matrices produced by Definiens Developer 7™ to assess the accuracy of classification for rulesets applied to each site (Congalton, 1991; Lillesand and Kiefer, 2000). The error matrices summarized errors of ommission (producer's accuracy) and commission (user's accuracy), overall accuracy, and Kappa coefficients per class and for the wetland. Producer's accuracy is the proportion of correctly classified samples of a class. In other words, it is the frequency of omitting the correct class for a given habitat feature. User's accuracy is the proportion of correctly classified samples of all samples in that class, or how often a sample in a particular class actually belongs to that class. Overall accuracy is computed as the proportion of all correctly classified testing samples and provides a means of presenting data in a manner understandable by an end user (Story and Congalton, 1986; Congalton, 1991). Kappa coefficients are measures of accuracy where 0.0-0.49 indicates poor agreement, 0.50-0.79 indicates reasonable agreement, and 0.80-1.00 indicates excellent agreement (Cohen, 1960). To maintain consistency and provide valid comparisons, the same testing dataset was used for each ruleset at each site.

Statistics

Statistical analyses were performed with SAS JMP v7.0 (SAS institute, Cary, NC, USA). We used ANOVA or t-tests as appropriate to determine significant differences among or between means, respectively. Where significant differences were determined by ANOVA, we used Tukey-Kramer to conduct pairwise comparisons.

Results

Mass Data Mining and Exploration

Vegetation classes across the three satellite scenes were found to be broadly homogeneous with respect to spectral properties from data mining and exploration. Across all 3 scenes, we detected no significant differences in mean spectral properties with respect to a single vegetation class, including mean band spectral values, mean band ratio spectral values, and mean Normalized Difference Vegetation Index (NDVI) values (ANOVA, $p>0.05$) based on 10,000 pixels. The meadow and shrub classes, however, had overlapping ranges in spectral signatures and would have been frequently misclassified if we had not combined these into one class in this study (Figure 1.6). This is the main reason for combining the two into one class of meadow/shrub, even though they each support distinctive bird and wildlife habitats (Maynard and Wilcox 1997). This class is still useful for identifying habitat because the focus of this study being on wet meadows which is already considered a habitat type. We are therefore identifying very narrow habitat ranges that can be merged without major consequence.

Ruleset Accuracies and Kappa Coefficients Across Scenes

When data across all scenes were considered, there were no significant differences in mean ruleset accuracies, with an overall mean accuracy of 76.05%, with <4% difference between the highest (77.8%) and lowest (74.2%) overall accuracy (Table 1.3). The range of wetland accuracies was from 54% to 93% (Table 1.3). As expected, the accuracy associated with each scene was generally dependent on the origin of the training set (Table 1.3). For example, when data from Black Rock West were used to produce the Tadenac ruleset, the mean accuracy across all wetlands was 81.4% for Tadenac Bay, compared with 78.3 and 72.5% for North Bay and Wood's Bay, respectively. When the rulesets from North Bay and Woods' Bay were applied to wetlands of Tadenac Bay, the accuracies dropped accordingly to 71.2 and 69.8%, respectively (Table 1.3). Nevertheless, no single ruleset emerged as being superior when applied to the other two scenes.

The Kappa coefficients for overall classifications can be similarly compared across the three scenes (Table 1.4). In this case, the Kappa value for Tadenac (0.62) was significantly lower than that for North Bay (0.67), but neither were significantly lower than that for Wood's Bay (ANOVA, Tukey-Kramer HSD, $p<0.05$). The range of wetland Kappa coefficients was 0.36 to 0.89 (Table 1.4). Similar to overall accuracy, North Bay was associated with the greatest overall Kappa across all scenes. The mean Kappa of all rulesets across all scenes in this study is an overall Kappa of 0.6458, indicating "reasonable agreement". The Kappa results were very similar to overall accuracy in that significant differences existed at the scene level, although there was generally lower agreement between classification and reference data for the former.

Producer and User Accuracies

Both producer- and user-accuracies show that emergent and meadow/shrub classes were classified with the greatest accuracies, and the dry and impervious classes of senescent and rock were classified with lowest accuracies (Table 1.5). These latter classes were, however, consistently misclassified across rulesets and scenes (Table 1.5). When all three scenes were taken into consideration, the North Bay ruleset had significantly greater producer accuracy, but had the lowest user accuracy with respect to emergent vegetation (ANOVA, Table 1.5). By comparison, the Tadenac ruleset had significantly greater producer accuracy and lower user accuracy with respect to meadow/shrub vegetation (ANOVA, Table 1.5).

To complement the overall Kappa coefficient of each wetland, individual class Kappa coefficients were computed in the accuracy assessment. The class Kappa results reflect the same trend in class agreement as the producer and user accuracies in that both emergent and meadow/shrub vegetation were classified with higher agreement with the reference data than were the senescent and rock classes (Table 1.6). We saw no single ruleset emerging as superior in agreement. The North Bay ruleset emerged with the highest Kappa for all 3 scenes while the Tadenac ruleset was found to have the lowest Kappa value (ANOVA, $p<0.05$; Table 1.6). The meadow/shrub class had the greatest level of agreement of all classes, with the Tadenac ruleset associated with the greatest mean Kappa coefficient, and the level of agreement approached 1.0 for the Wood's Bay scene (Table 1.6). Similar to both producer and user accuracies, there were no differences in class Kappa among rulesets or scenes for senescent vegetation (ANOVA, Table 1.6). The Kappa coefficients for the rock class showed no significant differences across scenes and rulesets.

Comparison of Areas for Each Class

We compared differences in class areas generated by the different rulesets for each scene. The Wood's Bay ruleset classified more dry and impervious classes, which reflect light and are visually bright. The Tadenac ruleset also identified significantly more meadow/shrub vegetation (Table 1.7). Across all scenes, the Tadenac Bay ruleset tended to identify more emergent vegetation and meadow/shrub area than did the other two rulesets. Similar to emergent vegetation, rock area differed significantly among each pair of rulesets across all scenes (paired t-test, $p<0.05$; Table 1.7). Senescent vegetation was unique in that there were no significant differences in area between pairs of rulesets for each individual scene. Across all scenes, however, the Wood's Bay ruleset classified significantly greater area of senescent vegetation than did the Tadenac ruleset (paired t-test, $p<0.05$; Table 1.7).

Ruleset Origin

There is a significant effect of ruleset origin on mean accuracy and Kappa. Mean accuracy for internally derived rulesets (ie. ruleset applied to the scene from which it was created) have significantly greater accuracy than externally derived rulesets (ArcSine transformed proportion wetland accuracy, t-test, $p<0.05$; Table

1.8; Figure 1.7). Similarly, Kappa of internally derived rulesets is significantly greater than that for externally derived rulesets (t-test, $p<0.05$; Table 1.9).

Discussion

In this study, we used IKONOS imagery to classify wet-meadow habitat in coastal wetlands of eastern Georgian Bay into 4 classes (meadow/shrub, emergent, senescent, and rock) with an overall accuracy of 76.05%. The mapping accuracies for each of the scenes were 74.17%, 77.79%, and 76.2% for Tadenac, North Bay, and Woods Bay respectively, and their associated Kappa values were 0.62. 0.67 and 0.65, respectively (Tables 1.3 and 1.4). These values indicate that we attained mapping accuracy that we consider very successful in all cases, because the focus of this study is on vegetation within a very narrow zone, wet meadow. We therefore conclude that IKONOS imagery should be used to map wet meadow habitat in eastern Georgian Bay. It is unlikely that we would ever achieve "excellent" mapping accuracy using only satellite imagery (> 85%), since the composition of wet meadows along the coast of eastern Georgian Bay consist of similar vegetation types whose boundaries are not clearly defined spectrally.

A second goal of this study was to evaluate the use of an object-based approach to map wetlands at a regional scale. In this study, we created rulesets that employed both spectral and contextual information (Table 1.2). Class accuracies varied greatly depending on the scene and ruleset used. We see that the wet/meadow shrub class was the most accurately classified, and this was followed by the emergent class. It was important for these two classes to be classified accurately because the separation of these classes is the boundary between land and water and represent the majority of the habitat of interest. The senescent and rock classes were not classified as accurately because they are spectrally similar and in many cases formed somewhat mixed image objects. These two classes often occurred adjacent to each other, and were difficult to separate out even with expert visual image interpretation. Since geographic coverage of the senescent class is related to soil moisture, it is worthwhile to investigate further how best to accurately detect this habitat feature so that interannual changes in this class could be monitored effectively as the climate continues to warm over the next several decades. This is the first study in the Great Lakes basin to use an image-object approach in mapping wetlands and we see that is has great implications for any future mapping projects focused on wetland habitat.

Dillabaugh and King (2008) also found it difficult to separate meadow from shrub classes in similar riparian systems using IKONOS imagery. Shrubs exist at the periphery of wetland/upland boundaries and are scattered among the wet meadow and emergent vegetation. We were able to identify peripheral shrubs part of the time, but always had difficulty identifying the scattered shrubs. One contributing factor to the difficulty in identifying peripheral shrubs is that shadows were often confused with vegetation, and Sawaya et al. (2003) have already warned of potential problems with shadows being artifacts of high-resolution imagery. Our inability to separate meadow vegetation from shrubs limited the usefulness of this approach to predict habitat quantity for specific bird and wildlife assemblages. Since shrub thickets and meadow vegetation provide habitat for different species, a combined estimate of meadow/shrub limits our ability to make specific predictions at the species level. This we feel is not a large impediment for the application of this approach to habitat mapping as we have been able to separate tall shrubs from other vegetation types much more successfully in upstream wetland habitats (Rokitnicki-Wojcik, unpub data.) The homogeneity of these habitat classes and the inability to separate them are a technological limitation at this point. We expect that this limitation would be easily adverted with the incorporation of LIDAR (Light Detection and Ranging) data, which can identify canopy and vegetation height. A potential future direction could be to use a hybrid approach where pixel-based classification is used for highly confused features and object-based classification for others.

In this study, we were able to use IKONOS and the object-based classification to map highly complex and specific habitat types at very fine spatial scales in small wetlands. This has very positive implications for wetland and habitat mapping of large natural shorelines like eastern Georgian Bay. Within 2-km of the Georgian Bay shoreline, majority of the wetlands that are upstream of wet meadow habitat include many swamps and fens. By incorporating high resolution LIDAR data, to the current approach used here, we will be able to develop classification rulesets to separate vegetation based on height, and thereby distinguish large shrubs/trees in swamps from the herbaceous meadow/mosses of fens and bogs.

We assessed the transferability of three rulesets derived independently to other scenes acquired during the same satellite pass. We know that the application of a model to a different scene usually results in lower accuracy because of the potential effect of spatial autocorrelation (Wei and Chow-Fraser 2008). The mapping accuracy and Kappa were significantly higher for scenes based on internally derived rulesets compared with externally derived rulesets, but these differences were relatively small (about 5%), and from a practical perspective, these differences should not dissuade a manager from using externally derived ruleset to identify habitat, given the high cost of field surveys. Since we found no significant differences in spectral and index values among classes in the initial data mining and exploration, we conclude that the scenes are sufficiently similar in spectral properties that transferability should be expected. In addition, there were very similar accuracies and Kappa coefficients associated with externally derived rulesets presented in Table 1.3 and 1.4. We present this as a tool to be used in future transferability studies. Classification producers should first select a broad range of exploratory pixels and test for differences among scenes, sites, or the unit that transferability is to be tested. Practical and ecologically meaningful differences should also be determined prior to classification development to aid in concluding whether transferability is sufficient for specific applications.

Acknowledgments

This research was funded by an NSERC PGS-M grant awarded to DR-W and a research grant from the GBA Foundation to PC-F. We thank everyone who helped in collecting ground-truth data and in mapping especially, R. de Catanzaro, M. Cvetkovic, K. Cimaroli, B. Gidley, A. Stevens, L. Smith, S. Yantsis, M. Crouch, and G. Honsberger. The technical advice from Jon Midwood was greatly appreciated. We are grateful for the help of Anhua Wei for his constructive comments in an earlier manuscript. We would like to thank the GBA foundation for the use of the IKONOS imagery and the Georgian Bay Association, especially Mary Muter, for helping with logistics during field sampling.

Literature Cited

Baker, C., Lawrence, R., Montagne, C., Patten, D., 2006. Mapping wetlands and riparian areas using LANDSAT ETM imagery and decision-tree-based models. *Wetlands*. 26: 465-474.

Belluco, E., Camuffo, M. Ferrari, S., Modenese, L. Silvestri, S. Marani, A. Marani, M. 2006. Mapping salt-marsh vegetation by multispectral and hyperscpectral remote sensing. Remote Sensing of Environment. 105: 54-67.

Chubey, M.S., Franklin, S.E., Wulder, M.A. 2006. Object-based analysis of Ikonos-2 imagery for extraction of forest inventory parameters. *Photogrammetric Engineering & Remote Sensing*. 72(4):383-394.

Cohen, J. 1960. A coefficient of agreement for nominal scales. *Educational and Psychological Measurement*. 20(1): 37-46.

Congalton, R.G., 1991. A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment*. 37:35-46.

Dechka, J.A., Franklin, S.E., Watmough, M.D., Bennett, R.P., Ingstrup, D.W., 2002. Classification of wetland habitat and vegetation communities using multi-temporal IKONOS imagery in southern Saskatchewan. *Canadian Journal of Remote Sensing*. 28(5): 679-685.

Definiens AG, 2007. Definiens Developer 7 Reference Book. Definiens AG, München, Document Version 7.0.0.843. 195pp.

Dillabaugh, K.A., King, D.J. 2008. Riparian marshland composition and biomass mapping using Ikonos imagery. *Canadian Journal of Remote Sensing.* 34(2):143-158.

Flanders, D., Hall-Beyer, M., Pereverzoff, J. 2003. Preliminary evaluation of eCognition object-based software for cut block delineation and feature extraction. *Canadian Journal of Remote Sensing.* 29(4): 441–452.

Fuller, L.M., Morgan, T.R., Aichele, S.S. 2006. Wetland delineation with IKONOS high-resolution satellite imagery, Fort Custer Training Center, Battle Creek, Michigan, 2005: U.S. Geological Survey, Scientific Investigations Report 2006-5051: 8pp.

Ghioca-Robrecht, D.M., Johnston, C.A., Tulbure, M.G. 2008. Assessing the use if multiseason Quickbird imagery for mapping invasive species in a Lake Erie coastal marsh. *Wetlands.* 28(4): 1028-1039.

Gluck, M., Rempel, R., Uhlig, P.W.C., 1996. An evaluation of remote sensing for regional wetland mapping applications. *Forest Research Report No. 137*; Ontario Research Institute; Sault Ste Marie, Ontario.

Grenier, M., Demers, A.M., Labreque, S., Benoit, M., Fournier, R.A., Drolet, B. 2007. An object-based method to map wetland using RADARSAT-1 and Landsat ETM images: test case on two sites in Quebec, Canada. *Canadian Journal of Remote Sensing.* 33(S1): 28-45.

Grenier, M., Labreque, S., Garneau, M., Tremblay, A. 2008. Object-based classification of a SPOT-4 image for mapping wetlands in the context of greenhouse gases emissions: the case of the Eastmain region, Quebec, Canada. *Canadian Journal of Remote Sensing.* 34: (S2): 398-413.

Ingram, J., Holmes, K., Grabas, G., Watton, P., Potter, B., Gomer, T., Stow, N. 2004. Development of a Coastal Wetlands Database for the Great Lakes Canadian Shoreline, Final Report to the Great Lakes Commission. 18pp.

Jensen, J.R., Cowen, D., Althausen, J., Narumalani, S., Weatherbee, O. 1993. An evaluation of the Coast Watch change detection protocol in South Carolina. *Photogrammetric Engineering & Remote Sensing.* 59: 1039-1046.

Laliberte, A.S., Rango, A., Havstad, K.M., Paris, J.F., Beck, R.F., McNeely, R., Gonzalez, A.L. 2004. Object-oriented image analysis for mapping shrub encraochment from 1937 to 2003 in southern New Mexico. *Remote Sensing of Environment.* 93:198-210.

Lawrence, R., Hurst, R., Weaver, T., Aspinall, R. 2006. Mapping prarie pothole communities with multitemporal Ikonos satellite imagery. *Photogrammetric Engineering & Remote Sensing.* 72(2): 169-174.

Li, J., Chen, W. 2005. A rule-base method for mapping Canada's wetland using optical, radar, and DEM data. *International Journal of Remote Sensing.* 26(22): 5051-5069.

Lillesand, T., Kiefer, R. 2000. Remote sensing and image interpretation. 4th ed. Lehigh Press. New York 724pp.

Maynard, L., Wilcox, D. 1997. Coastal wetlands of the Great Lakes. State of the

Lakes Ecosystem Conference 1996. U.S. Environmental Protection Agency. 99 pp.

Mitch, M.J., Gosslink, J.G. 2000. Wetlands. 3rd ed. Wiley. New York. 920pp.

Navulur, K. 2006. Multispectral image analysis using the object-oriented paradigm. CRC press. New York. 165pp

OMNR 1993. Ontario Wetland Evaluation System. Northern Manual. Ontario Ministry of Natural Resources (OMNR), No.50254.

Ozesmi, S.L., Bauer, M.E., 2002. Satellite remote sensing of wetlands. *Wetlands ecology and management*. 10: 381-402.

Poulin, M., Careau, D., Rochefort, L., and Desrochers, A., 2002. From satellite imagery to peatland vegetation diversity: How reliable are habitat maps? *Conservation Ecology*. 6(2):16-56.

Sawaya, K.E., Olmanson, L.G., Hein, N.J., Brezonic, P.L., Bauer, M.E., 2003. Extending satellite remote sensing to local scales: land and water resource monitoring using high-resolution imagery. *Remote Sensing of Environment*. 88: 144-156.

Snell, E.A. 1987. Wetland Distribution and Conversion in Southern Ontario. Canada Land Use Monitoring Program. Working Paper No. 48. Inland Waters and Lands Directorate, Environment Canada.

Story, M., Congalton, R. 1986. Accuracy Assessment: A user's perspective. *Photogrammetric Engineering & Remote Sensing*. 52(3):397-399.

Töyrä, J., Pietroniro, A., Martz, L.W. Multisensor hydrologic assessment of a freshwater wetland. *Remote Sensing of Environment.* 75:162–173.

Wang, L. Sousa, W.P., Gong, P. 2004. Integration of object-based and pixel-based classification for mapping mangroves with IKONOS imagery. *International Journal of Remote Sensing*. 25(24): 5655-5668.

Wei, A., Chow-Fraser, P. 2007. Use of IKONOS imagery to map coastal wetlands of Georgian Bay. *Fisheries*. 32(4): 167-173.

Wei, A., Chow-Fraser, P. 2008. Testing the transferability of a marsh-inundation model across two landscapes. *Hydrobiologia*. 600:41-47.

Wolter, P.T., Johnston, C.A., Niem, G., J., 2005. Mapping submergent aquatic vegetation in the US Great Lakes using QuickBird data. *International Journal of Remote Sensing*. 26(23): 5255-5274.

Wulder, M.A., Hall, R.J., Coops, N.C., Franklin, S.E. 2004. High spatial resolution remotely sensed data for ecosystem characterization. *BioScience* 54(6): 511- 22.

Zhou, W., Troy, A., Grove, M., 2008. Object-based land cover classification and change analysis in the baltimore metropolitan area using multitemporal high resolution remote sensing data. *Sensors.* (8):1613-1636.

Table 1.1: Summary of the 5 classes sampled and mapped in this study including dominant vegetation and class descriptions.

Class	Description	Dominant Vegetation
Emergent	Transitionary vegetation linking low marsh and high marsh zones	Sedge sp. (*Carex sp.*), Marsh Spike Rush (*Eleocharis smallii*), Cattail sp. (*Typha sp.)*, Bullrush sp. (*Schoenplectus sp.*)
Meadow	Wet meadow vegetation including grasses, sedges, and herbaceous vegetation	Sedge sp. (*Carex sp.*), Canada Blue Joint (*Calamagrostis canadensis*), Manna Grass sp. (*Glyceria sp.*), Swamp Candles (*Lysimachia terrestris*), Spotted Joe-Pye weed (*Eupatorium maculatum*), Canada Goldenrod (*Solidago canadensis*)
Senescent	Dry and/or dead vegetation	Mixture of meadow and emergent species usually indistinguishable at the species level
Shrub	Robust woody vegetation	Sweet gale (*Myrica gale*), Speckled Alder (*Alnus incana*), Slender-leaved willow (*Salix petiolaris*)
Rock	Rock and impervious surfaces	No vegetation

Table 1.2: Object-based classification features and algorithms used in the creation of wet meadow rulesets. Features presented are exclusive to Definiens Developer v7 (Definiens Imaging GmbH, München, Germany). For more detailed feature and algorithm information, see Definiens Developer 7 Reference Book (Definiens AG, 2007).

Feature Type	Algorithm	Feature Description
Segmentation	Multiresolution	Creates objects from pixels that are grouped according to the level of importance of shape or spectral properties and scale
Spectral	HSI Transformations	Separates Hue, Saturation, and Intensity of colour-space tranformations of RBG and combinations of NBG bands
Spatial	Area	Identifies objects according to a pre-defined size maximum or minimum
Relational	Border to	Indentifies objects that are bordering the specified class(es) (from borders of 0 to 100%)
	Existence of	Indentifies objects in contact with the specified class(es)
Contextual	Enclosed by class	Identifies all objects completely surrounded by the specified class(es)
Custom Features		Rules that combine 2 or more of the above-mentioned algorithms

Table 1.3: Summary of mean accuracy of wetlands for each ruleset. Mean refers to the mean accuracy for each scene and overall mean refers to the accuracy for each ruleset. Values with different letter superscripts indicate they are significantly different (ANOVA, Tukey-Kramer; $p<0.05$).

		Accuracy of Ruleset		
Scene	**Wetland**	**Tadenac**	**North Bay**	**Wood's Bay**
Tadenac	Black Rock North	88.44	80.89	64.67
	Black Rock West[t]	79.93	80.37	77.32
	Blasted Channel	79.88	78.27	68.61
	Coffin Rock	83.62	78.70	71.90
	East of Thunder	83.43	77.10	77.81
	Miner's Creek	84.70	89.80	90.35
	Pamplemousse	83.19	80.90	69.25
	Petite Pamplemousse	76.11	72.60	67.45
	Thunder Bay	78.89	75.80	74.78
	West of Black Rock	76.03	68.80	62.93
	Mean	**81.42**^{A}	**78.32**^{A}	**72.51**^{B}
North Bay	North Bay 1	68.12	72.59	72.12
	North Bay 2	71.50	73.13	72.38
	North Bay 4 East[t]	75.70	90.48	90.10
	North Bay 4 West	81.40	62.29	54.40
	North Bay River North	60.74	72.35	71.85
	North Bay River South	70.54	93.30	91.30
	North Bay River	61.66	74.37	72.83
	Treasure Bay North	80.05	81.44	77.02
	Mean	**71.21**^{A}	**77.49**^{B}	**75.25**^{AB}
Wood's Bay	Blackstone 1	71.17	78.18	78.34
	Blackstone 2	64.13	71.90	74.69
	Grapps Marsh[t]	58.91	73.80	78.59
	Moon River 1	78.25	82.38	88.42
	Port Rawson	67.63	74.76	75.14
	Wood's Bay 1	79.10	84.40	89.78
	Mean	**69.87**^{A}	**77.57**^{B}	**80.83**^{B}
	Overall Mean	**74.17**^{A}	**77.79**^{A}	**76.20**^{A}

[t] indicates that portion of the wetland data was used in ruleset creation

Table 1.4: Summary of mean Kappa coefficient (Cohen, 1960) associated with each ruleset. Mean refers to mean Kappa for each scene and overall mean refers to the mean Kappa for each ruleset. Values with different letter superscripts indicate they are significantly different (ANOVA, Tukey-Kramer; $p<0.05$).

		Kappa Coefficient of Ruleset		
Scene	**Wetland**	**Tadenac**	**North Bay**	**Wood's Bay**
Tadenac	Black Rock North	0.8360	0.7344	0.5187
	Black Rock West[ŧ]	0.7324	0.7379	0.6983
	Blasted Channel	0.7207	0.6965	0.5687
	Coffin Rock	0.7774	0.7137	0.6250
	East of Thunder	0.7780	0.6901	0.7030
	Miner's Creek	0.7147	0.8176	0.8290
	Pamplemousse	0.7706	0.7360	0.5893
	Petite Pamplemousse	0.6724	0.6173	0.5707
	Thunder Bay	0.7012	0.6620	0.6606
	West of Black Rock	0.6697	0.5815	0.4993
	Mean	**0.7373**^{A}	**0.6987**^{B}	**0.6263**^{C}
North Bay	North Bay 1	0.5471	0.6150	0.6094
	North Bay 2	0.5208	0.5579	0.5563
	North Bay 4 East[ŧ]	0.6462	0.8638	0.8613
	North Bay 4 West	0.7404	0.4646	0.3940
	North Bay River North	0.3203	0.5336	0.5305
	North Bay River South	0.5357	0.8987	0.8685
	North Bay River	0.3620	0.5885	0.5614
	Treasure Bay North	0.7146	0.7365	0.6795
	Mean	**0.5484**^{A}	**0.6573**^{B}	**0.6326**^{AB}
Wood's Bay	Blackstone 1	0.5444	0.6615	0.6656
	Blackstone 2	0.4020	0.5477	0.5924
	Grapps Marsh[ŧ]	0.3701	0.5990	0.6728
	Moon River 1	0.6854	0.7470	0.8380
	Port Rawson	0.3980	0.5483	0.5552
	Wood's Bay 1	0.6998	0.7812	0.8570
	Mean	**0.5166**^{A}	**0.6475**^{B}	**0.6968**^{B}
	Overall Mean	**0.6192**^{A}	**0.6721**^{B}	**0.6460**^{AB}

[ŧ] indicates that wetland data were used in ruleset creation

Table 1.5: Summary of individual class producer and user accuracies with respect to each scene and across all scenes. Values with different letter superscripts indicate they are significantly different (ANOVA, Tukey-Kramer; $p<0.05$).

		Mean Ruleset Class Producer Accuracy			Mean Ruleset Class User Accuracy		
Class	**Scene**	**Tadenac**	**North Bay**	**Wood's Bay**	**Tadenac**	**North Bay**	**Wood's Bay**
Emergent	Tadenac	80.0^{A}	93.2^{A}	81.3^{AB}	94.5^{A}	76.1^{B}	93.3^{A}
	North Bay	62.5^{A}	76.5^{A}	70.9^{A}	96.9^{A}	89.2^{A}	95.1^{A}
	Wood's Bay	86.5^{A}	98.3^{B}	96.6^{AB}	96.4^{A}	84.7^{A}	91.1^{A}
	Overall	$\mathbf{75.8^{A}}$	$\mathbf{88.9^{B}}$	$\mathbf{81.7^{AB}}$	$\mathbf{95.8^{A}}$	$\mathbf{82.6^{B}}$	$\mathbf{93.4^{A}}$
Meadow/ Shrub	Tadenac	87.5^{A}	73.6^{AB}	67.3^{B}	84.0^{A}	93.2^{B}	93.0^{B}
	North Bay	96.5^{A}	90.2^{A}	88.3^{A}	64.1^{A}	76.0^{A}	76.0^{A}
	Wood's Bay	99.8^{A}	98.2^{B}	98.7^{AB}	62.8^{A}	77.7^{A}	78.8^{A}
	Overall	$\mathbf{93.6^{A}}$	$\mathbf{85.3^{AB}}$	$\mathbf{82.2^{B}}$	$\mathbf{72.1^{A}}$	$\mathbf{83.7^{B}}$	$\mathbf{83.8^{B}}$
Senescent	Tadenac	78.2^{A}	72.5^{A}	50.5^{B}	67.7^{A}	66.2^{A}	58.6^{A}
	North Bay	40.8^{A}	56.2^{A}	49.6^{A}	80.1^{A}	79.1^{A}	75.8^{A}
	Wood's Bay	23.4^{A}	40.6^{A}	44.4^{A}	56.9^{A}	65.1^{A}	78.4^{A}
	Overall	$\mathbf{52.0^{A}}$	$\mathbf{59.1^{A}}$	$\mathbf{48.8^{A}}$	$\mathbf{69.1^{A}}$	$\mathbf{70.2^{A}}$	$\mathbf{69.3^{A}}$
Rock	Tadenac	62.4^{A}	59.3^{A}	85.1^{B}	74.8^{A}	79.9^{A}	48.1^{B}
	North Bay	46.3^{A}	46.3^{A}	59.2^{A}	58.5^{A}	58.5^{A}	38.5^{A}
	Wood's Bay	10.6^{A}	10.6^{A}	34.7^{A}	15.4^{A}	16.7^{A}	59.0^{A}
	Overall	$\mathbf{44.1^{A}}$	$\mathbf{42.8^{A}}$	$\mathbf{63.8^{B}}$	$\mathbf{54.5^{A}}$	$\mathbf{57.0^{A}}$	$\mathbf{47.6^{A}}$

Table 1.6: Summary of class Kappa coefficients among the three rulesets for each scene and across all scenes. Values with different letter superscripts indicate they are significantly different (ANOVA, Tukey-Kramer; $p<0.05$).

		Mean Ruleset Class Kappa		
Class	**Scene**	**Tadenac**	**North Bay**	**Wood's Bay**
Emergent	Tadenac	0.7494^{A}	0.9029^{B}	0.7674^{A}
	North Bay	0.5714^{A}	0.7220^{A}	0.6583^{A}
	Wood's Bay	0.8316^{A}	0.9774^{B}	0.9534^{B}
	Overall	**0.7103^{A}**	**0.8612^{B}**	**0.7774^{AB}**
Meadow/Shrub	Tadenac	0.8344^{A}	0.6708^{A}	0.6034^{B}
	North Bay	0.9519^{A}	0.8696^{A}	0.8431^{A}
	Wood's Bay	0.9937^{A}	0.9615^{B}	0.9753^{AB}
	Overall	**0.9134^{A}**	**0.8097^{A}**	**0.7763^{B}**
Senescent	Tadenac	0.7059^{A}	0.6142^{A}	0.3604^{B}
	North Bay	0.3211^{A}	0.4653^{A}	0.4080^{A}
	Wood's Bay	0.1745^{A}	0.3253^{A}	0.3626^{A}
	Overall	**0.4448^{A}**	**0.4924^{A}**	**0.3768^{A}**
Rock	Tadenac	0.5793^{A}	0.5605^{A}	0.8249^{A}
	North Bay	0.4432^{A}	0.4432^{A}	0.5785^{A}
	Wood's Bay	0.0967^{A}	0.0975^{A}	0.3348^{A}
	Overall	**0.4133^{A}**	**0.4056^{A}**	**0.6203^{A}**

Table 1.7: Summary of differences in class areas (m^2) among the three rulesets for each scene and across all scenes. Values with different letter superscripts indicate they are significantly different (ANOVA, Tukey-Kramer; $p<0.05$).

		Mean ruleset class area (m^2)		
Class	**Scene**	**Tadenac**	**North Bay**	**Wood's Bay**
Emergent	Tadenac	4006^{A}	6878^{B}	4825^{AC}
	North Bay	6305^{A}	9582^{AB}	7014^{B}
	Wood's Bay	8191^{A}	14541^{A}	10698^{A}
	Overall	**5819^{A}**	**9695^{B}**	**7023^{C}**
Meadow/Shrub	Tadenac	26351^{A}	22747^{B}	22122^{B}
	North Bay	30079^{A}	25907^{B}	24522^{C}
	Wood's Bay	58475^{A}	51045^{B}	51858^{B}
	Overall	**35625^{A}**	**30875^{B}**	**30356^{B}**
Senescent	Tadenac	6798^{A}	7739^{A}	8054^{A}
	North Bay	8707^{A}	9688^{A}	10112^{A}
	Wood's Bay	4138^{A}	5239^{A}	6748^{A}
	Overall	**6769^{A}**	**7764^{AB}**	**8414^{B}**
Rock	Tadenac	1045^{A}	892^{B}	3254^{C}
	North Bay	1499^{A}	1415^{A}	4916^{A}
	Wood's Bay	519^{A}	397^{B}	2115^{AB}
	Overall	**1065^{A}**	**942^{B}**	**3523^{C}**

Table 1.8: Summary of mean ruleset accuracy and ruleset origin. Diagonal accuracies in bold are internally derived and all others are externally derived. Overall refers to the mean accuracy for all internally and externally derived rulesets, which were found to be significantly different (t-test, $p<0.0001$).

	Ruleset Accuracy				
Scene	**Tadenac**	**North Bay**	**Wood's Bay**	**Internally Derived**	**Externally Derived**
Tadenac	**88.44**	80.89	64.67	-	-
North Bay	68.12	**72.59**	72.12	-	-
Wood's Bay	71.17	78.18	**78.34**	-	-
Overall				79.96	74.26

Table 1.9: Summary of mean Kappa coefficient for each ruleset origin. Diagonal kappa coefficients in bold are internally derived and all others are externally derived. Overall refers to the mean Kappa coefficient for all internally and externally derived rulesets, which were found to be significantly different (t-test, $p<0.0001$).

	Ruleset Kappa Coefficient				
Scene	**Tadenac**	**North Bay**	**Wood's Bay**	**Internal Derived**	**External Derived**
Tadenac	**0.7373**	0.6987	0.6263	-	-
North Bay	0.5484	**0.6573**	0.6326	-	-
Wood's Bay	0.5166	0.6475	**0.6968**	-	-
Overall				0.7005	0.6184

List of Figures

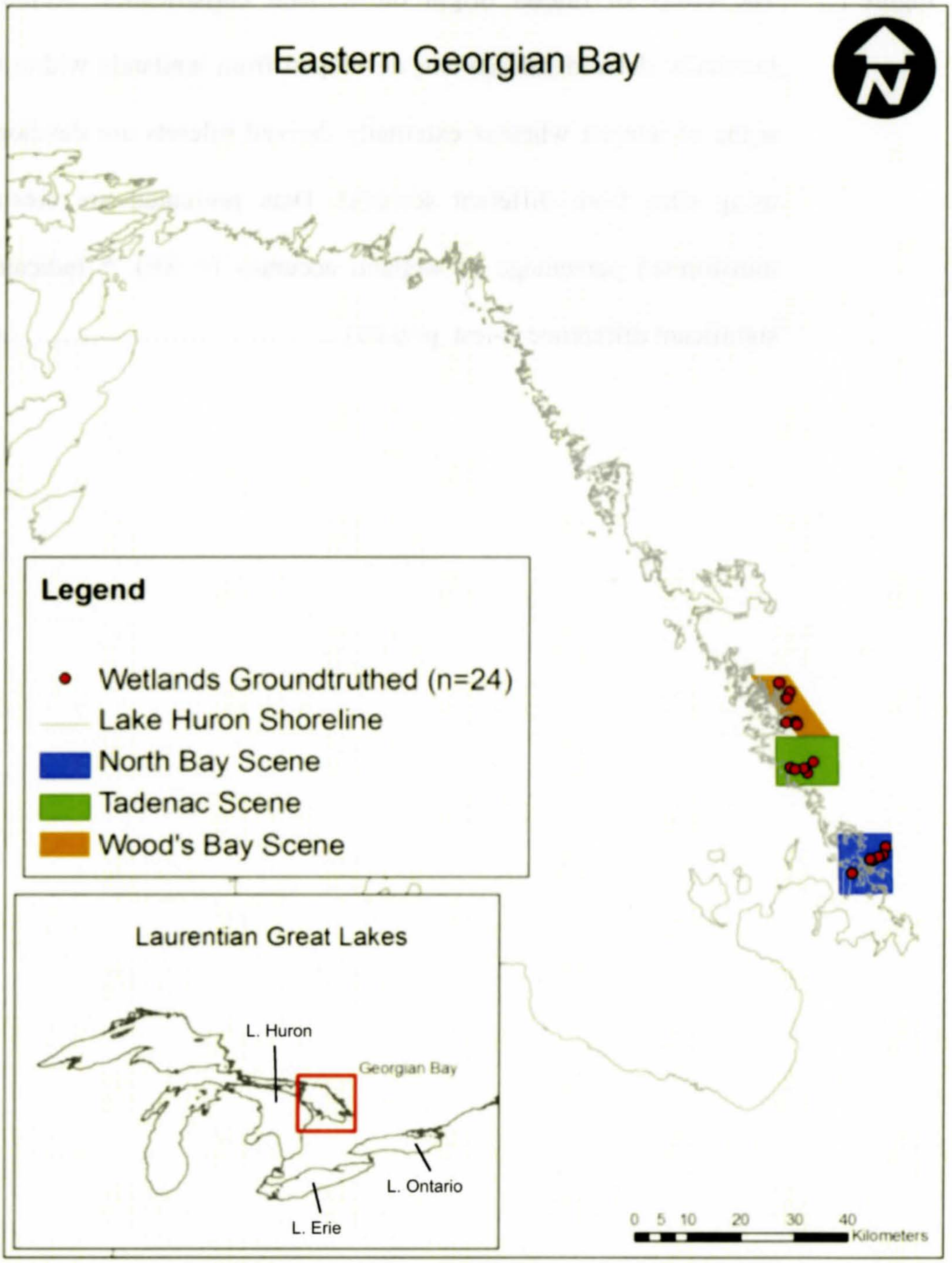


Figure 1.1. IKONOS scenes and wetlands sampled for classification groundthruthing in eastern Georgian Bay, Lake Huron. Each coloured polygon represents a satellite image with the wetlands sampled indicated by points.

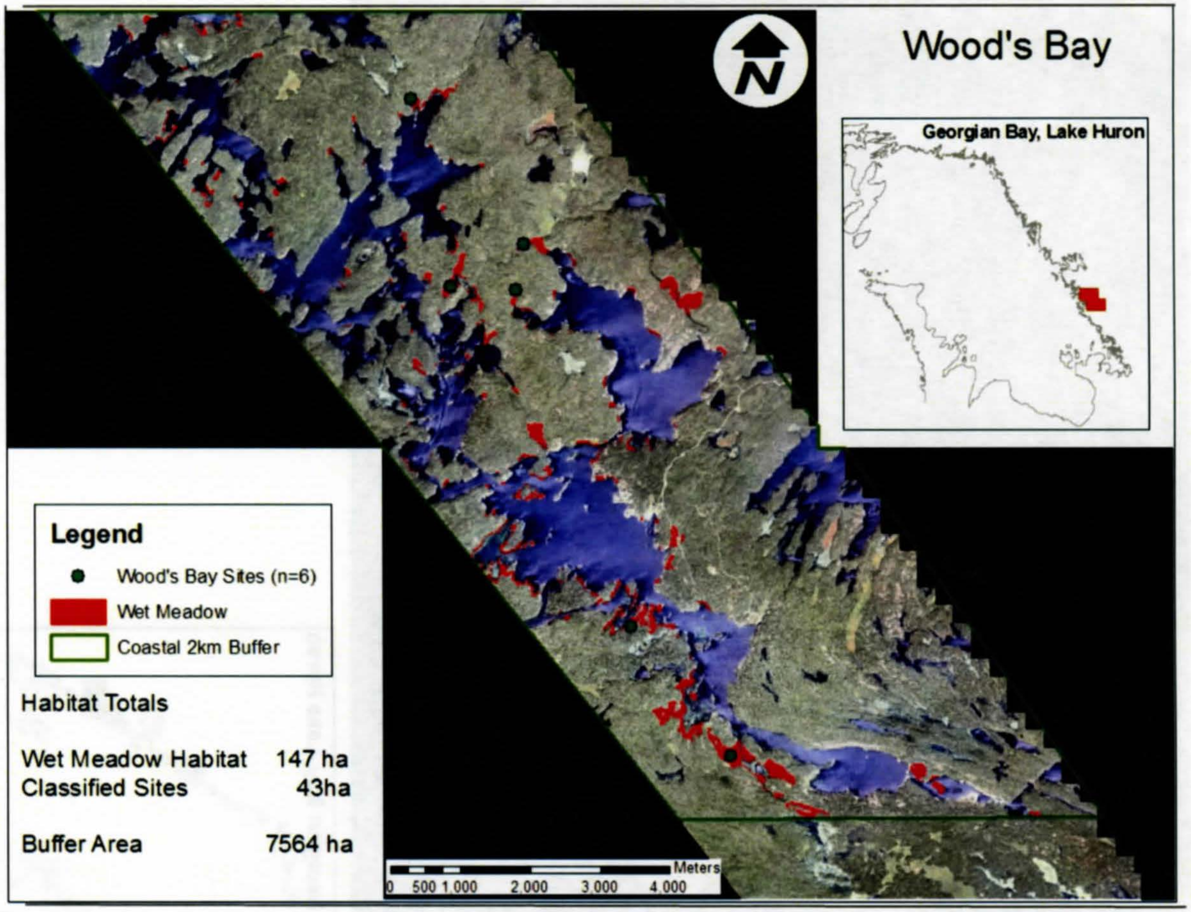


Figure 1.2: IKONOS 1m-resolution satellite image of Wood's Bay, eastern Georgian Bay, Lake Huron. Six wetlands were ground-truthed and mapped, totaling 43 ha of a possible 147 ha within the image.

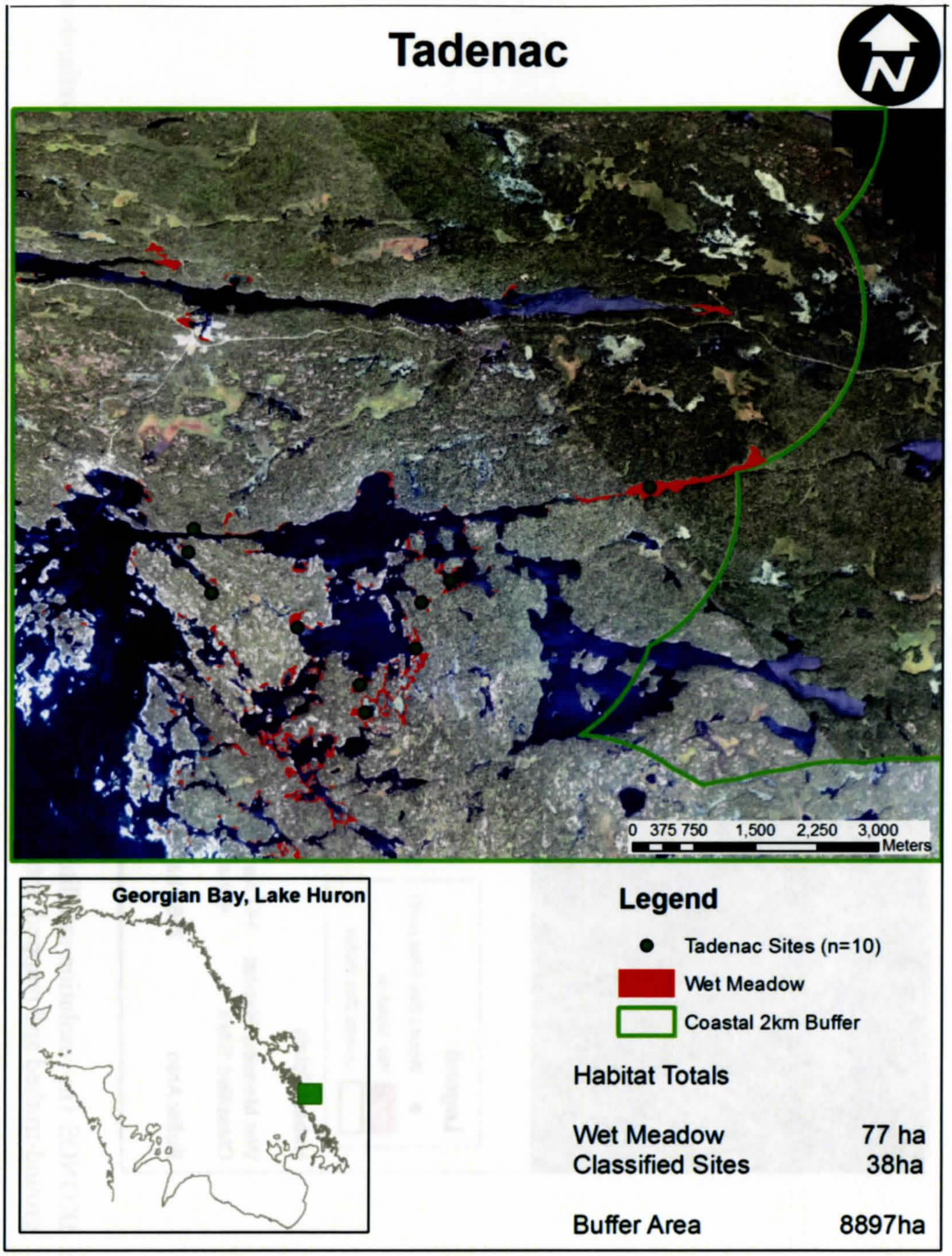


Figure 1.3: IKONOS 1m-resolution satellite image of Tadenac, eastern Georgian Bay, Lake Huron. Ten sites were ground-truthed and mapped, totaling 38 ha of a possible 77 within the image.

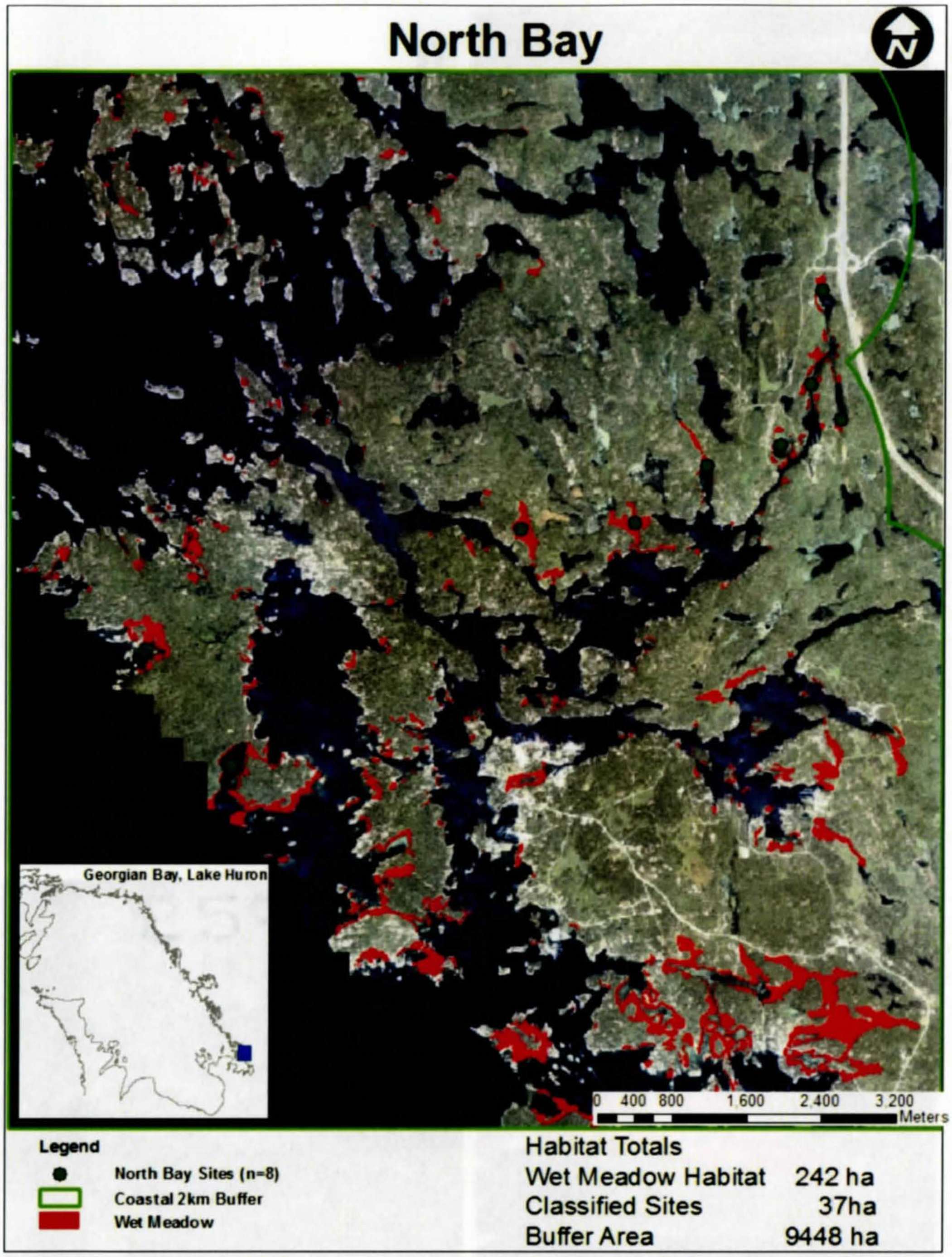


Figure 1.4: IKONOS 1m-resolution satellite image of North Bay, eastern Georgian Bay, Lake Huron. Eight sites were groundtruthed and mapped, totaling 37 ha of a possible 242 ha within the image.

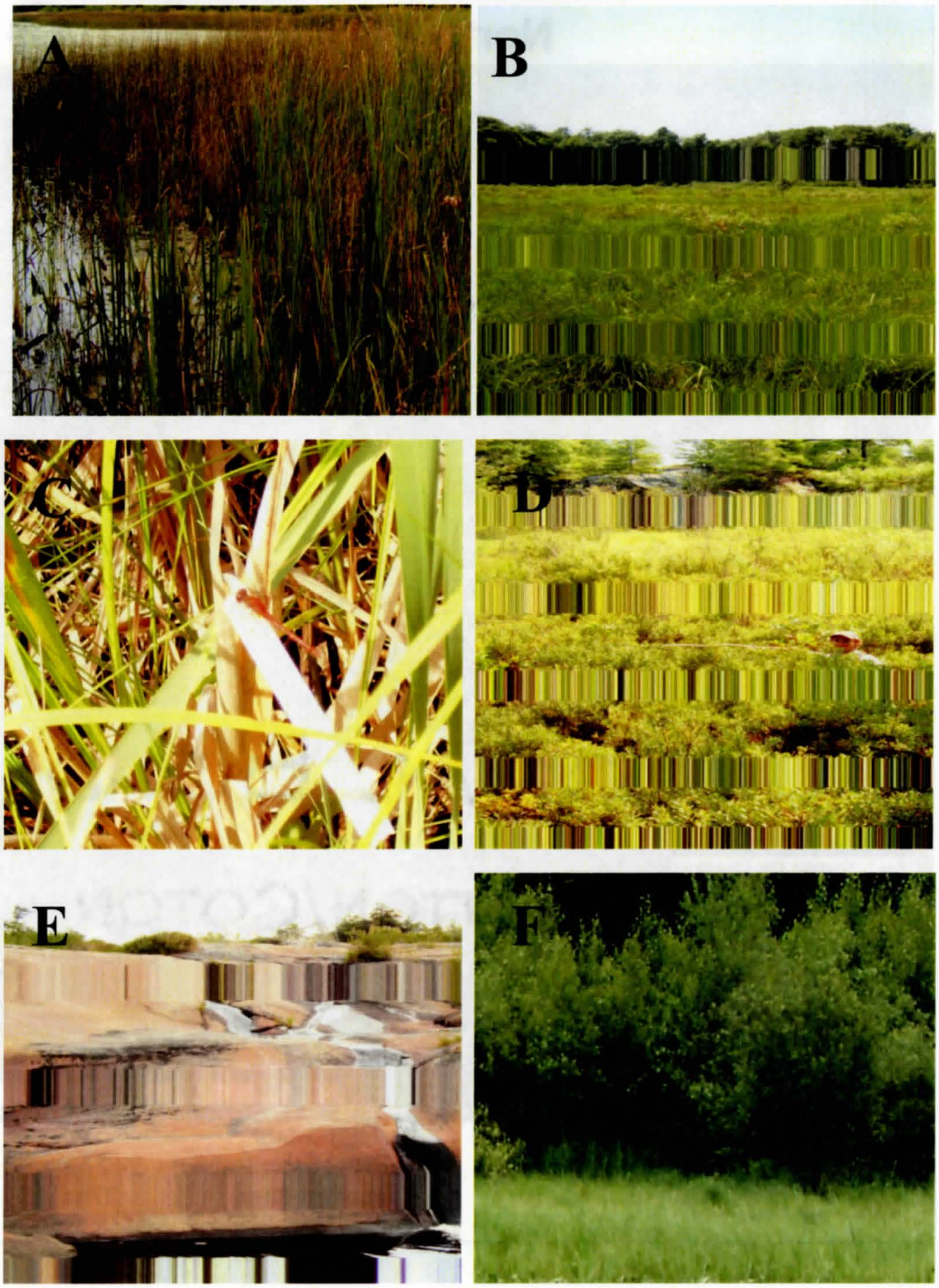


Figure 1.5: Examples of the coastal wet meadow wetland vegetation and non-vegetation classes including: (A) Emergent, (B) Meadow, (C) Senescent vegetation, (D) Shrub, (E) Rock and the eventual merged class of (F) Meadow/Shrub. See table 1.1 for class descriptions.

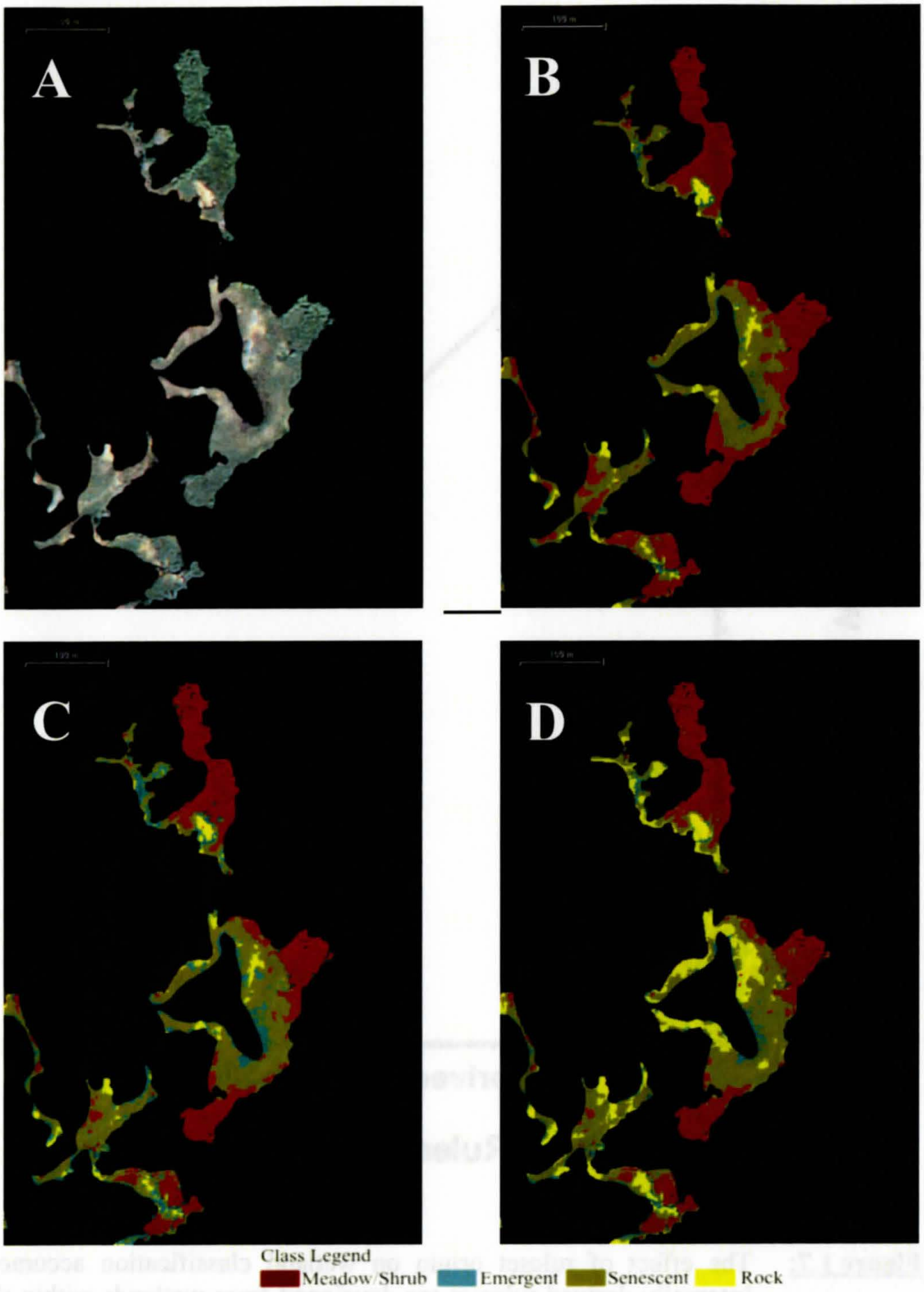


Figure 1.6: A) Unclassified image of Black Rock Bay North in the Tadenac Bay scene. Classified image of Black Rock Bay using B) Tadenac ruleset (88.4% accuracy), C) North Bay ruleset (80.9% accuracy), and D) Wood's Bay ruleset (64.7% accuracy).

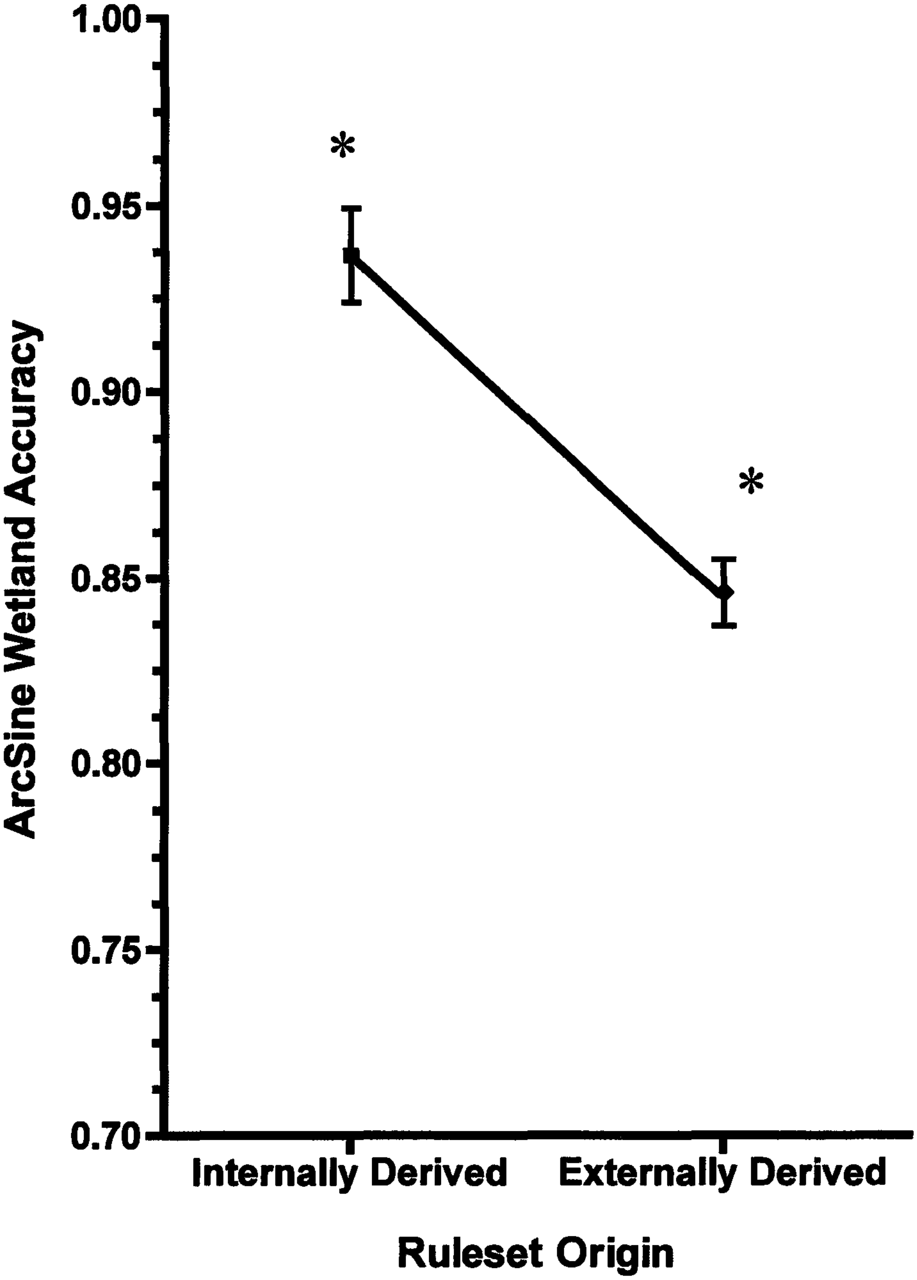


__Figure 1.7:__ The effect of ruleset origin on wetland classification accuracy. Internally derived rulesets are developed from wetlands within the scene of interest whereas externally derived rulesets are developed using sites from different scene(s). Data presented are arcsine-transformed percentage of wetland accuracy (± SE). * indicate a significant difference (t-test, $p<0.05$).

Chapter 2:

Assessing the relative importance of vegetated deep-water habitat in valuation of Georgian Bay coastal wetlands: implications for the Ontario Wetland Evaluation System (OWES)

by

Daniel Rokitnicki-Wojcik

and

Patricia Chow-Fraser

Abstract

By definition in Canada, wetlands are lands saturated with water long enough to promote wetland or aquatic processes as indicated by poorly drained soils, hydrophytic vegetation and various kinds of biological activity which are adapted to a wet environment. In coastal wetlands of large lakes, the vegetated deep-water zone (>2m) adjacent to emergent vegetation is dominated by submerged hydrophytes and hydric soils, but these are not considered part of the wetland according to the Ontario Wetland Evaluation System (OWES). Since this deep-water zone is important fish habitat, their exclusion in OWES assessments means that wetlands dominated by submerged hydrophytes are under-valued. In this study we assess the impact of including this vegetated deep-water habitat in OWES evaluations for 16 wetlands in eastern Georgian Bay that vary in size and inundation characteristics. Sites were divided into small (≤ 25ha) versus large wetlands, and in each size category, we included those that had a dominant aquatic (emergent and vegetated deep-water and greater than 67% low marsh) zone and those with a dominant terrestrial (wet meadow and greater than 67% high marsh) zone. We investigate how inclusion of this aquatic zone changes the overall OWES score with respect to several criteria including productivity, biodiversity, and fish habitat. Inclusion of vegetated deep-water habitat significantly increased wetland area (mean of 48%) especially for sites dominated by aquatic habitat (mean of 75%). Nevertheless, the impact of this increased area had minimal effect (< 5%) on OWES component scores with

respect to productivity, biodiversity, biological, and the Great Lakes coastal wetlands category. Mean fish habitat scores increased 30%, arising mainly from valuation of "low marsh" habitat. Our results illustrate that relative increases in only a few of these existing OWES criteria do not greatly influence the final OWES scores, even though vegetated deep-water habitats greatly increased total wetland area for our study sites. This under-valuation of fish habitat has grave implications for fisheries in Lake Huron and for the conservation of these unique habitats that the OWES was developed to identify. We recommend that the OWES be modified to account for the vegetated deep-water habitat, which is very important for fish in coastal wetlands, and that this become a component for valuation. We further recommend that "submergent" vegetation become an umbrella term for a series of additional forms that could be assessed (rosette, canopy, and submerged free floating) to fully reflect and value diverse aquatic environments.

Introduction

Wetlands are valued for the ecosystem goods they provide and the services they perform. These include flood attenuation, water purification, nutrient assimilation, resource extraction and provision of critical wildlife habitat (Mitsch and Gosselink, 2000). Coastal wetlands of the Laurentian Great Lakes provide additional value in the form of critical habitat for diverse fish assemblages, a large portion of which utilize coastal wetlands in at least one stage of their lifecycle (Jude and Pappas, 1992). Fish habitat exists as diverse aquatic vegetation that includes near-shore emergents, floating, canopy, and rosette vegetation.

Wetlands are defined as lands "saturated with water long enough to promote wetland or aquatic processes as indicated by poorly drained soils, hydrophytic vegetation and various kinds of biological activity which are adapted to a wet environment" (National Wetlands Working Group, 1988) and inclusion of deep-water habitat of submerged vegetation seems logical, since wetlands include areas dominated by hydrophytes and hydric soils (Yin and Lu, 2006). Currently, however, the deepwater (>2m depth) zone is not considered wetland habitat according to many definitions because emergent vegetation rarely establishes beyond that point. Hence, exclusion of this deep-water zone in routine wetland evaluations by government agencies may be grossly undervaluing certain wetlands dominated by aquatic habitat. This is even more problematic in areas such as eastern Georgian Bay and the North Channel in Lake Huron, where hundreds of smaller island and lacustrine wetlands are often dominated by deep-water habitats.

In 1983, the Ontario Ministry of Natural Resources (OMNR) published the Ontario Wetland Evaluation System (OWES) as a commitment to identify and protect high-quality wetlands under the legislative power of the Planning Act (1990). The OWES outlines four main areas of societal value for wetlands, which include biological, social, hydrological, and special or unique features. The system includes an objective assessment of ecological function and socio-economic valuation, so that wetlands that hold great value are singled out for conservation while those of lesser value are protected from harmful human impacts through potential changes in land-use planning. The OWES produces a score (maximum of 1000) for each wetland that is evaluated; a score of 600+ points overall or 250 points in any of the four key components confers provincial significance and protection of the wetland.

About a third of southern Ontario's wetlands have been evaluated in the last 20 years (Hogg and Todd, 2007) and far fewer have been assessed in central/northern Ontario. Georgian Bay, Lake Huron contains a large concentration of high quality coastal wetlands (Cvetkovic et al 2009) in central/northern Ontario that have extensive areas of coastal submerged aquatic vegetation in waters deeper than 2 m (referred to as deep-water habitat in Cowardin et al. 1979). In this study, we assess the impact of including this vegetated deep-water habitat in OWES evaluations for 16 wetlands in eastern

Georgian Bay that vary in size and inundation characteristics. We compare standard OWES evaluations with a modified system that includes a proposed vegetated deep-water habitat to answer the following questions:

1) Does the inclusion of vegetated deep-water habitat significantly increase scores for components of the OWES that include measures of fish habitat?
2) Does wetland area significantly increase with inclusion of this habitat?
3) Are scores different among 4 categories of wetlands that differ in size and inundation as follows: small aquatic, large aquatic, small terrestrial, large terrestrial?

We expect that inclusion of vegetated deep-water habitat in the modified system of OWES would result in a significant increase in total wetland area. We also expect significantly higher scores for each criterion and for the overall score for all criteria assessed. We predict that increased OWES scores resulting from the proposed system would disproportionately benefit small, aquatically-dominated wetlands because the modifications differentially affect aquatic versus terrestrial habitat in coastal wetlands.

Methods

Study Location

Sixteen coastal wetlands (Table 2.1) were sampled across the entire eastern coast of Georgian Bay, Lake Huron (Figure 2.1) during the summer of 2008. The wetlands sampled encompassed all wetlands types (marsh, swamp, fen, and bog) with marsh comprising the largest areal extent. The wetlands were mostly coastal lacustrine wetlands, except for two riverine wetlands (see Table 2.1; site types classified according to OMNR, 1993). Since Georgian Bay is relatively uninhabited, and majority of the residents are seasonal dwellers, the dominant land-use adjacent to wetlands is forested with small areas used for recreation (cottage), parkland (National Park), and First Nations Reserve (Table 2.1).

Cvetkovic et al. (2009) have confirmed the original observation by Chow-Fraser (2006) that coastal wetlands in eastern Georgian Bay are some of the least-impacted in the Laurentian Great Lakes. These high-quality coastal wetlands have high submergent plant diversity, with correspondingly high diversity of wetland fish assemblages that depend on the deep-water habitat (up to 6 m by SCUBA observation, J. Midwood, unpub. data). Therefore, a modified OWES procedure that takes into account the deep-water habitat would preferentially benefit the many small wetlands of eastern Georgian Bay whereas it may not affect the evaluation of degraded coastal wetlands of Lakes Ontario and Erie that lack the diverse submergent plant communities extending beyond the upper deep-water boundary of 2 m.

We used 1-m pan-sharpened IKONOS satellite imagery (Geoeye, Dulles, VA, USA) to select sixteen sites based on size and dominance of aquatic or terrestrial habitat in eastern Georgian Bay and the North Channel (see Figure 2.1). Size was determined by visual interpretation of the imagery in a GIS where initial wetland boundaries were delineated and area (ha) was determined. The final size calculated for each wetland was different from the pre-determined area based on the IKONOS imagery because field-surveying was required to determine the lower boundary of the vegetated deepwater zone. The final size threshold (25 ha) separating large from small sites was optimized to provide equal size of testing groups for statistical analyses.

The total wetland area ranged from a small wetland of 2 ha to the largest wetland of 77 ha using OWES wetland boundary definitions (OMNR, 1993). We used the threshold criterion of > 67% low marsh to define aquatic dominated sites; remainder of the sites were considered terrestrial dominated sites. All terrestrial sites had >67% high marsh vegetation, except for Treasure Bay (TB), which only had 50% high marsh. The small aquatically dominated sites are typical of the large number of small marshes along the Georgian Bay coast (McMaster Coastal Wetland Inventory, Chow-Fraser, unpub. data). These 2 thresholds for size and inundation characteristics separated the 16 sites into 6 small aquatic, 3 small terrestrial, 3 large aquatic, and 4 large terrestrial (Table 2.1, Figures 2.2-2.6).

Ontario Wetland Evaluation System (OWES)

We want to empirically determine how inclusion of vegetated deep-water habitat would affect specific OWES components concerning aquatic biota, especially fish. We followed the protocol established by OMNR (1993) for OWES and focused on 1) the entire **Biological Component** 2) the Fish Habitat and Great Lakes coastal wetlands subcomponents within the **Special Features Component** and 3) **wetland area.**

1) The Biological Component includes productivity, biodiversity and size subcomponents. To calculate productivity, we estimated the number of growing days, and assigned the most basic soil type with the lowest score (granite) for every wetland because we did not analyze soil for each wetland. As required, we determined the fractional areas of both wetland type(s) and site type(s) present in each wetland. To calculate the biodiversity subcomponent, we determined the number of wetland types present, diversity of vegetation communities, adjacent land-use and habitat, proximity to other wetlands, interspersion (measure of how convoluted/complex the vegetation communities are determined by hand-drawn grids overlain on the wetland map), and the pattern of open water in the wetland. We also calculated the size subcomponent by summing all prior subcomponent scores and added wetland area to derive an additional score.

2) The subcomponents within Special Features of interest to us are the Fish Habitat section and the Great Lakes coastal wetlands subcomponent. The fish habitat section included an assessment of area of low marsh, high marsh, and swamp occupied by specific plant species that was subsequently used to indicate the quality of the fish habitat. We did not include the spawning and migration habitat as these are not relevant to vegetated deep-water habitat. To calculate the Great Lakes coastal wetlands score, we determined the total area of the wetland in question, and assigned scores according to a given size schedule in OWES. 10 points were given for wetlands < 10 ha and 25 points for every 25-ha increment up to 75 points for wetlands >100 ha.
3) Although no actual score was given for total wetland area, wetland size is an important variable to estimate accurately because it can influence the score of many OWES sub-components (see above), including some not listed in this study.

Sampling Vegetated Deep-Water Habitats

To determine the effect of including vegetated deep-water habitats on OWES scores, we followed the conventional OWES protocol for field surveys, but extended the surveying beyond 2 m to where the percent cover of submergent vegetation was ≥20% (using SCUBA divers). This additional information allowed us to modify the lake-ward boundary of the wetland and to collect additional information on aquatic plant species that do not currently exist in

OWES. At 5 sites, where divers were not available to conduct surveys, we used a garden rake and a graduated rope attached to a Secchi disk to determine the modified wetland boundary. (Data collected for Treasure Bay were supplemented by SCUBA observations that were taken at a different time). Even though the size estimates for these five wetlands should be considered conservative for the deep-water zone, the three terrestrially-dominated sites (Caswell, Treasure and Sawdust Bay) had very small aquatic components.

Comparison of OWES and Modified OWES

Since OWES scores do not account for vegetated deep-water habitats in wetlands, we created a Modified evaluation system (Mod OWES) that incorporates this aquatic habitat feature. We imported the respective IKONOS imagery for the 16 study sites into GIS to delineate the area of each vegetation community and the wetland boundaries corresponding to both evaluation systems.

Statistical analyses to determine significant differences between methods and among the four-wetland categories were conducted in SAS JMP 7.0 (SAS institute, Cary, NC, USA). We used paired-tests to determine the overall differences between the two methods. Where paired t-tests showed significant differences between methods, we used them to determine the broad differences between the size (large versus small wetlands) or inundation dominance (aquatic versus terrestrial dominant wetlands) categories; and ANOVA and the Tukey Kramer post hoc test to determine differences among the four-wetland categories (small aquatic, small terrestrial, large aquatic, and large terrestrial).

Results

Detailed vegetation maps prescribed by OWES have been generated for each wetland of interest and can be found in Appendix A (attached CD). Since these maps have 16 categories of vegetation communities, we have provided simplified versions of these to illustrate wetland type, vegetation community boundaries, and the proposed vegetated deep-water habitat that we are investigating in this study (See Figures 2.2-2.6).

Biological Component

The Biological Component of the OWES is divided into productivity, biodiversity, and size subcomponents (see methods). There were no significant differences between OWES and Mod OWES with respect to productivity, biodiversity, and overall Biological Component scores; including the vegetated deep-water habitat increased the scores on average by 1% (0.23 points), 1.3% (1 point), and 1.29% (1.1 points) respectively for each of these sub-components. Thirteen of the 16 sites did not show any change in productivity scores, 6 sites did not show any change in biodiversity score, while 4 sites did not show any change in overall Biological Component score (Table 2.2).

Special Features Component

We assessed the Fish Habitat section and Great Lakes coastal wetlands subcomponent of the Special Features Component (see methods). The Fish Habitat score of the Mod OWES was significantly greater than that for the

OWES, with an increase of 36% (3.29 points). The driver of this difference was a significant overall increase in the low-marsh score (72%, 3.29 points). As would be expected, neither the high-marsh nor swamp scores differed significantly between systems (t-test, $p>0.05$). There was no difference in low-marsh score among the wetland categories; however, large aquatic sites had a significantly greater overall Fish Habitat score when calculated according to Mod OWES (ANOVA, $p<0.05$; Table 2.2). Similar to the Biological Component scores, OWES and Mod OWES did not differ significantly with respect to Great Lakes coastal wetlands scores; this is highlighted by the lack of change between evaluation systems for 13 of 16 sites (Table 2.2).

All Criteria Assessed

Inclusion of vegetated deep-water habitats significantly increased the score for all criteria assessed in this study by an average of 8.6 points (6.2%; t-test, $p<0.05$). There were no differences among wetland categories with respect to the overall criteria score (Table 2.3); however, 14 of 16 sites exhibited net positive change overall between evaluation systems. The greatest positive change was associated with Jumbo Bay, a relatively large wetland that is dominated by aquatic habitat (see Table 2.1); the North Bay 1 wetland increased by 36 points, while Garden Channel wetland registered no change in score (Table 2.3).

Wetland Area

Including the vegetated deep-water habitat in our wetland surveys significantly increased wetland area by an average of 9.2 ha (45.6%), although there were no systematic changes according to size and inundation characteristics (Table 2.3). Nevertheless, sites dominated by aquatic habitat exhibited significantly greater change compared with sites dominated by terrestrial habitat (t-test, $p<0.05$). This comparison may be driven by the large increase in Jumbo Bay that increased by 57.3 ha (215.4%; Table 2.3) when the Mod OWES was used (see red polygon in Figure. 2.4A)

Discussion

In this study, we quantified how incorporating a modification of field surveys to include the vegetated deep-water habitat (below 2 m) would affect OWES scores for 16 wetlands in eastern Georgian Bay. We expected that the modified system would significantly increase wetland area and the total Component scores for all wetlands, and would disproportionately benefit small aquatically-dominated sites compared with the other three categories (i.e. small terrestrially-dominated, large aquatically-dominated and large terrestrially-dominated sites). We found no significant effect of the modification on Biological Components scores among the 4 categories, nor did we see any effect on Great Lakes coastal wetland valuation. We did, however, note a significant effect of the modification on Fish Habitat, overall score valuation, and wetland area, although these effects were similar across the four categories.

Our results are not consistent with initial expectations that the modified system would increase valuation of the stated components, and that this would disproportionately benefit small aquatically-dominated wetlands. Although inclusion of the vegetated deep-water habitat significantly increased valuation of Fish Habitat, overall scores and wetland area, the average increase amounted to only 8.6 points out of a possible 450 points for these components. Therefore, such point gains would not result in a change in the wetland's designation within the existing OWES. This has serious implications for the valuation of this unique habitat as its addition currently does not change OWES scores.

Wetlands of eastern Georgian Bay are known to be very high quality compared with wetlands in the lower lakes (see Cvetkovic et al. 2009), and many contain species that are endangered, threatened, or of special concern such as the eastern massasauga rattlesnake (*Sistrurus catenatus catenatus*) and the common musk turtle (*Sternotherus oderatus*) (Table 2.1). These wetlands tend to be small, and have a lower diversity of habitat types, but have relatively high species diversity with respect to submersed aquatic vegetation (see Croft and Chow-Fraser 2007, 2009). The addition of the vegetated deep-water habitat did not enhance wetland diversity/complexity in the current OWES, because only the "submergent" form is recognized, even though a typical submergent community may contain up to four different forms and 15 species. We recommend that the Biological Component be revised to incorporate additional vegetative forms: rooted basal rosettes, rooted submergent, unrooted submergent, and submergent canopy (after Croft and Chow-Fraser 2009; Table 2.4). Incorporating these other aquatic forms would increase the habitat complexity of the wetland, and permit more appropriate representation of aquatic flora, since 8 of the 16 vegetative forms currently used in OWES are strictly terrestrial, 2 are for dead wood, 2 amphibious, 4 strictly aquatic, and 1 unvegetated (OMNR, 1993).

As expected, total wetland area significantly increased by an average of 9.2 ha (Table 2.3) when submergent habitat deeper than 2m was included. In many coastal wetlands of eastern Georgian Bay, the submergent community routinely exceeds 2m to about 5.5m (J. Midwood, unpub. data). There is currently no globally accepted definition for wetlands, but the definition used in Canada states that "saturated with water long enough to promote wetland or aquatic processes as indicated by poorly drained soils, hydrophytic vegetation and various kinds of biological activity which are adapted to a wet environment" (National Wetlands Working Group, 1988). This definition should include the vegetated deep-water habitat (below 2 m) that is currently ignored in OWES and other classification systems that favour emergent over submergent vegetation (Zoltai et al, 1975; Cowardin et al 1979; Zoltai and Vitt, 1995; Warner and Rubec, 1997). As explained by Cowardin et al. (1979) two decades ago,

> "Wetlands and deepwater habitats are defined separately because traditionally the term wetland has not included deep permanent water; however, both must be considered in an ecological approach to classification."

The amphibious nature of emergent vegetation (Daubenmire, 1968) should be used to define boundaries between terrestrial and aquatic systems, but we stress that it should not be used to delineate the lower wetland boundary, especially for coastal wetlands of large lakes.

A brief search revealed that there isn't a worldwide shift towards inclusion of vegetated deep-water habitat in classification systems (e.g. those of European CORINE, South Africa, MedWet (Mediterranean) and RAMSAR) due the modeling of their respective systems after Cowardin and colleagues (1979) (RAMSAR, 2002). We argue strongly for inclusion of this important ecological habitat in wetland evaluations, and that the vegetated deep-water habitat be formally incorporated as a component of "wetlands". This should be done, irrespective of how inclusion of this habitat may affect the OWES score and the wetland's designation for conservation purposes.

The OWES identifies wetland complexes as wetlands that are within 750m straight line distances from wetland boundaries; however, it states that shoreline (lacustrine) wetlands connected via submergent communities within 750m may not be complexed. We believe that this will be a large impediment for creating large wetland complexes in Georgian Bay. Preliminary data from the McMaster Coastal Wetland Inventory (Chow-Fraser, unpub data), suggests that the majority of critical fish habitat exists in small aquatically-dominated wetlands that could potentially be complexed into large contiguous wetlands, if not for this rule regarding submergent vegetation. Since the smallest allowable wetland size is 2 ha (or if evidence is present for there being "significant" habitat < 2 ha), most of these would be too small for consideration on their own. If we modified the OWES rule for wetland complexing, however, the high density of coastal wetlands along the Georgian Bay coastline could lead to creation of a single or several large complexes, spanning the entire eastern coast of Georgian Bay. If so, these would be the largest freshwater wetland complexes in the world, and would bolster the current designation of eastern Georgian Bay as a world biosphere reserve for its high quality, diversity and uniqueness. Therefore, additional area corresponding to the deep-water habitat has very important implications for wetland complexing and wetland designations.

In the Mod OWES protocol, we incorporated contributions of all submergent vegetation, including those of exotic invasive species. Alien species do not tend to dominate the unimpacted wetlands of Georgian Bay, but in Sawdust Bay, we found a dense canopy of Eurasian Milfoil (*Myriophyllum spicatum*) that extended beyond 2 m to just over 5m depth. Although the presence of *M. spicatum* increased the boundary of the wetland, it is not necessarily considered good habitat for fish (Keast, 1984). We have not considered how best to treat exotic invasive species (both terrestrial and aquatic species), but this is clearly an important consideration in the overall evaluation process. We point out; however, that many coastal wetlands throughout the other Great Lakes that have problems with invasive species, are still designated as provincially significant wetlands.

If protection of fish habitat is a priority for the Great Lakes, then exclusion of vegetated deep-water habitat in OWES must be quickly resolved, especially where eastern Georgian Bay is concerned. Wetlands of Georgian Bay have been experiencing prolonged episodes of low water levels, and consequently, the emergent and meadow habitat have been increasing over the past 6 years (see Chapter 3). Fisheries in the Great Lakes basin are a large industry worth in the billions of dollars (Maynard and Wilcox, 1997). The protection and incorporation of fish habitat has more far reaching implications than conservation alone. If we do not make a concerted effort to sample the deep-water habitat, we will not be able to determine the long-term impacts of this sustained water-level decline on fish habitat. The nature of water level fluctuations in the Lake Michigan-Huron system means that the arbitrary 2m aquatic lower boundaries of wetlands are dynamic. In the recent past when water levels were high in the late 1980s (See figure 3.2 – Chapter 3), the 2m boundary would have moved landward and what was the old 2m boundary would now be considered non-wetland deep-water habitat. Although still containing the same biota and performing the same wetland ecological services such a providing habitat for fish, this habitat is no longer wetland or have the possibility of being protected. This scenario truly reflects the grave implications of creating an arbitrary boundary without any sound ecological rationale.

This is the first study in which IKONOS imagery has been used in multiple stages of OWES assessment (pre-field sampling, during field sampling, and completing the evaluation mapping). The 1m-resolution of IKONOS performs comparably to aerial photography in orienting sites during pre-field sampling as well as during in-field mapping. Creation of evaluation maps was very simple to do in GIS. Very little modification of pre-digitized upland/wetland boundaries was needed during the field survey. Our one caveat with IKONOS imagery is that some isolated and forested wetlands are difficult to distinguish from the upland forest; however, these difficulties are also encountered when using aerial photos and any satellite imagery (Ozesmi and Bauer, 2002; Lillesand and Kiefer, 2000). We highly recommend the use of IKONOS in OWES evaluations because it represents a cost-effective alternative to aerial photography

(Wei and Chow-Fraser, 2007) and has better resolution than LANDSAT to distinguish the fine details required for evaluation mapping (Ozesmi and Bauer, 2002).

We acknowledge that it is difficult to sample at depths below 2 m without the use of SCUBA divers; however, alternative approaches are being developed to estimate the lake-ward extent of submergent vegetation. We suggest applying a depth threshold of 6 m because field surveys consistently reveal that significant plant colonization (<20% cover) ceases at this depth in Georgian Bay wetlands. Underwater photography could also be used to determine the maximum extent of submergent colonization at deeper sites.

Recommendations

Within "Fish Habitat " section of the Special Features component, we recommend that "Great Lakes coastal wetlands" be given greater value because they are unique systems that are critical for majority of the Great Lakes fish species, including both wetland obligates and generalists (Jude and Pappas, 1992) (Table 2.4). Within the "Spawning and Nursery Habitat" subsection of the Fish Habitat section, we argue that vegetated deep-water habitat should be included as low marsh. The way in which Great Lakes coastal wetlands are scored in the Special Features component could also be improved. We recommend that the lower size thresholds and intervals be changed to account for importance of smaller wetlands in the landscape (Gibbs, 1993; Semlitsch and Brodie, 1998), especially since there are so many of these small aquatic marshes in eastern

Georgian Bay. A new point system should also be developed to properly account for the value of smaller wetlands.

In order to completely account for submergent wetland habitat we must first understand the colonization characteristics of macrophytes at the lakeward boundary of wetlands. This would involve identifying physical and morphological constraints on the growth characteristics of individual plant species and vegetative forms. Until we can accurately predict where we will observe the wetland-lake boundary, we will not be able to to accurately map this feature that is so critical to the persistence of Great Lakes fishes.

This is the first empirical study to examine the effects of protocol modifications on OWES score outcomes, and we hope it will lay the groundwork for critical examination of evaluation protocols that have implications for conservation decisions. We also hope that authors of future editions of wetland evaluation manuals will use our results and recommendations to improve their protocols. We have focused this study in Georgian Bay as these wetlands still have diverse submergent communities that are absent in more human-impacted systems in the lower Great Lakes. We surmise that a similar study involving wetlands of Lakes Ontario and Erie may arrive at quite different conclusions, given that the high water turbidity in disturbed wetlands may preclude establishment of plants in the deep-water habitat (Lougheed et al, 1999; Croft and Chow-Fraser 2007).

Acknowledgements

Funding for this study was provided by an NSERC PGS-M grant awarded to DR-W and a research grant from the GBA Foundation to PC-F. We thank the GBA Foundation for the use of the IKONOS imagery and the Georgian Bay Association, especially Mary Muter for logistical help during field sampling. We greatly appreciate the help of J. Midwood for the data obtained from diving, and all other McMaster students who helped to collect field data.

Literature Cited

Cowardin, L.M., Carter, V., Golet, F.C., and LaRoe, E.T. 1979. Classification of wetlands and deepwater habitats of the United States. US Dept of Interior – Fish and Wildlife Service. Washington D.C., 103pp.

Chow-Fraser, P 2006. In Simon, T.P and Stewart, P.M. (eds) "Coastal wetlands of the Laurentian Great Lakes: health, habitat and indicators". Chapter 5. Indiana Biological Survey, Bloomington, Indiana. p.137-166.

Croft, M.V.,Chow-Fraser, P. 2007. Development of the wetland macrophyte index to detect degree of water-quality impairment in Great Lakes coastal marshes. J Great Lakes Res 33 (Special issue 3): 172–197.

Croft, M.V., Chow-Fraser, P. 2009. Non-random sampling and its role in habitat conservation: a comparison of three wetland macrophyte sampling protocols. *Biodiversity Conservation.* Published on-line February 2009.

Cvetkovic, M., DeCatanzaro, R. and Chow-Fraser, P. 2009. Ecological indicatorsand road density in assessing habitat quality of coastal marshes in Georgian Bay, Lake Huron. *Biodiversity and Conservation.* In submission.

Daubenmire, R. 1968 . Plant communities. Harper & Row, New York, 300pp.

Gibbs, J.P., 1993. Importance of small wetlands for the persistence of local populations of wetland-associated animals. *Wetlands.* 12(1): 25-31.

Hogg, A.R., Todd, K.W. 2007. Automated discrimination of upland and wetland using terrain derivatives. *Canadian Journal of Remote Sensing.* 33(S1): 68-83.

Jude, D.J., Pappas, J. 1992. Fish utilization of Great Lakes coastal wetlands. *Journal of Great Lakes Research.* 18(4): 651-672.

Keast, A. 1983. The introduced aquatic macrophytes, *Myriophyllum spicatum*, as habitat for fish and their invertebrate prey. *Canadian Journal of Zoology.* 62(7): 1289-1303.

Lillesand, T., Kiefer, R. 2000. Remote sensing and image interpretation. 4th ed. Lehigh Press. New York 724pp.

Lougheed, V.L., Crosbie, B. and Chow-Fraser, P. 2001. Primary determinants of macrophyte community structure in 62 marshes across the Great Lakes basin. *Canadian Journal of Fisheries and Aquatic Sciences* 58: 1603-1612.

Maynard, L., Wilcox, D. 1997. Coastal wetlands of the Great Lakes. State of the Lakes Ecosystem Conference 1996. U.S. Environmental Protection Agency. 99 pp.

Mitch, M.J. and Gosselink, J.G. 2000. Wetlands. 3rd ed. Wiley. New York. 920pp.

OMNR 1993. Ontario Wetland Evaluation System. Northern Manual. Ontario Ministry of Natural Resources (OMNR), No.50254.

Ozesmi, S., Bauer, M. 2002. Satellite remote sensing of wetlands. *Wetlands Ecology and Management.* 10:381-402.

RAMSAR, 2002. Wetland Classifications. In A framework for wetland inventory. Retrieved April 13, 2009. <http://ramsar.org/key_guide_inventory_e.htm>

Sculthorpe, C.D. 1967. The biology of aquatic vascular plants. Edward Arnold Ltd., London. 610pp.

Semlitsch, R.D., Bodie, J.R., 1998. Are small, isolated wetlands expendable? *Conservation Biology.* 12(5): 1125-1130.

Warner, B.G., Rubec, C.D.A. 1997. eds. The Canadian wetlands classification system. 2nd ed. Wetlands Research Centre, University of Waterloo. 95 pp.

Wei, A., Chow-Fraser, P. 2007. Use of IKONOS imagery to map coastal wetlands of Georgian Bay. *Fisheries.* 32(4): 167-173.

Welch, P.S. 1952. Limnology. 2nd ed. McGraw-Hill. New York. 538pp.

Yin, S., Lu, X., 2006. Theory and method for wetland boundary delineation. *Chinese Geographical Science.* 16(6): 56-62.

Zhadin, V.L., Gerd, S.V. 1963. Fauna and flora of the rivers, lakes, and reservoirs of the U.S.S.R. Oldbourne Pres. London. 626pp.

Zoltai, S. C., Pollett, F. C., Jeglum, J. K., & Adams, G. D. 1975. Developing a wetland classification for Canada. In: Forest soils and forest land management. Proc. 4th North American Forest Soils Conference 497–511.

Zoltai, S.C., and Vitt, D.H. 1995. Canadian wetlands: Environmental gradients and classification. *Plant Ecology.* 118(1-2):121-137.

Table 2.1: Summary information for the 16 eastern Georgian Bay coastal wetlands sampled with the corresponding wetland code and habitat features. * indicates that SCUBA was not employed in field surveying.

				Habitat Features			
Category	**Wetland Name**	**Wetland Size (ha)**	**Code**	**ETSC Species**	**Landuse Type**	**Dominant Vegetation**	**Site Type**
Small Aquatic	North Bay 1	7	NB1	Reptiles	Recreation	Submergent	Lacustrine
	North Bay 2	7	NB2	Reptiles	Recreation	Submergent	Lacustrine
	North Bay River *	24	NBR	N/A	Recreation	Submergent	Riverine
	Pamplemousse Bay	4	PMB	Reptiles	Forest	Submergent	Lacustrine
	Red Sand Beach	6	RSB	N/A	Reserve	Submergent	Lacustrine
	Roseborough	2	RB	N/A	Forest	Submergent	Lacustrine
Small Terrestrial	Caswell Bay *	19	CB	Reptiles	Reserve	Meadow	Lacustrine
	Garden Channel	22	GC	Reptiles	Forest	Emergent	Lacustrine
	Treasure Bay *	20	TB	Reptiles	Park	Meadow	Lacustrine
Large Aquatic	Jumbo Bay	27	JB	N/A	Forest	Submergent	Lacustrine
	Hole in the Wall *	38	MIW	N/A	Forest	Floating	Lacustrine
	Oak Bay	61	OB	Reptiles	Recreation	Emergent	Lacustrine
Large Terrestrial	Iroquois Island	39	IQI	Reptiles	Forest	Meadow	Lacustrine
	Miner's Creek	39	MC	N/A	Forest	Meadow	Riverine
	Sawdust Bay (3rd) *	29	SB3	N/A	Forest	Shrub	Lacustrine
	Scow Bay	77	SWB	Plants	Forest	Moss	Lacustrine

Table 2.2: Summary of changes in OWES scores by accounting for vegetated deep-water habitat for two components. Numbers in parentheses in the headings indicate maximum OWES score. Data presented are the absolute score change with the proportional change in parentheses.

Category	Site Code	Change in Biological Component: Productivity (50)	Biodiversity (150)	Overall (250)	Change in Special Features Component: Low Marsh (75)	Overall Fish Habitat (100)	Great Lakes Coastal Wetlands (75)
Small Aquatic	NB1	0	0	0	0	0	0
	NB2	0	0	0	+2 (+66.7)	+2 (+40.0)	0
	NBR	0	+1 (-1.6)	+1 (+1.0)	+4 (+66.7)	+4 (+33.0)	0
	PMB	0	-13 (-23.2)	-15 (-16.9)	+2 (+100.0)	+2 (+50.0)	0
	RSB	2 (+8.7)	+4 (+8.2)	+6 (+7.6)	+3 (+150.0)	+3 (+60.0)	+15 (+150.0)
	RB	0	-3 (-8.3)	-3 (-4.8)	+2 (+100.0)	+2 (+67.0)	0
	Mean	**+0.33 (+1.5)**	**-1.83 (-3.6)**	**-1.83 (-2.2)**	**$+2.17^{A}$ (+80.6)**	**$+2.17^{A}$ (+42.0)**	**+2.5 (+25.0)**
Small Terrestrial	CB	0	+2 (+4.2)	+2 (+2.5)	+2 (+100.0)	+2 (+11.0)	0
	GC	0	0	0	0	0	0
	TB	0	0	+1 (+1.0)	+2 (+28.6)	+2 (+17.0)	0
	Mean	**0**	**+0.67 (+1.4)**	**+1 (+1.2)**	**$+1.33^{A}$ (+42.9)**	**$+1.33^{A}$ (+9.0)**	**0**
			0				
Large Aquatic	JB	0	-1 (-1.6)	+1 (+1.0)	+10 (+142.9)	+10 (+143.0)	+25 (+100.0)
	HIW	1 (+4.2)	+2 (+2.5)	+4 (+3.5)	+7 (+63.6)	+7 (+64.0)	0
	OB	0	+4 (+4.7)	+4 (+2.9)	0	0	0
	Mean	**+0.33 (+1.4)**	**+1.67 (+1.9)**	**+3 (+2.5)**	**$+5.67^{A}$ (+68.8)**	**$+5.67^{B}$ (+69.0)**	**+8.33 (+33.0)**
Large Terrestrial	IQI	0	+5 (+7.7)	+6 (+6.2)	+2 (+33.3)	+2 (+11.0)	0
	MC	1 (+4.7)	+7 (+12.5)	+2 (+2.3)	+8 (+200.0)	+8 (+33.0)	+25 (+100.0)
	SB3	0	0	0	+5 (+100.0)	+5 (+46.0)	0
	SWB	0	+2 (+2.2)	+4 (+3.1)	+1 (+50.0)	+1 (+9.0)	0
	Mean	**+0.25 (+1.2)**	**+3.5 (+5.6)**	**+3 (+2.9)**	**$+4^{A}$ (+95.8)**	**$+4^{A}$ (+25.0)**	**+6.25 (+25.0)**
Overall Mean		**+0.23 (+1.0)**	**+1.00 (+1.3)**	**+1.29 (+1.1)**	**+3.29* (+72.0)**	**+3.29* (+36.0)**	**+4.27 (+0.21)**

* indicates significant increase in score with respect to the modified protocol (paired t-test; $p<0.05$) and different superscript letters within a column indicates significant differences (ANOVA; Tukey-Kramer HSD; $p<0.05$) among wetland categories for a criteria.

Table 2.3: Summary of change in OWES scores with inclusion of vegetated deep-water habitat for all criteria listed in Table 2 along with changes in wetland area for the 4 wetland categories. Numbers in parentheses in the headings indicate maximum OWES criteria score. Data presented are the absolute change with proportional change in parentheses.

Category	Wetland Code	All Criteria assessed (425)		Area (ha)	
Small Aquatic	NB1	0		+2.5	(+35.3)
	NB2	+2	(+1.8)	+1.2	(+18.0)
	NBR	+5	(+3.8)	+3.4	(+14.1)
	PMB	-13	(-13.0)	+3.7	(+104.0)
	RSB	+24	(+26.0)	+9	(+140.0)
	RB	-1	(-1.3)	+2.6	(+118.6)
	Mean	**+2.8^{A}**	**(+2.9)**	**+3.7^{A}**	**(+71.7)**
Small Terrestrial	CB	+4	(+3.2)	+0.9	(+4.9)
	GC	0		+0.5	(+2.3)
	TB	+3	(+2.2)	+4.4	(+22.2)
	Mean	**+2.3^{A}**	**(+1.8)**	**+1.9^{A}**	**(+9.8)**
Large Aquatic	JB	+36	(+28.0)	+57.3	(+215.4)
	HIW	+11	(+6.9)	+10.9	(+28.8)
	OB	+4	(+1.9)	+4.5	(+7.4)
	Mean	**+17^{A}**	**(+12.0)**	**+24.2^{A}**	**(+83.7)**
Large Terrestrial	IQI	+8	(+5.7)	+4.9	(+12.7)
	MC	+27	(+20.0)	+12.4	(+32.0)
	SB3	+5	(+3.6)	+5.4	(+18.8)
	SWB	+5	(+2.6)	+3.9	(+5.0)
	Mean	**+11.3^{A}**	**(+7.9)**	**+6.7^{A}**	**(+17.1)**
Mean for all categories		**+8.6***	**(+6.2)**	**+9.2***	**(+45.6)**

* indicates significant increase in score with respect to the modified protocol (paired t-test; $p<0.05$). Different superscript letters within a column indicates significant differences (ANOVA, Tukey-Kramer; $p<0.05$) among wetland categories for the specific criterion.

Table 2.4: Summary of recommendations for the OWES. The criteria studied with their corresponding identifiers in parentheses on the left describe current wetland evaluation protocol with the authors' recommendations on the right. Wetland area is included for its influence on valuation but it is not a separate criterion.

Ontario Wetland Evaluation System	Recommendations for a Modified System
(1.0) Biological Component	
(1.1) Productivity	None
(1.2) Biodiversity	Restructure and separate into different submergent vegetation forms as follows (after Croft and Chow-Fraser, 2009): • Rooted basal rosettes • Rooted submergent • Unrooted submergent • Submergent canopy
(4.0) Special Features Component	
(4.2) Significant Features and Habitats	
(4.2.7) Fish Habitat	Great Lakes coastal wetlands should be given greater value for their role as nursery habitat and critical habitat for over 80 fish species (Jude and Pappas, 1992)
(4.2.7.1) Spawning and Nursery Habitat	Include vegetated deepwater habitat as low marsh
(4.4) Great Lakes Coastal Wetlands	Re-assign intervals and thresholds to increase value of small wetlands (Gibbs, 1993; Semlitsch and Brodie, 1998) and extensive complexes of small wetlands (especially in eastern Georgian Bay; McMaster Coastal Wetland Inventory, Chow-Fraser, unpub. data)
Wetland Area	Include vegetated deep-water habitat in future protocol to completely account for aquatic wetland habitat

List of Figures

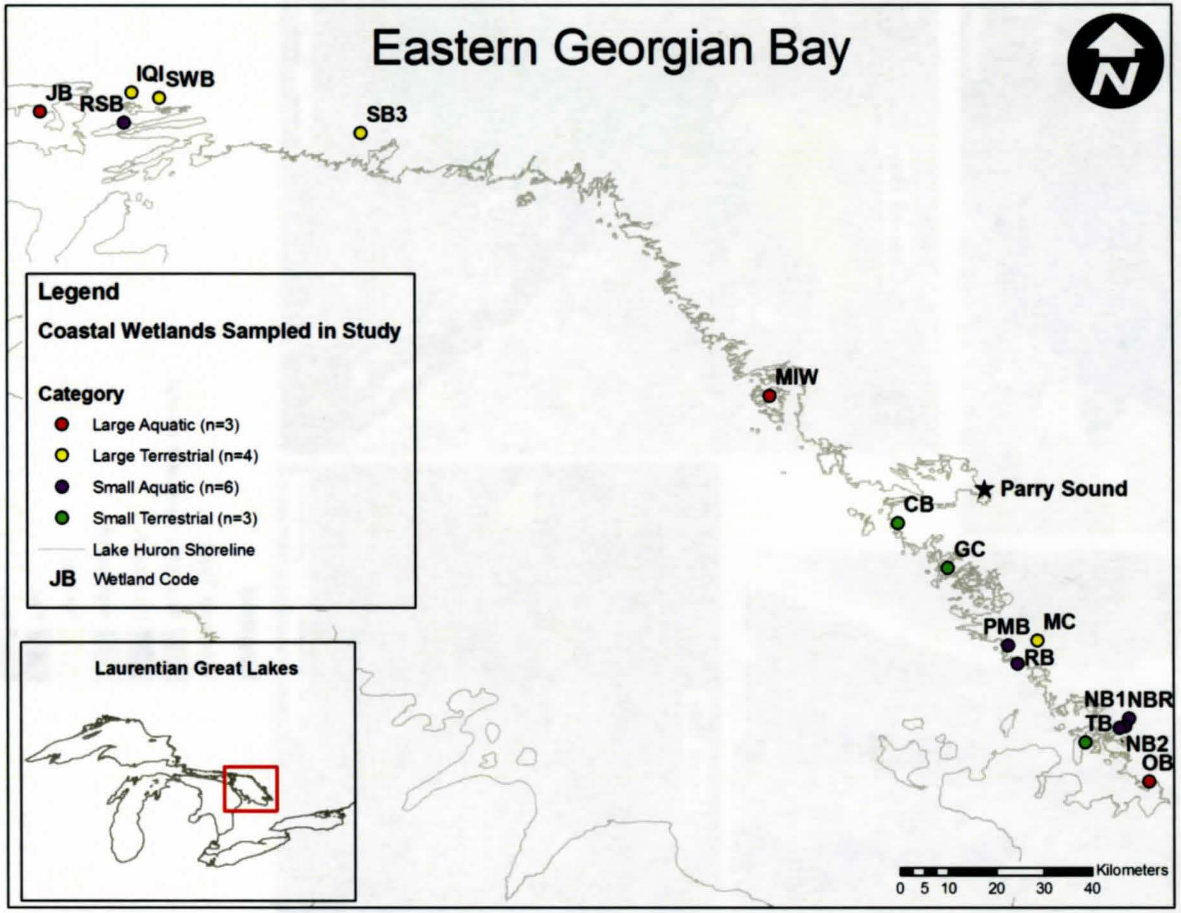


Figure 2.1: Map of the 16 coastal wetlands sampled in eastern Georgian Bay in this study. The colour of each sampling point indicates the category of the wetland as either small aquatic, small terrestrial, large aquatic, or large terrestrial. More specific information and maps can be found in Table 2.1 and Figures 2.2-2.6.

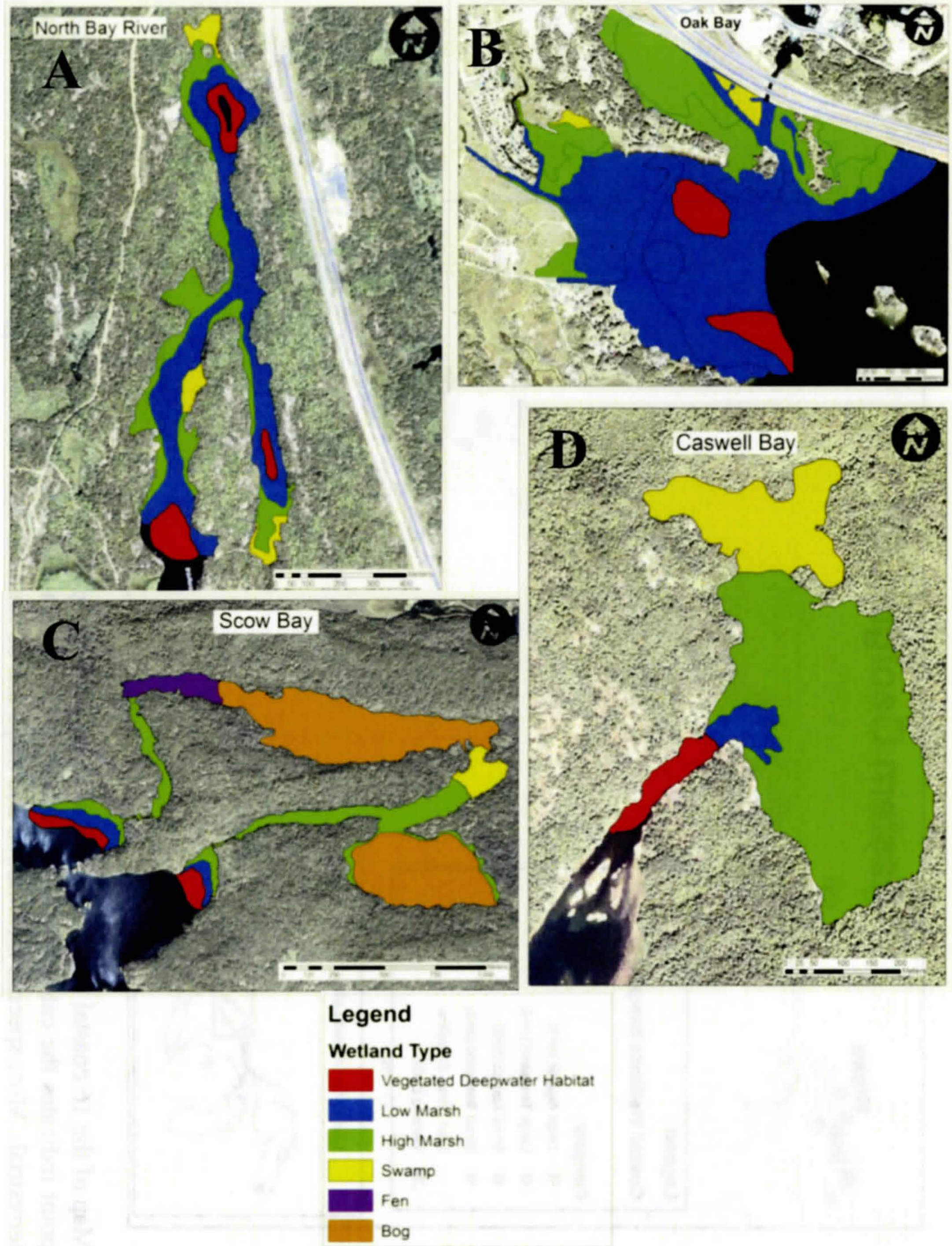
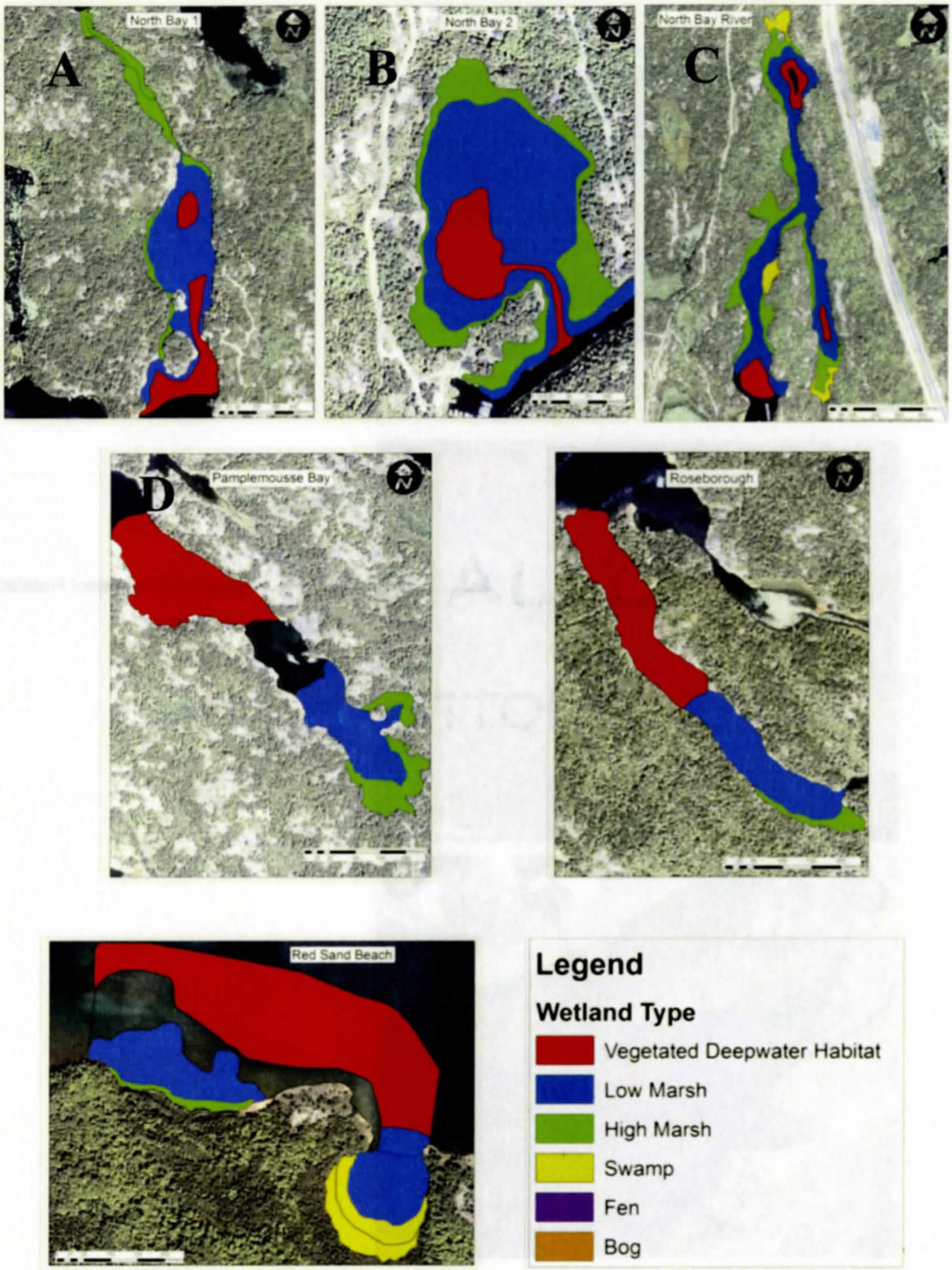


Figure 2.2: Examples of modified OWES maps for each of the 4 categories sampled: A) small aquatic B) large aquatic C) large terrestrial and D) small terrestrial. Each polygon represents one of the OWES vegetation communities (OMNR, 1993), including the vegetated deep-water habitat proposed in this study



<u>Figure 2.3</u>: Simplified OWES maps of the six small aquatically-dominated, coastal wetlands sampled in eastern Georgian Bay Each polygon represents an OWES (OMNR 1993) vegetation community including the vegetated deep-water habitat proposed in this study

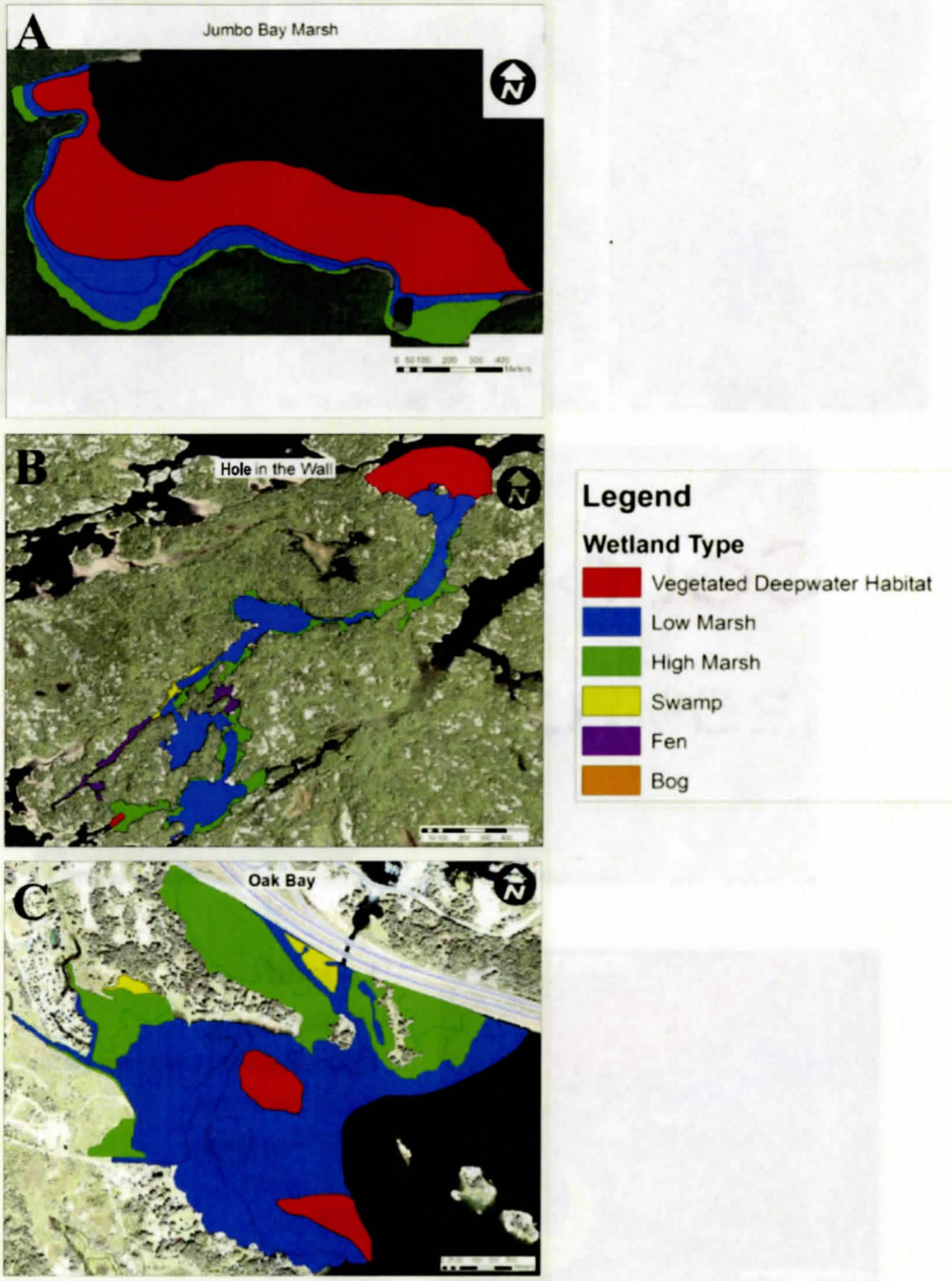


Figure 2.4: Simplified OWES maps of the three large aquatically-dominated, coastal wetlands sampled in eastern Georgian Bay. Each polygon represents an OWES (OMNR 1993) vegetation community including the vegetated deep-water habitat proposed in this study

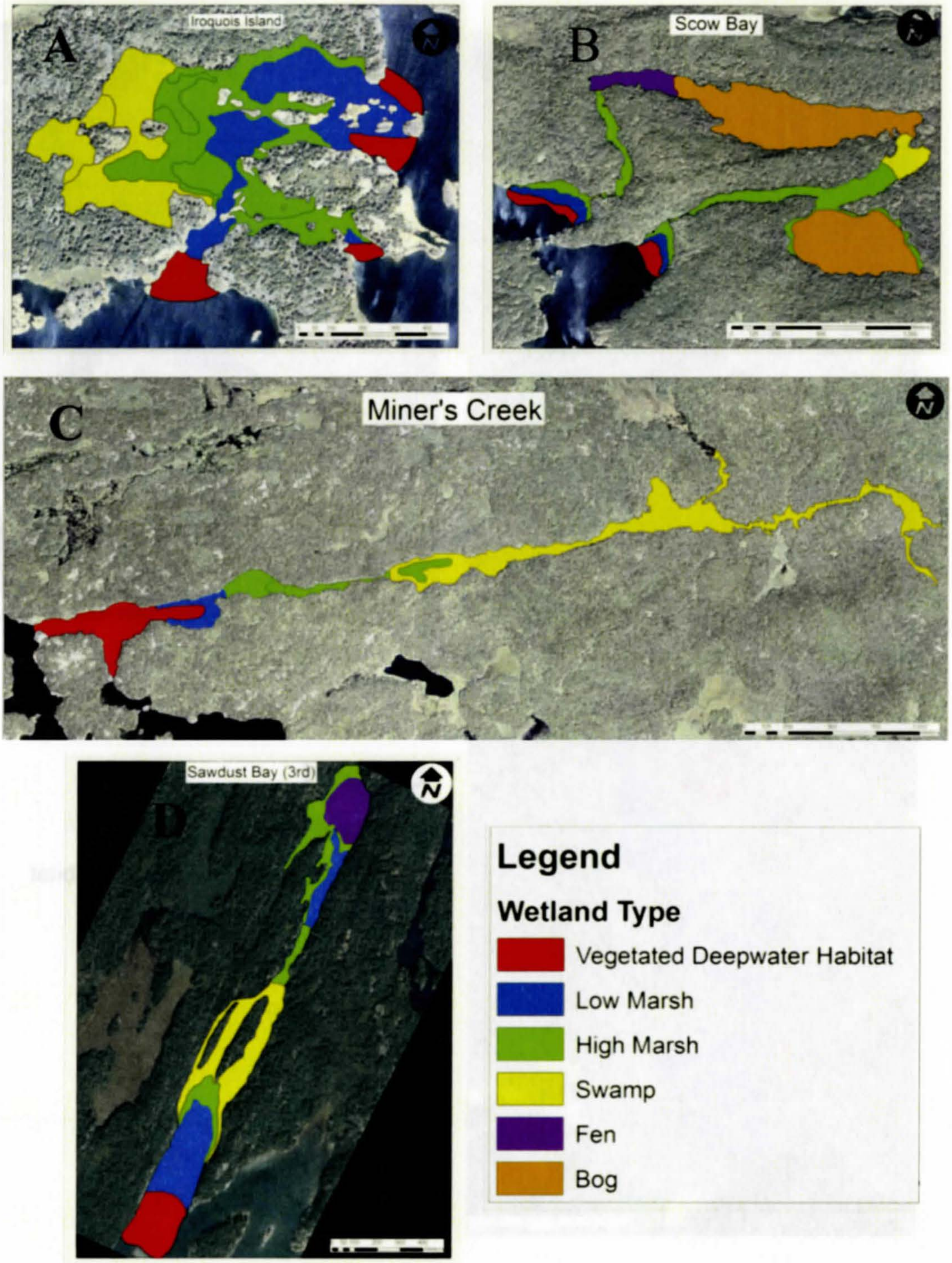


Figure 2.5: Simplified OWES maps of the four large terrestrially-dominated, coastal wetlands sampled in eastern Georgian Bay. Each polygon represents an OWES (OMNR 1993) vegetation community including the vegetated deep-water habitat proposed in this study

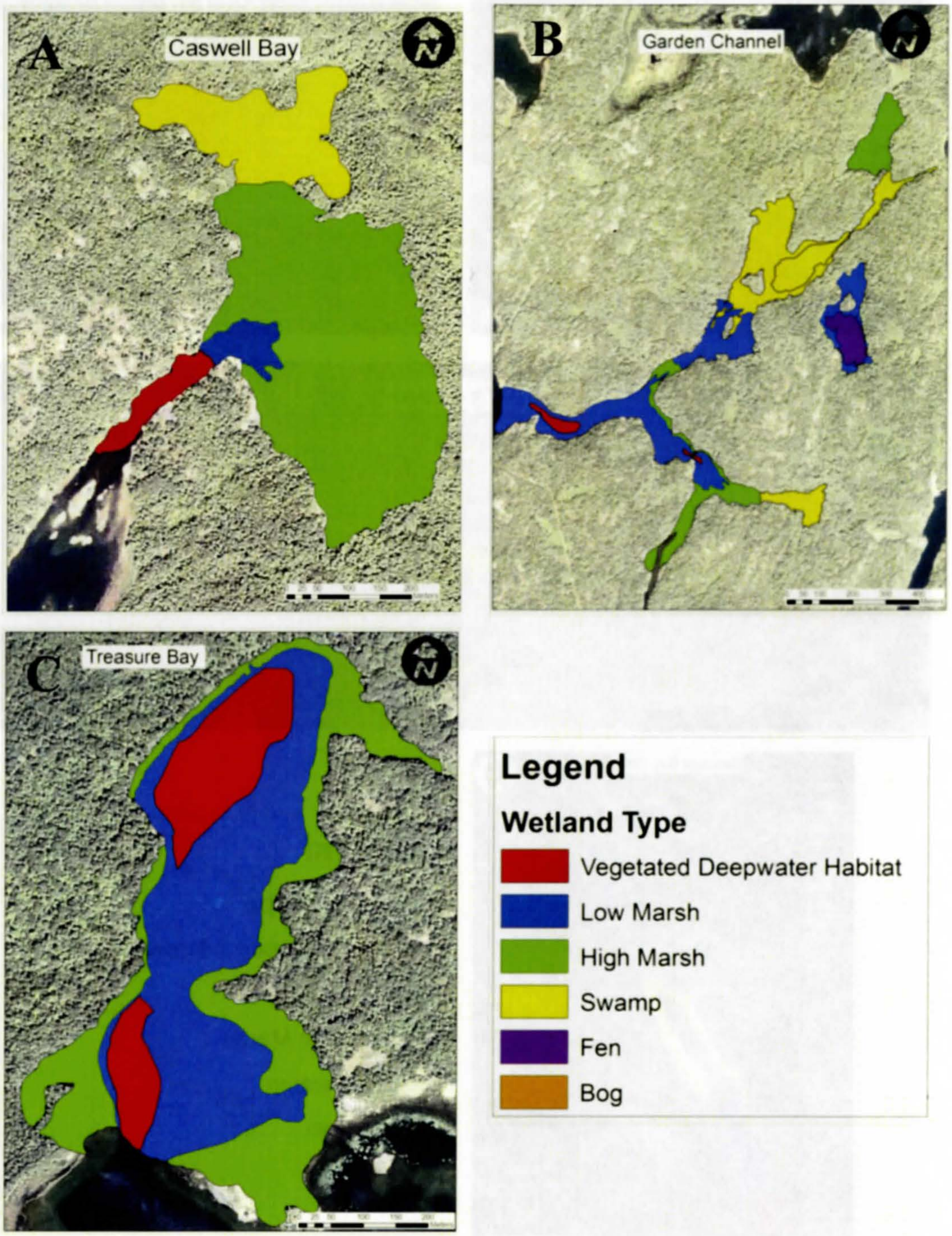


Figure 2.6: Simplified OWES maps of the four large terrestrially-dominated, coastal wetlands sampled in eastern Georgian Bay. Each polygon represents an OWES (OMNR 1993) vegetation community including the vegetated deep-water habitat proposed in this study

Chapter 3

Use of IKONOS satellite imagery to quantify temporal changes in coastal wetland habitats in two regions of Georgian Bay with contrasting human disturbance

By

Daniel Rokitnicki-Wojcik

and

Patricia Chow-Fraser

Abstract

Georgian Bay coastal wetlands are becoming increasingly impacted by two very different disturbances: anthropogenic impacts from recreational development and sustained water level decline. To address the need for widespread spatial monitoring of coastal zones, we evaluated the use of multi-temporal IKONOS imagery to quantify changes in coastal marsh area over a 6-year interval (2002 to 2008). Wetlands were manually delineated in a Geographic Information System (GIS) for low and high marsh zones to compare the potential losses and gains in aquatic and terrestrial habitats over the 6-year interval during which there was a net 10cm water level decline and an overall trend in lower water levels. We used the number of buildings within 250-, 500-, 750-, and 1000-m buffers of the wetland boundary as a measure of human disturbance to select wetlands with high and low human impacts. The total amount of aquatic and terrestrial wetland habitat increased significantly from 2002 to 2008 (mean of 4.54 to 4.94 ha, respectively), representing a 16.6% increase in habitat (paired t-test; $P<0.0001$). We did not find any significant effect of human disturbance on wetland area, but there was a negative trend towards lower net increase as the number of buildings increased within a 500-m buffer of wetlands. We also found a significant decrease in the percentage of low marsh in 2008 relative to that in 2002 (41.7 vs 48.6%, respectively), and a corresponding increase in the percentage of high marsh over this period (58.3 vs 51.4%, respectively). There is

some urgency for us to develop landscape-level monitoring tools to assess the high-quality marshes of Georgian Bay before they succumb to the negative impacts of human development and sustained low water levels. The approach used here to map wetlands can be easily applied to map broad habitat types at large regional scales because it is cost effective and requires very little training.

Introduction

Monitoring ecosystem change has long been the goal in conservation efforts from both scientific and management/institutional perspectives. Coastal wetlands of eastern Georgian Bay are some of the highest quality and highest density in the Great Lakes basin (Cvetkovic et al, 2009), but they are under increasing pressure from both natural and anthropogenic disturbances. These include sustained decline in water level over the past decade and increased human-disturbance related to recreational and urban development. These wetlands provide valuable ecosystem goods and services (Maynard and Wilcox, 1997) and need to be managed and protected from these disturbances.

Historic water level fluctuations are a natural disturbance resulting from climatic variability that has influenced the formation of wetlands over millennia (Keddy and Reznicek, 1986). Seasonal and annual variability of water levels has shaped the biotic communities and has helped to maintain the diversity of both aquatic and terrestrial forms (Maynard and Wilcox, 1997; Mortsch, 1998). It has been hypothesized, however, that the recent sustained decline in water levels of Lake Huron-Georgian Bay may be linked to both climate change (Sellinger et al 2008) and the increased outflow from historic dredging of the St. Clair River (Argyilan and Forman, 2003; Baird, 2005). Climate change predictions for the region call for further declines in water levels (Hartmann, 1990; Lofgren, 2002) and presents an uncertain future for the overall health of coastal wetlands.

Current understanding of how wetlands respond to a reduction in water levels suggests that terrestrial vegetation would colonize newly available dry land and that aquatic habitat would also shift lake-ward. Although many studies exist that document how emergent and terrestrial vegetation (also referred to as "high marsh" by OMNR (1993)) respond to water level fluctuations (Williams and Lyon, 1997; Wei and Chow-Fraser 2005; Wilcox and Nichols, 2008), few have examined the lake-ward migration of submergent vegetation. Hence, the effect of water level on what has been referred to as "low marsh" vegetation (OMNR, 1993) has not been explored in the literature.

Human impacts on coastal wetlands in Georgian Bay consist mainly of those associated with recreational activities and recreational development of cottages and roads which can lead to loss of wetland habitat from conversion to other landuses such a residential. Road density in the watershed has been shown to be a good predictor of the water quality in these wetlands where watersheds with higher road densities contain wetlands that show more signs of degradation (DeCatanzaro et al., 2009). Building density can be used as another measure of human impact because cottages are usually built in areas that are protected from wind and wave action that correspond to where wetland habitat can develop. This can lead to a loss of wetland habitat from human conversion. This has already been used a measure of wetland loss where building density within a 750m buffer of a wetland centroid has been used to establish building thresholds, that if surpassed would result in water-quality impairment. Anthropogenic impacts on coastal wetlands can include habitat loss, nutrient enrichment, invasive species introduction, and loss of aquatic diversity and can potentially interact with water level impacts to shape and change these communities (Wei and Chow-Fraser, 2005).

Monitoring these complex systems that are distributed across a large spatial scale requires the use of landscape ecological tools. Remote sensing has become increasingly useful for detecting temporal changes in wetlands and wetland habitats (Lillesand and Kiefer, 2000; Ozesmi and Bauer, 2002; Lu et al., 2004). Wetlands monitoring traditionally involved the interpretation of aerial photography (Johnson, 1990; Williams and Lyon, 1997; Frieswyk and Zedler, 2007). However, with the advent of high-resolution satellites, it is now possible to increase both spatial and temporal coverage. Data-rich imagery can also be used to map vegetation types within wetlands as well as distinguish among wetland types wetlands over a large region (Jensen et al., 1993; Grenier et al., 2007; Hogg and Todd, 2007; Wei and Chow-Fraser, 2007; Grenier et al., 2008).

Here, we compare how the areal extent of aquatic (low marsh) and terrestrial (high marsh) habitat in coastal marshes of southeastern Georgian Bay have changed between 2002 and 2008, a 6-year interval during which water levels exhibited a downward trend, with a net decline of 10 cm over the 6 years. We focus on 2 regions with contrasting human density to account for the potentially confounding effect of human disturbance. Using image interpretation, habitat of 30 randomly selected wetlands were manually delineated to answer the following questions:

1) Are there differences in aerial extent of high marsh and low marsh habitats over a 6-year period?
2) Does a relationship exist between human impact and wetland habitat change?
3) Does aquatic habitat exhibit a concomitant lake-ward migration with terrestrial habitat when water level declines?
4) Can IKONOS imagery be successfully used in fine scale multi-temporal monitoring of small marshes?

Temporal changes in wetland habitat have been quantified in past studies (Williams and Lyon, 1997; Wilcox, et al., 2003; Wei and Chow-Fraser 2006; Frieswyk and Zedler, 2007; Mortsch et al., 2008) and generally show that during periods of lower water levels, terrestrial vegetation colonize lake-ward. We therefore expect an overall increase in high marsh habitat in 2008 relative to 2002. We speculate that wetlands may also be adversely affected by human activities in more densely populated areas, and that this may confound the response of wetlands to water-level declines. Hence, we needed to monitor impacts of water levels in both human-disturbed as well as a reference sites.

We expect to see little shift lake-ward of low marsh habitat with water level decline because factors influencing submergent plant colonization are much more complex at the lake/wetland boundary because it involves creation of new wetland habitat. Nutrients, substrate, light, and physical disturbances all influence the potential establishment of this low marsh habitat (Dale, 1986; Chambers, 1987; Chambers and Prepas, 1988; Lacoul and Freedman, 2006). Such parameters limit the establishment of plants in deep-water and we expect that they will limit the migration of the lower boundary of plants lakeward over the time scale of this study. At the low marsh/high marsh boundary (shoreline), declining water levels should result in newly dried habitat that could facilitate establishment of terrestrial vegetation. We expect that this colonization would be detectable over the study period, since it is far easier to colonize habitat with established communities than to colonize new wetland habitat on bare substrate. IKONOS imagery has been successfully used to map similar freshwater wetland habitat (Dechka et al., 2002; Lawrence et al., 2006; Wei and Chow-Fraser, 2007; Dillabaugh and King, 2008), and therefore, we expect to be able to successfully identify and quantify habitat using multi-temporal imagery.

Methods

The coastal wetlands mapped in this study are marshes situated in southeastern Georgian Bay, Lake Huron, Ontario, Canada (Figure 3.1). For the purposes of this study we consider coastal wetlands as wetlands with direct hydrological connectivity to the lake via surface water and that occur at the shoreline of Georgian Bay. We used multi-temporal satellite scenes (images) covering 3 regions, Tadenac, North Bay and Oak Bay (Figure 3.1) to produce wetland maps. The images were acquired in 2002 and 2008 and are 1-m resolution summer IKONOS (Geoeye, Dulles, VA, USA) images. The 2002 images were acquired during the same satellite pass on July 1st, 2002. In 2008, the North Bay and Tadenac images were acquired during the same pass on July 16, 2008. The Oak Bay image; however, was acquired at a later date on August 26, 2008. All images are cloud free, multispectral (red, blue, green, and near infrared bands), and were acquired during the summer to capture the wetlands during maximal vegetative growth and full extent of the habitats. The 2008 images were georeferenced to the 2002 images using image-to-image registration in ENVI™ (ITT Visual Informations Solutions, White Plains, New York, U.S.A.; v4.1).

Majority of the Tadenac image covers a pristine area owned and managed by a private fishing club that restricts the use of the club and its lands by no more than a couple dozen club members and guests at any one time. Access to this area is by boat only, and the coastal wetlands found within The Tadenac Club's land have served as reference sites in previous studies because the surrounding upland forests have been left undisturbed since the last century (Croft and Chow-Fraser, 2009; Cvetkovic et al, 2009; DeCatanzaro et al. 2009). These reference sites have some of the best water-quality conditions in the Great Lakes (Chow-Fraser, 2006). North and adjacent to the Tadenac Club is Twelve Mile Bay, a rapidly developing area in Georgian Bay that has greatly increased its population density within the past 10 years. Twelve Mile Bay is at the north end of the image and provides an area with high human impact for this study.

The North and Oak Bay images covers a contiguous area between Port Severn, located in the southereast corner of Georgian Bay, and Honey Harbour, a major recreational port that is gateway to areas north of Honey Harbour. These two images have much greater human densities with a greater number of cottages, high road density, and a large number of coastal wetlands (McMaster Coastal Wetland Inventory, Chow-Fraser, unpub data).

All coastal marshes were first identified via expert image interpretation of the three IKONOS scenes in a Geographic Information Systems (GIS). A total of 131 coastal marshes were identified in the three satellite scenes that included a range of wetland sizes and a large mix of aquatic and terrestrial habitat. In most cases, these coastal marshes contained a diverse assemblage of aquatic and wet meadow vegetation. Upstream wetlands included extensive swamp, fen, and some bog habitats but these have been excluded in the present study.

Habitat Identification

A subset of 30 wetlands were randomly selected from the pool of 131 for habitat delineation. Low marsh (aquatic) and high marsh (terrestrial) habitat were delineated for each wetland. Low marsh included the emergent zone and floating vegetation, but an accurate boundary of the submergent vegetation in the deep-water zone could not be identified using the imagery. The aquatic habitat delineations reported here are therefore underestimates of the true boundary, because it excludes the vegetated deep-water habitat that can extend much further below the limit of emergent and floating vegetation (see Chapter 2). The high marsh included all other habitat up to the upland forest boundary, upland rock outcrop boundary, or transition to another wetland type (e.g. swamp, fen or bog).

Habitat delineations were first completed for the 2002 imagery and the marsh type of each habitat polygon was input as attribute data in a GIS. The 2002 delineations were then overlain on the 2008 images and polygons were modified on a case-by-case basis to reflect changes in habitat size or type. These polygons created from the 2002 delineations were named to reflect the type of conversion as follows: from low marsh to high marsh, from high marsh to low marsh, from non-wetland to low marsh, from non-wetland to high marsh, from low marsh to non-wetland, and from high marsh to non-wetland. Area was generated for each polygon in a GIS and exported for statistical analyses.

Determination of Human Impact

We used the number of buildings occurring within 250-, 500-, 750-, and 1000-m buffers of the wetland boundary as a measure of human impact. We define human impact or disturbance as any action that would reduce wetland area or habitat through destruction or loss of wetland vegetation. Buffers were created around the delineated wetlands for both years to generate building numbers. We used the Ontario Base Map building layer from 2000 and updated the remaining buildings through manual digitizing of the IKONOS images. We determined high human impact at wetlands that had values greater than the median for a given buffer. The break-points were determined to be 15 buildings within 250 m buffer, 35 within 500 m buffer, 60 within 750 m buffer, and 80 within 1000 m buffer. Wetlands with building numbers greater or equal to the break-points were arbitrarily assigned high human impact.

Water-Level Data for Lake Huron

Mean annual water-level data were obtained from Canadian Hydrographic Services (Department of Fisheries and Oceans). Plots of water levels were produced covering the period from 1918 to 2008.

Data Analysis

Statistical analyses were performed in SAS JMP v7.0 (SAS institute, Cary, NC, USA). We used paired t-tests to determine differences in absolute amount and proportion of area of each marsh types, and to determine difference between years, and between levels of human impact.

Results

The large interannual fluctuations in water levels of Georgian Bay/Lake are characteristic of all Great Lakes (Argyilan and Forman 2003; Chow-Fraser 2005) (Figure 3.2A). Unlike previous drops in water level experienced in the 1930s and 1960s, however, the current low water levels have persisted over the past 10 years and have not yet recovered to the long-term mean. Compared with water levels in the 1980s and 1990s, current water levels are lower by almost one meter. The change in water level between 2002 and 2008 is not much more than 10 cm, although mean annual levels have generally declined consistently since 2004 (Figure 3.2B).

Forty-three percent of the wetlands identified in this study were smaller than1 ha and only 20% were greater than 5 ha (Table 3.1a and b); therefore majority of the wetlands we studied would have been too small to be evaluated for conservation purposes (see Chapter 2). In this study we do not delineate submergent habitat due to the technological limitations of the satellite imagery. If we extrapolate from the differences in wetland area when you include the full extent of submergent habitat at a mean of 48% increase (see Chapter 2), we would see much greater total wetland area and even greater increase in low marsh habitat. Overall, we found significantly more wetland habitat (both aquatic and terrestrial) in 2008 compared with 2002 (means of 4.94 vs 4.55 ha, respectively, paired t-test $p = 0.0001$; Table 3.1a and b), and this represents a 16.6% increase in wetland habitat over the 6 years. We could not attribute any changes in total wetland area over the 6 years to differences in human impact since there were no significant differences between wetland areas corresponding to the high and low impact categories (Paired t-test; $P>0.05$). We did, however, find that a few wetlands associated with fewer buildings within the 500-m buffers tended to have a greater net increase in wetland habitat (Figure 3.3).

The absolute amount of low- and high-marsh habitat did not change significantly over the 6-year period, but when we calculated the proportion of wetland by marsh type, we found a significantly higher percentage of high marsh in 2008 compared with 2002 (58.3 vs 51.43%), and a correspondingly lower percentage of low marsh (41.7 vs 48.6%) (Table 3.2).

Habitat conversion occurred equally between the creation of low marsh habitat and the conversion of low marsh to high marsh (Table 3.1a and b). As indicated earlier, mean percentages of the 2008 wetland area of both these conversion types were similar for the two human impact levels (Table 3.1a and b). There were some instances of other conversion types; however, they occurred far less frequently (Table 3.1a and b).

Discussion

We delineated broad marsh habitat to determine the changes in aquatic and terrestrial habitat between 2002 and 2008. We found a significant shift in the proportion of total wetland area of each marsh type over this period. In 2002, the mean proportion of wetland composed of low and high marsh was nearly equal but this balance shifted to roughly a 40:60 split in low- to high-marsh in 2008.

The implications of this shift in aquatic to terrestrial habitat is that if water level continues to decline as predicted in climate change scenarios, we may witness a disproportionate dominance of terrestrial habitat in coastal wetlands and a loss of low marsh habitat. This has serious implications for the Great Lakes fishery because coastal low marsh habitats (including vegetated deep-water habitat) are critical for life cycles of many Great Lakes fishes (Jude and Pappas, 1992).

Trends in habitat conversion illustrate how the creation of new aquatic habitat (conversion of non-wetland to low marsh) has been equal to the mean loss of aquatic habitat (conversion of low marsh to high marsh), which was about 12% of the 2008 area. This is contrary to our expectations that the migration or creation of new aquatic habitat lake-ward would be lower than the expansion rate of terrestrial vegetation. It is important to point out, however, that creation of low marsh kept pace with loss rates since equal amounts of low marsh have been converted into high marsh over this period. Therefore, proportionate gains in terrestrial habitat (high marsh) have been at the expense of the low-marsh habitat.

We have already pointed out that delineation of the low-marsh habitat was conservative since we did not have sufficient field information to determine the depth of colonization by submerged aquatic vegetation in these wetlands. What we identified as low-marsh habitat was primarily expansion of the floating vegetation towards the lake. It is possible that the submergent vegetation community also moved lake-ward, but without field verification, this should not be assumed. This limitation of remote-sensing technology to map vegetation below the water surface is a major reason for including other approaches to model the effect of water level on the entire community of wetland vegetation.

The fact we are currently unable to detect any significant impact of human disturbance should not make us complacent, since we did not have sufficiently large sample size to properly test this effect. As human pressures increase in the region, however, we may quickly exceed the threshold for human impacts. We have witnessed what human impacts can do as the current extent of coastal wetlands in the southern Great Lakes is >80% less than pre-European settlement conditions (Snell, 1991). Therefore, it is imperative that managers carry out regular monitoring at appropriate temporal and spatial scales to ensure that coastal wetland habitat is conserved.

Water levels varied a great deal in Lake Huron between 2002 and 2008, even though the total change was only 10 cm when the annual means for the two years are compared. There is no doubt that vegetation requires a certain lag time before they respond, and what we see now is a reflection of several years of gradual decline in water levels since 2004.

The methods presented here provide an effective and efficient monitoring protocol that may be completed quickly with limited manpower. Many of the sites mapped in this study were <1ha, which are usually overlooked in mapping protocols due to the general focus on conserving large tracts of habitat. One reason for the high biodiversity in Georgian Bay is the interconnectedness of a large number of small and spatially distinct wetlands that form a network of refugia for fish and wildlife. The Ontario Wetland Evaluation System, the method of cataloguing and ranking wetlands for protection in Ontario (OMNR, 1993), generally excludes wetlands <2ha unless they provide highly unique features. Here we present a method that can easily monitor small wetlands that is feasible and management oriented. We recommend that this method be used to catalogue and monitor broad habitat types in small marshes where vegetation classification by other remote sensing methods may be inaccurate. The persistence of a connected matrix of small wetlands is valuable to the ecology and high diversity of this region, as small wetlands are those most likely to succumb to anthropogenic pressures.

Acknowledgements

Funding for this study was provided by an NSERC PGS-M grant awarded to DR-W and by the Greater Bay Area (GBA) Foundation to PC-F. We thank the Greater Bay Area (GBA) Foundation for the use of the IKONOS imagery. We greatly appreciate the GIS work of T. Hurley for his help with digitizing and K. Cimaroli for her help with georeferencing.

Literature Cited

Argyilan, E.P., Forman, S.L. 2003. Lake level response to seasonal climatic variability in the Lake Michigan-Huron system from 1920-1995. *Journal of Great Lakes Research.* 29(3):488-500.

Baird, W.F., 2005. Regime change (man made intervention) and ongoing erosion in the St. Clair River and impacts on Lake Michigan-Huron lake levels. W.F. Baird & Associates. Document 10814.

Chambers, P.A., 1987. Nearshore occurrence of submersed aquatic macrophytes in relation to wave action. *Canadian Journal of Fisheries Aquatic Sciences.* 44: 1666-1669.

Chambers, P.A., Prepas, E.E., 1988. Underwater spectral attenuation and its effect on the maximum depth of angiosperm colonization. *Canadian Journal of Fisheries Aquatic Sciences.* 45: 1010-1017.

Chow-Fraser, P. 2005. Ecosystem response to changes in water level of Lake Ontario marshes: lessons from the restoration of Cootes Paradise Marsh. *Hydrobiologia.* 539:189-204

Chow-Fraser, P 2006. In Simon, T.P and Stewart, P.M. (eds) "Coastal wetlands of the Laurentian Great Lakes: health, habitat and indicators". Chapter 5. Indiana Biological Survey, Bloomington, Indiana. p.137-166.

Cvetkovic, M., DeCatanzaro, R. and Chow-Fraser, P. 2009. Ecological indicators and road density in assessing habitat quality of coastal marshes in

Georgian Bay, Lake Huron. *Biodiversity and Conservation.* In submission.

Dale, H.M. 1986. Temperature and Light: The Determining Factors in Maximum Depth Distribution of Aquatic Macrophytes in Ontario, Canada. *Hydrobiologia.* 133: 73-77.

DeCatanzaro, R., Cvetkovic, M., Chow-Fraser, P. 2009. The relative importance of natural watershed features and anthropogenic influence on the water quality of Georgian Bay coastal marshes. *Environmental Management.* In submission.

Dechka, J.A., Franklin, S.E., Watmough, M.D., Bennett, R.P., Ingstrup, D.W., 2002. Classification of wetland habitat and vegetation communities using multi-temporal IKONOS imagery in southern Saskatchewan. *Canadian Journal of Remote Sensing.* 28(5): 679-685.

Dillabaugh, K.A., King, D.J. 2008. Riparian marshland composition and biomass mapping using Ikonos imagery. *Canadian Journal of Remote Sensing.* 34(2):143-158.

Frieswyk, C.B., Zedler, J.B. 2007. Vegetation change in Great Lakes coastal wetlands: deviation from historical cycle. *Journal of Great Lakes Research.* 33:366-380.

Grenier, M., Demers, A.M., Labreque, S., Benoit, M., Fournier, R.A., Drolet, B. 2007. An object-based method to map wetland using RADARSAT-1 and Landsat ETM images: test case on two sites in Quebec, Canada. *Canadian Journal of Remote Sensing.* 33(S1): 28-45.

Grenier, M., Labreque, S., Garneau, M., Tremblay, A. 2008. Object-based classification of a SPOT-4 image for mapping wetlands in the context of greenhouse gases emissions: the case of the Eastmain region, Quebec, Canada. *Canadian Journal of Remote Sensing*. 34: (S2): 398-413.

Hartmann, H.C. 1990. Climate change impacts on Laurentian Great Lakes levels. *Climate Change*. 17:49-67.

Hogg, A.R., Todd, K.W. 2007. Automated discrimination of upland and wetland using terrain derivatives. *Canadian Journal of Remote Sensing*. 33(S1): 68-83.

Jensen, J.R., Cowen, D., Althausen, J., Narumalani, S., Weatherbee, O. 1993. An evaluation of the Coast Watch change detection protocol in South Carolina. *Photogrammetric Engineering & Remote Sensing*. 59: 1039-1046.

Johnson, L.B. 1990. Analyzing spatial and temporal phenomena using geographical information systems. *Landscape Ecology*. 4(1):31-43.

Jude, D.J., Pappas, J. 1992. Fish utilization of Great Lakes coastal wetlands. *Journal of Great Lakes Research*. 18(4): 651-672.

Keddy, P.A., Reznicek, A.A. 1986. Great Lakes vegetation dynmaics: the role of fluctuating water levels and buried seeds. *Journal of Great Lakes Research* 12(1): 25-36.

Lacoul, P., Freedman, B. 2006. Environmental influences on aquatic plants in freshwater ecosystems. *Environmental Reviews*. 14:89-136.

Lawrence, R., Hurst, R., Weaver, T., Aspinall, R. 2006. Mapping prarie pothole communities with multitemporal Ikonos satellite imagery. *Photogrammetric Engineering & Remote Sensing.* 72(2): 169-174.

Lillesand, T., Kiefer, R. 2000. Remote sensing and image interpretation. 4th ed. Lehigh Press. New York 724pp.

Lofgren, B.M., Quinn, F.H., Clites, A.H., Assel, R.A., Eberhardt, A.J., Luukkonen, C.L. 2002. Evaluation of potential impacts on Great Lakes water resources based on climate scenarios of two GCMs. *Journal of Great Lakes Research.* 28(4):537-554.

Lougheed, V.L., Crosbie, B. and Chow-Fraser, P. 2001. Primary determinants of macrophyte community structure in 62 marshes across the Great Lakes basin. *Canadian Journal of Fisheries and Aquatic Sciences* 58: 1603-1612.

Maynard, L., Wilcox, D. 1997. Coastal wetlands of the Great Lakes. State of the Lakes Ecosystem Conference 1996. U.S. Environmental Protection Agency. 99 pp.

Mortsch, L.D, 1998. Assessing Impact of Climate Change on Great Lake Shoreline Wetlands. *Climate Change.* 40(2):391-416.

Mortsch, L., Sabila, G., Deadman, P. 2008. Response of vegetation communities in three Lake Huron fens to historical water level fluctuations. *Aquatic Ecosystem Health and Management.* 11(2):167-181.

OMNR 1993. Ontario Wetland Evaluation System. Northern Manual. Ontario

Ministry of Natural Resources (OMNR), No.50254.

Ozesmi, S.L., Bauer, M.E., 2002. Satellite remote sensing of wetlands. *Wetlands ecology and management*. 10: 381-402.

Sellinger, C.E., Stow, C.A. Lamon, E.C., Qian, S.S. 2008. Recent water level declines in the Lake Michigan-Huron system. *Environmental Science and Technology*. 42(2):367-373.

Smith, P.G.R., Glooschenko, V., Hagen., D.A. 1991. Coastal wetlands of the three Canadian Great Lakes: Inventory, current conservation initiatives and patterns of variation. *Canadian Journal of Fisheries and Aquatic Sciences*. 48:1581-1594.

Wei, A., Chow-Fraser, P. 2005. Untangling the confounding effects of urbanization and high water level on the cover of emergent vegetation in Cootes Paradise Marsh, a degraded coastal wetland of Lake Ontario. *Hydrobiologia*. 544:1-9.

Wei, A., Chow-Fraser, P. 2007. Use of IKONOS imagery to map coastal wetlands of Georgian Bay. *Fisheries*. 32(4): 167-173.

Wilcox, K.L, Petrie, S.A., Maynard, L.A., Meyer, S.W. 2003. Historical distribution and abundance of *Phragmites australis* at Long Point, Lake Erie, Ontario. *Journal of Great Lakes Research*. 29(4):664-680.

Wilcox, D.A., Nichols, S.J. 2008. The effects of water-level fluctuations on vegetation in a Lake Huron wetland. *Wetlands*. 28(2):487-501.

Williams, D.C., Lyon, J.G. 1997. Historical aerial photographs and a geographic information system (GIS) to determine effects of long-term water level fluctuations on wetlands along the St. Marys River, Michigan, USA. *Aquatic Botany*. 58:363-378.

Table 3.1a: Summary data for 16 randomly selected coastal marshes in southeastern Georgian Bay where level of human impact was deemed to be low. This was based number of buildings (in parentheses) within a 500-m buffer of wetland boundary. %Diff=net change in wetland area between 2008 and 2002 as a percentage of the area in 2002. Conversion types include 2008 area conversions from low marsh to high marsh (LM to HM), non-wetland to low marsh (N-W to LM), non-wetland to high marsh (N-W to HM), and low marsh to non-wetland (LM to N-W). Area is presented in hectares.

	Percent 2002 Area		Percent 2008 Area						Percent of 2008 Area Converted			
ID	Low Marsh	High Marsh	Low Marsh	High Marsh	2002 Area	2008 Area	%Diff	Human Impact	LM to HM	N-W to LM	N-W to HM	LM to N-W
7	47	53	29	71	0.76	0.76	0	L (31)	18			
12	26	74	26	74	0.43	0.52	21	L (0)	13	18		
17	26	74	26	74	1.37	1.60	17	L (0)	6	13	4	
21	63	37	57	43	1.60	1.67	4	L (0)	7	4	0.5	
22	56	44	52	48	2.30	2.55	11	L (0)	8	9	0.8	
29	23	77	23	77	0.57	0.64	12	L (5)	9	12		
32	69	31	82	18	0.26	0.55	112	L (6)	4	54		
33	61	39	58	42	0.28	0.33	18	L (5)	9	16		
38	18	82	34	86	0.91	0.96	5	L (15)	8	5		
46	100	0	54	46	1.00	1.61	61	L (0)	46	38		
62[α]	62	38	56	44	22.96	23.71	3	L (20)	7	3		
72	67	33	67	33	0.82	1.01	23	L (33)	7	18		
105	35	65	20	80	0.21	0.24	14	L (30)	8	12		
116	67	33	39	61	1.68	1.85	10	L (0)	31	10		
126	36	64	13	87	0.36	0.46	28	L (32)	21	6	17	
131	15	85	11	89	0.60	0.60	0	L (30)	5	0.7		
Mean$_L$	**48**	**52**	**41**	**61**	**2.26**	**2.44**	**21**	**13**	**13**	**14**	**1.4**	**0**

Table 3.1b: Summary data for 14 randomly selected coastal marshes in southeastern Georgian Bay where level of human impact was deemed to be high. This was based number of buildings (in parentheses) within a 500-m buffer of wetland boundary. %Diff=net change in wetland area between 2008 and 2002 as a percentage of the area in 2002. Conversion types include 2008 area conversions from low marsh to high marsh (LM to HM), non-wetland to low marsh (N-W to LM), non-wetland to high marsh (N-W to HM), and low marsh to non-wetland (LM to N-W). Area is presented in hectares.

	Percent 2002 Area		Percent 2008 Area						Percent of 2008 Area Converted			
ID	Low Marsh	High Marsh	Low Marsh	High Marsh	2002 Area	2008 Area	%Diff	Human Impact	LM to HM	N-W to LM	N-W to HM	LM to N-W
35	51	49	52	48	2.38	2.60	9	H (41)	3	8		
51	47	53	59	41	1.11	1.53	38	H (45)	3	32		
54	15	85	26	74	2.83	3.34	18	H (59)	2	15		
60	72	28	66	34	10.76	11.06	3	H (34)	7	4		2
63	31	69	22	78	1.09	1.09	0	H (120)	8			
67	66	34	66	34	9.49	10.89	15	H (94)	5	13		
71	45	55	46	54	8.36	9.24	11	H (51)	5	9		
74	68	32	65	35	3.99	4.64	16	H (195)	8	13	0.4	
86	74	26	69	31	4.80	5.54	15	H (39)	8	13		
103	49	51	37	63	0.34	0.39	15	H (42)	18	12		
106	60	40	30	70	0.71	0.73	3	H (55)	31	3		
107[β]	44	56	11	89	0.66	0.67	2	H (52)	35	2	1	
110[β]	28	72	25	75	25.10	26.59	6	H (49)	8	7		1
111	36	64	30	70	28.68	30.79	7	H (68)	10	7	0.4	0.3
Mean$_{H}$	**51**	**49**	**43**	**57**	**7.16**	**7.79**	**11**	**67**	**11**	**10**	**0.1**	**0.2**
Mean$_{Overall}$	**49**	**51**	**41**	**59**	**4.55**	**4.94**	**17**	**38**	**12**	**12**	**0.8**	**0.1**

[α] indicates the site that exhibited high marsh to low marsh conversion (Site 62 = 0.2% of 2008 area)
[β] indicates the site that exhibited high marsh to non-wetland conversion (Site 107 = 3%; Site 110 = 0.1% of 2008 area

Table 3.2: Mean (±SE in parentheses) area (ha) by marsh type for 30 wetlands in eastern Georgian Bay delineated from 2002 and 2008 IKONOS imagery. P-value corresponds to the paired t-test to determine if 2008 means are significantly lower/higher than the 2002 means.

		Year		
Parameter	**Marsh Type**	**2002**	**2008**	**P-value**
Total Area	Both	4.547 (1.40)	4.938 (1.48)	0.001
Percentage of total area	Low marsh	48.6% (3.78)	41.7% (3.65)	0.0058
Percentage of total area	High marsh	51.4% (3.79)	58.3% (3.76)	0.0022

List of Figures

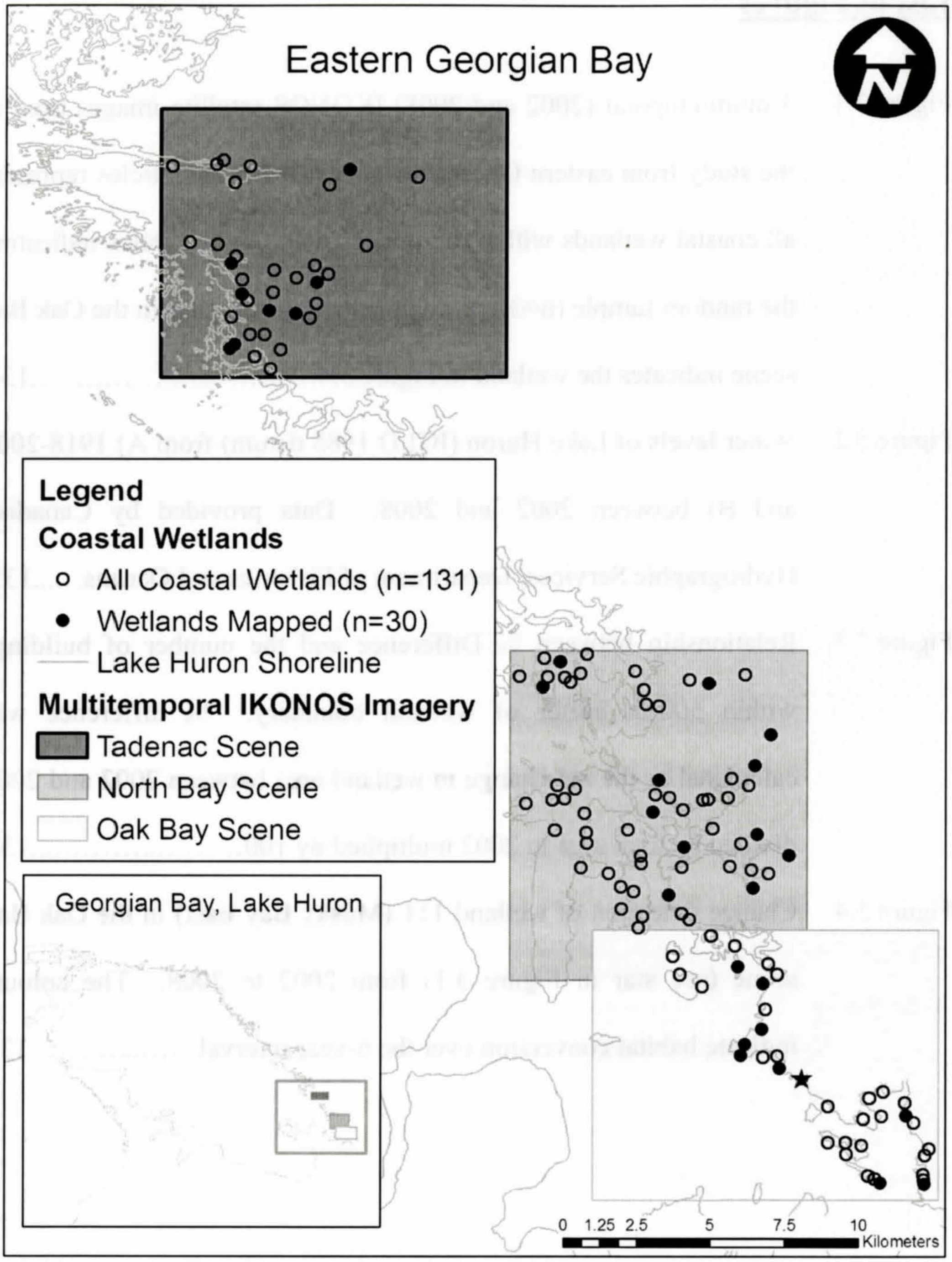


Figure 3.1. 3 multitemporal (2002 and 2008) IKONOS satellite images used in the study from eastern Georgian Bay, Lake Huron. Circles represent all coastal wetlands within the images with closed circles indicating the random sample (n=30) used in the study. The star in the Oak Bay

scene indicates the wetland in Figure 3.4.

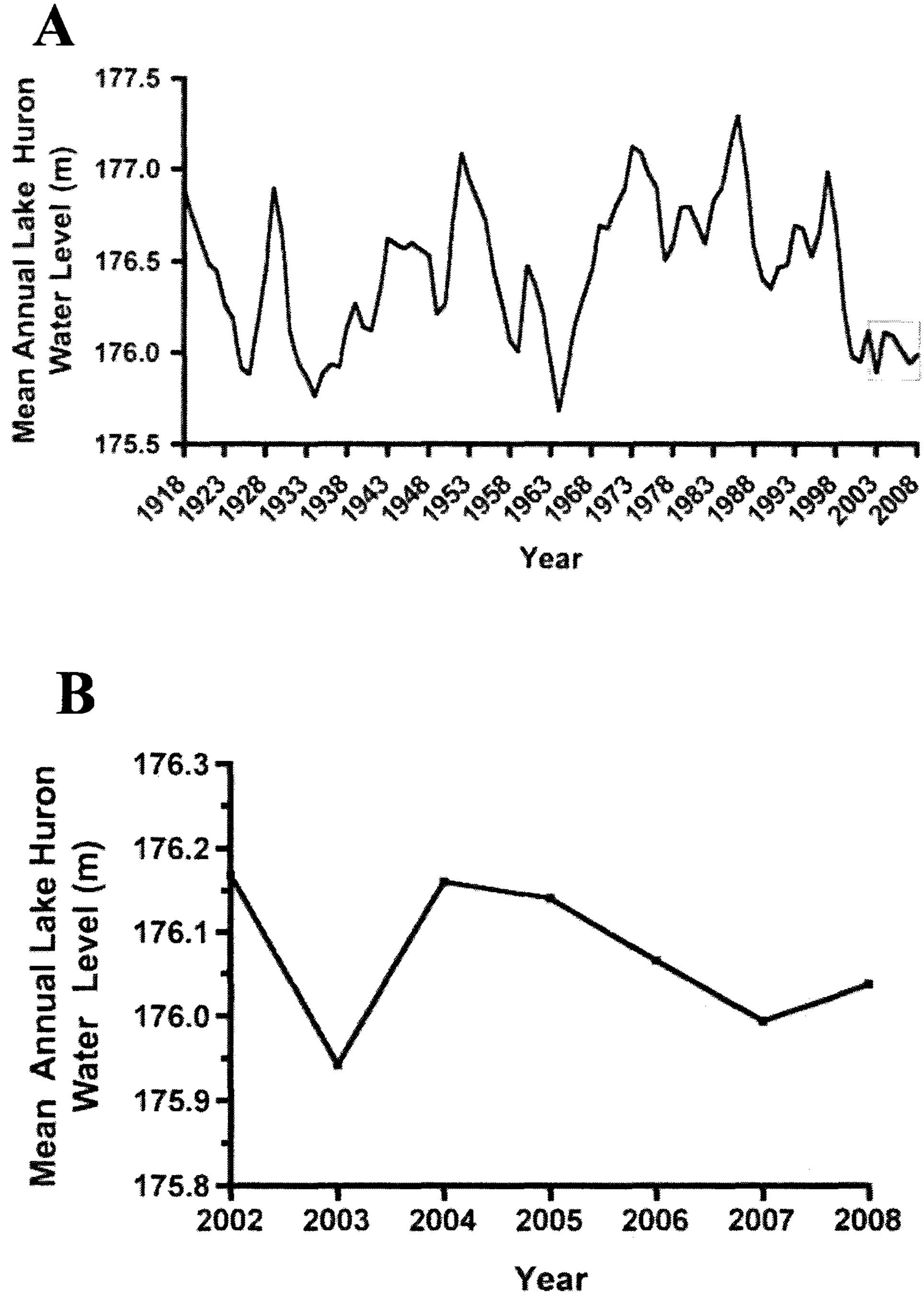


Figure 3.2: Water levels of Lake Huron (IGLD 1985 datum) from A) 1918-2008 and B) between 2002 and 2008. Data provided by Canadian Hydrographic Services, Department of Fisheries and Oceans.

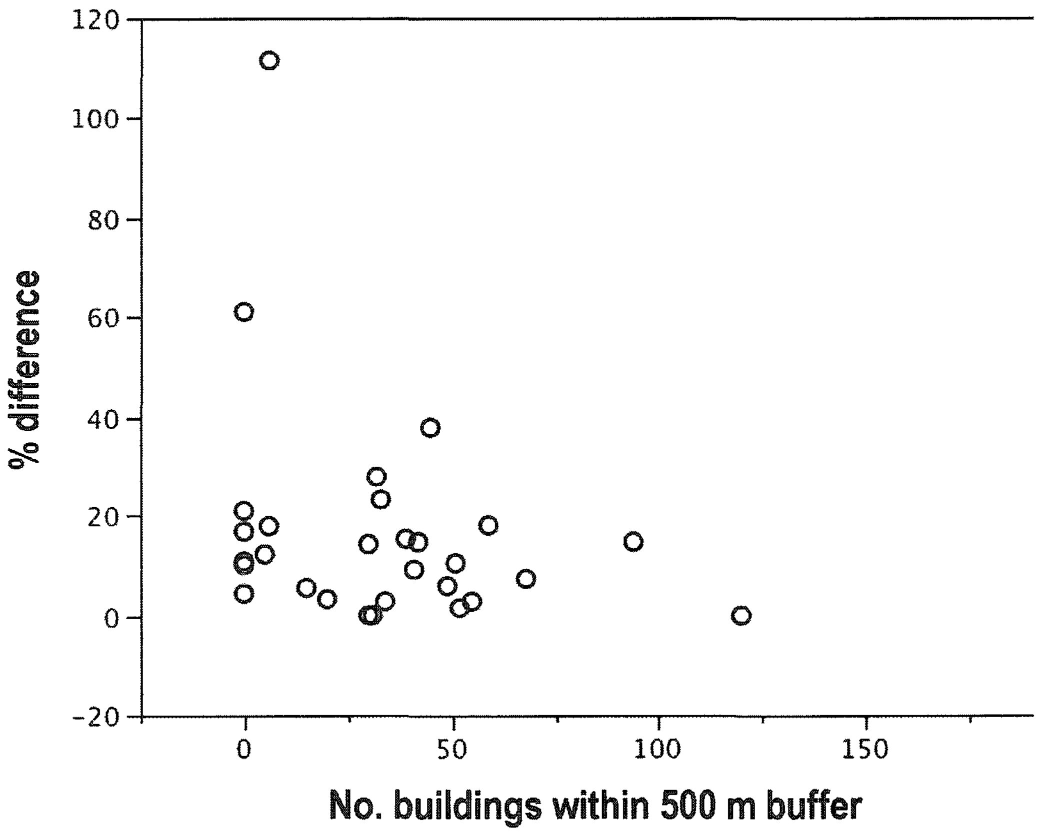


Figure 3.3: Relationship between % Difference and the number of buildings within 500-m buffer of wetland boundary. % difference was calculated as the net change in wetland area between 2002 and 2008 divided by total area in 2002 multiplied by 100.

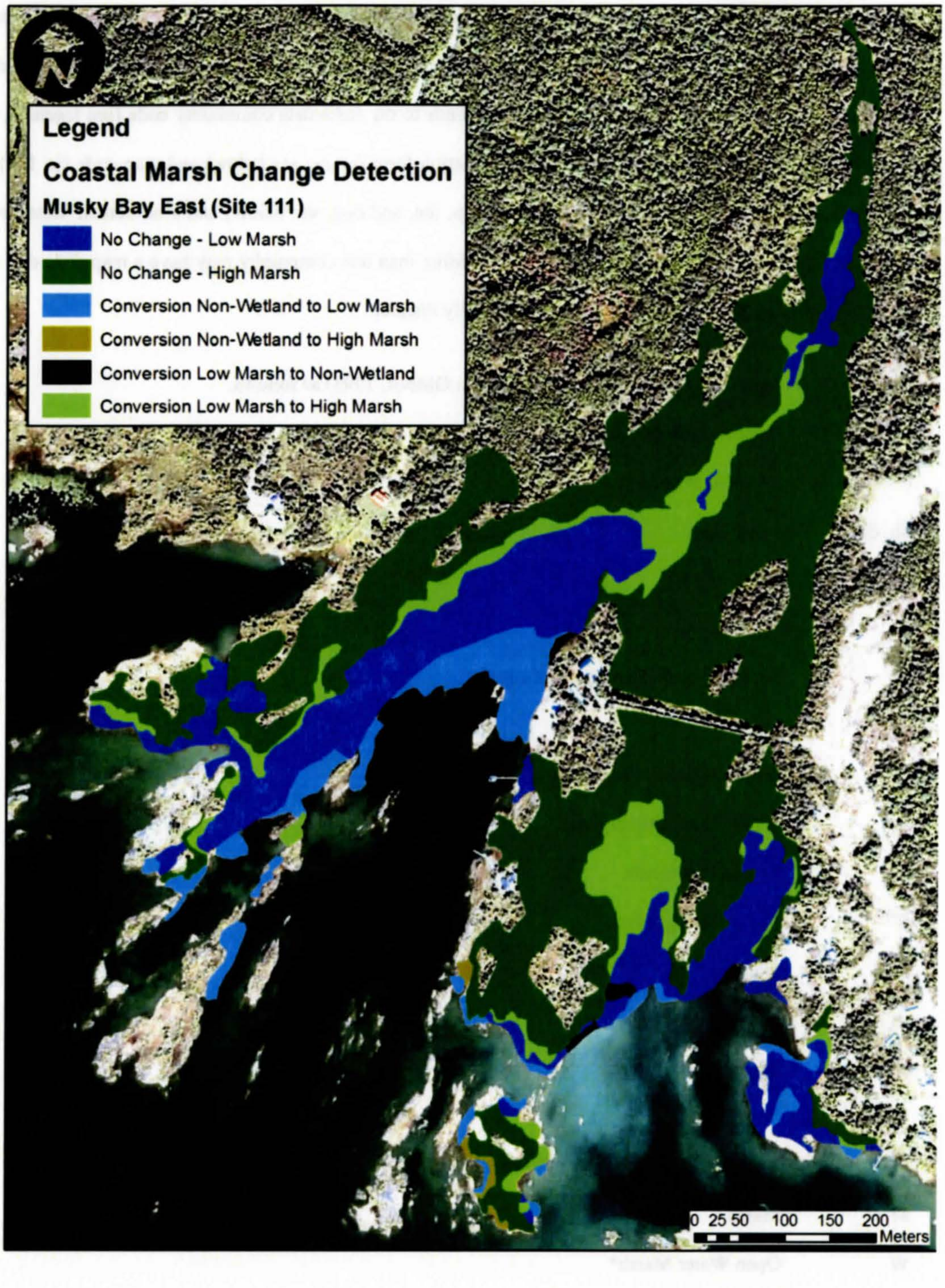


Figure 3.4: Change detection of wetland 111 (Musky Bay East) in the Oak Bay scene (see star in Figure 3.1) from 2002 to 2008. The colours indicate habitat conversion over the 6-year interval.

Appendix A

The following maps depict the vegetation communities identified from field surveying in Chapter 2. Each map includes the wetland boundary and vegetation community boundaries. Each community is labeled with the first identifier being its colour that corresponds to the field–data community code (see legends). Each community is also identified by the dominant vegetation form (ie. ne; see below) and map code (ie. M2). The map code indicates the wetland type (marsh, swamp, fen, and bog; see below) and a numerical identifier that indicates the assemblage of the vegetation form(s). More than one community may have a map code due to the same composition of vegetation forms but are spatially distinct.

The OWES includes 16 vegetation forms (outlined in OMNR, 1993) as follows:

h	Harwood (Decidusous Trees)
c	Coniferous Trees
dh, dc	Dead Trees
ts	Tall Shrubs
ls	Low Shrubs
gc	Ground Cover (Herbaceous Growth)
m	Moss
ne	Narrow-Leaved Emergents
be	Broad-Leaved Emergents
re	Robust Emergents
ff	Free-Floating Plants
f	Floating Plants (Rooted)
su	Submerged Plants
u	Unvegetated

The OWES includes 5 wetland types as follows:

M	Marsh
W	Open Water Marsh*
S	Swamp
F	Fen
B	Bog

*Vegetation communities with a map code with W+ indicate vegetated deep-water habitat included in the Modified OWES (ModOWES) protocol.

The following maps are organized by the 4 wetland categories identified in chapter 2 (small aquatic, small terrestrial, large aquatic, large terrestrial) and include a blank IKONOS image of the wetland and an accompanying image with the vegetation communities overlain.

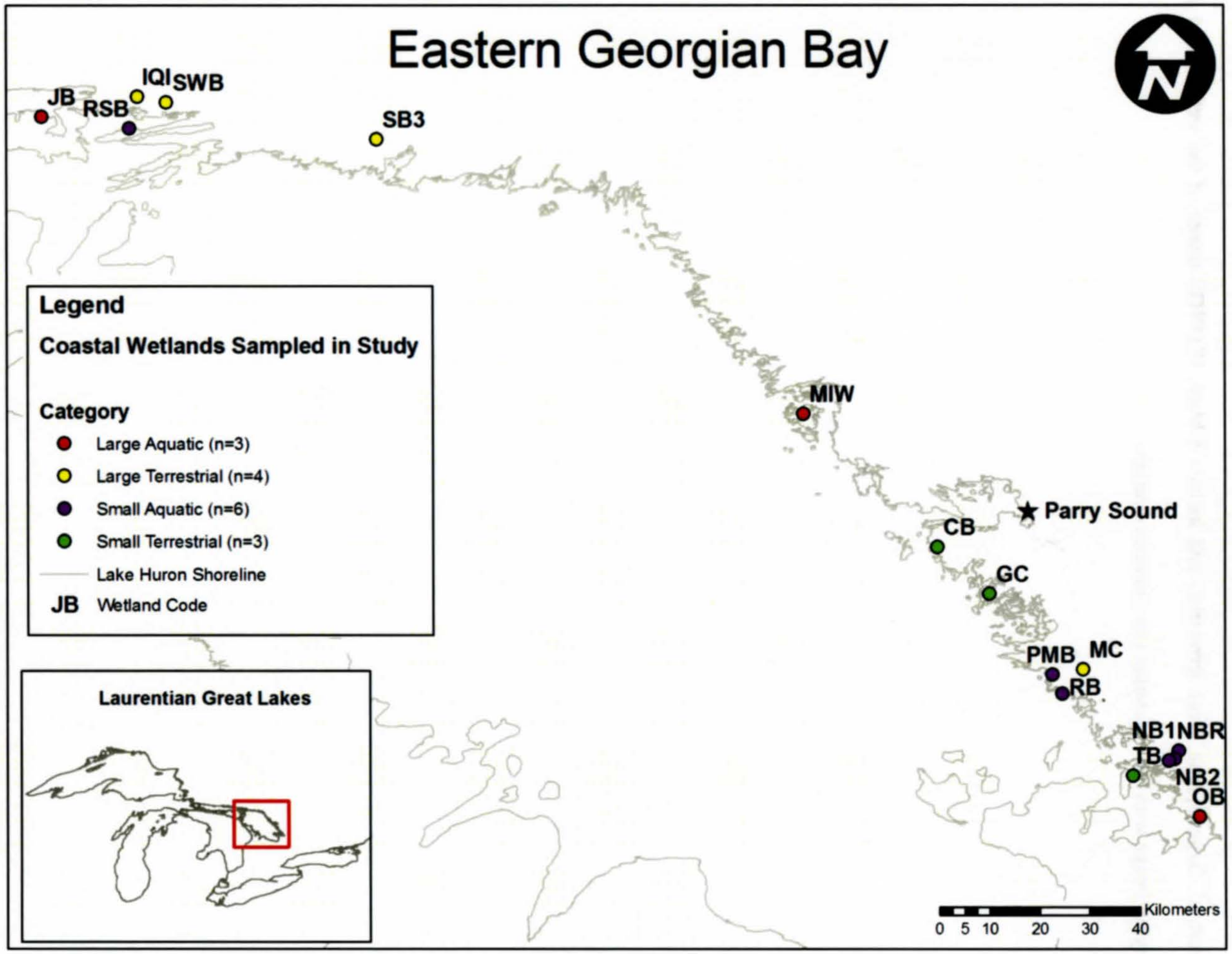
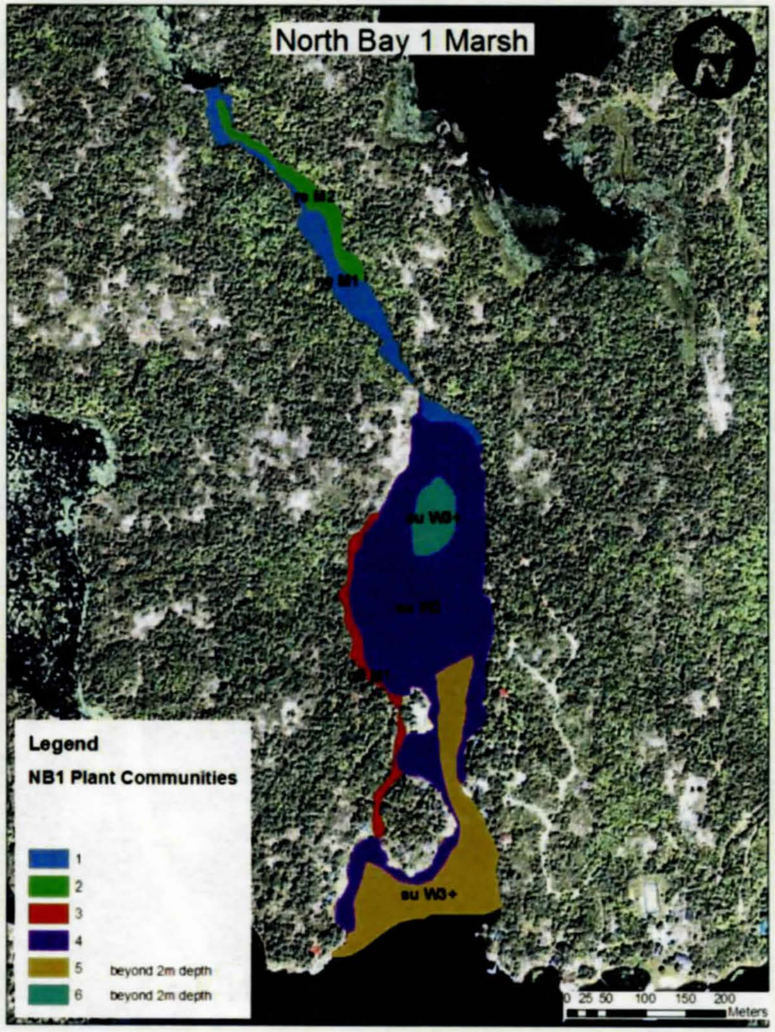
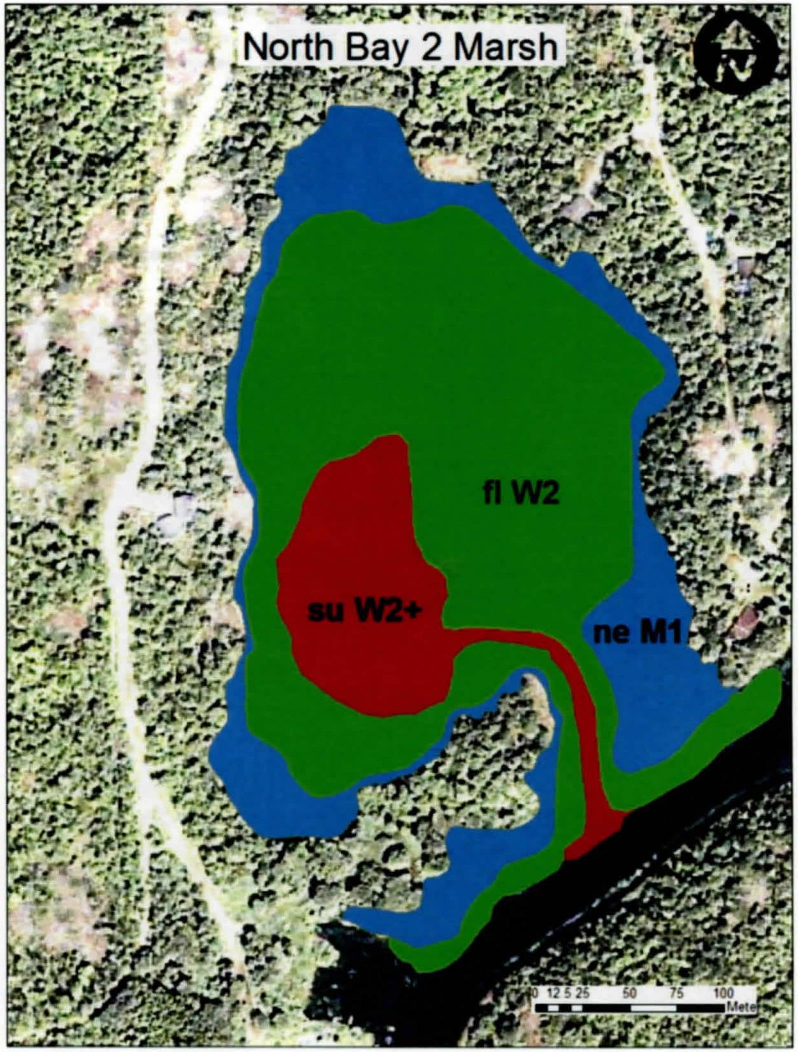


Figure 2.1: Map of the 16 coastal wetlands sampled in eastern Georgian Bay. The colour of the point indicates the category of the wetland as either small aquatic, small terrestrial, large aquatic, or large terrestrial. More specific information and maps can be found in Table 2.1 and Figures 2.2-2.6 and in Appendix A.

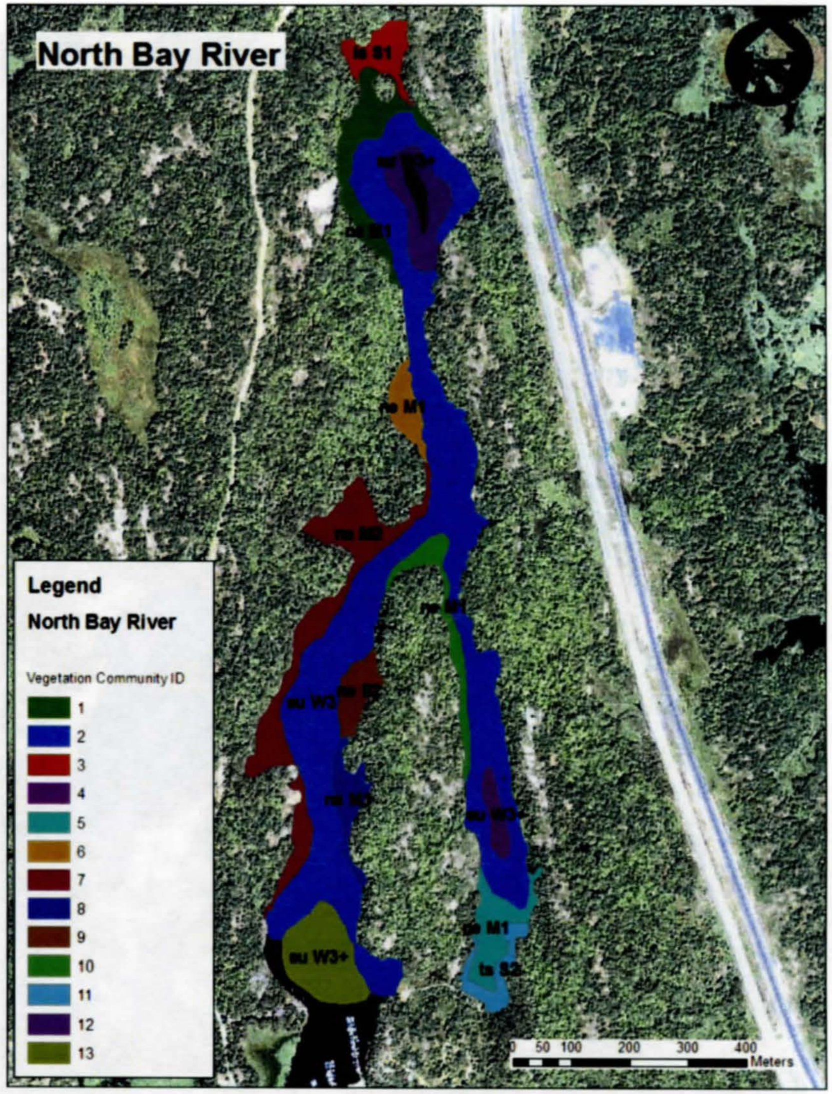
Small Aquatic

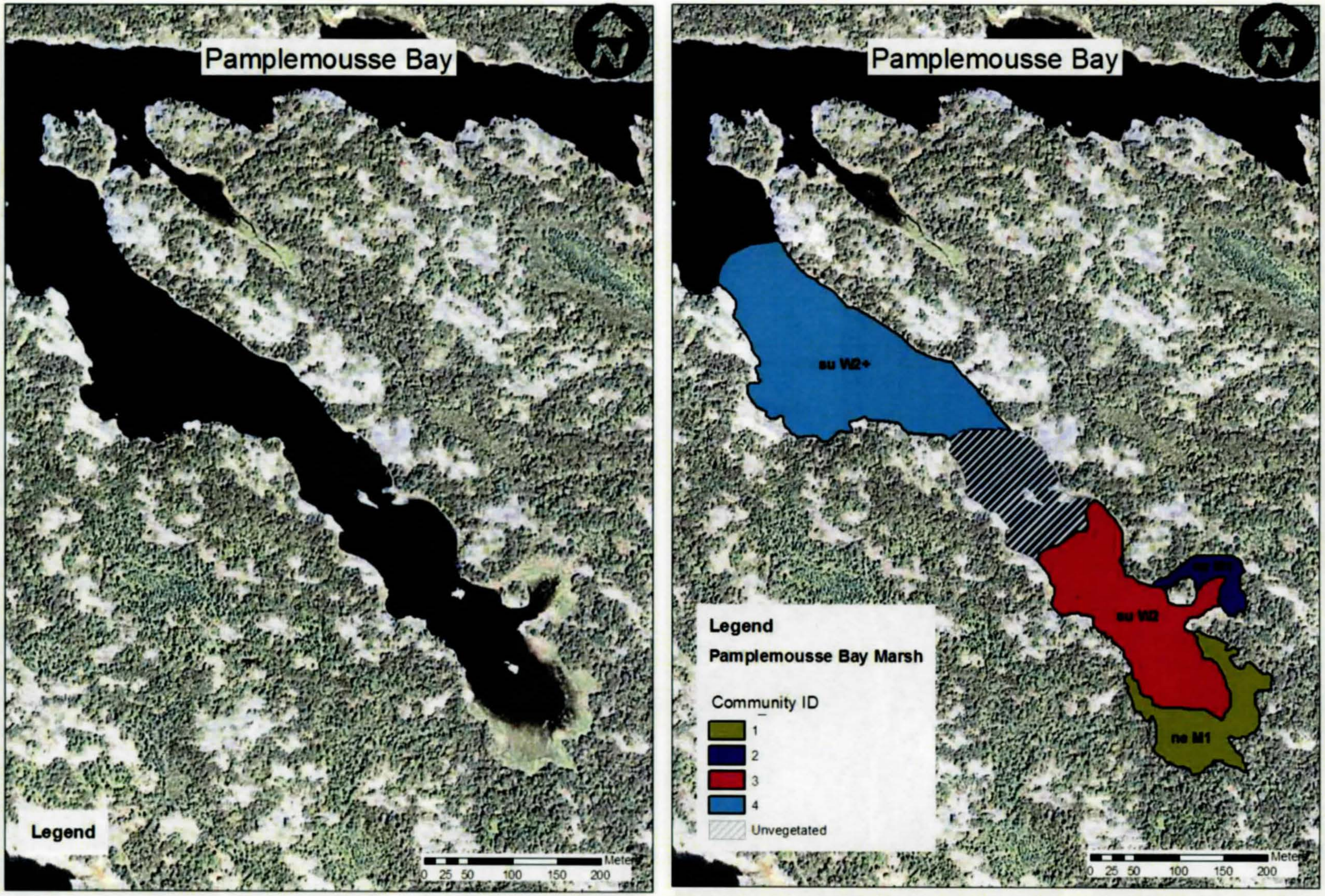



North Bay 2 Marsh

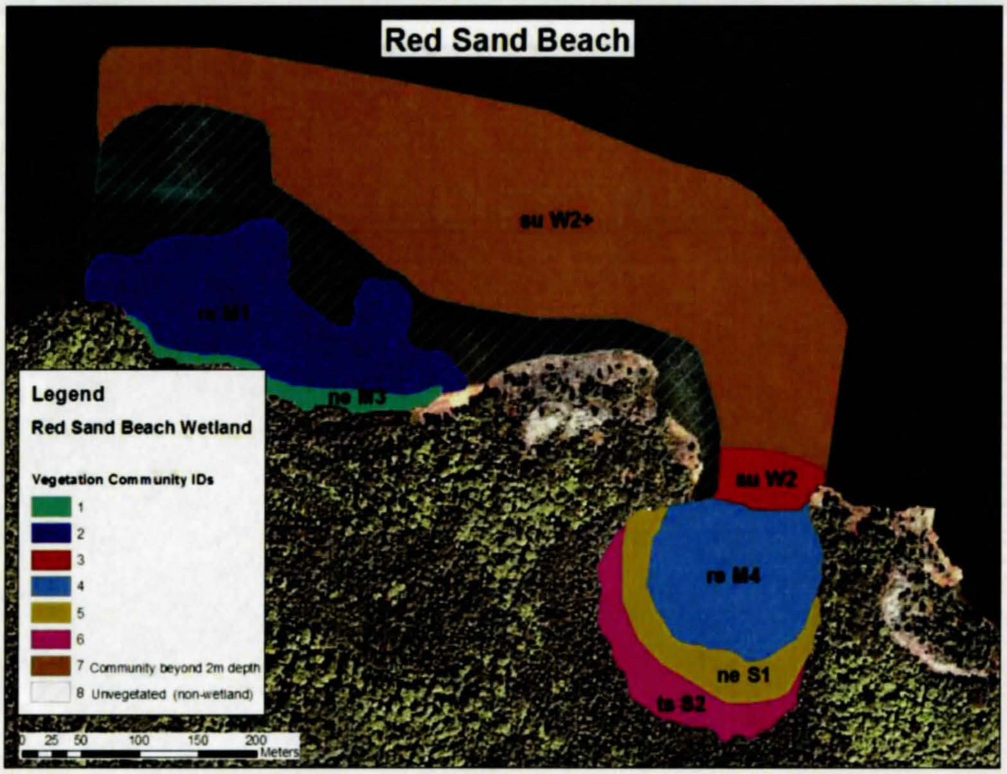

North Bay 2 Marsh
fl W2
su W2+
ne M1


North Bay River
0 50 100 200 300 400
Meters

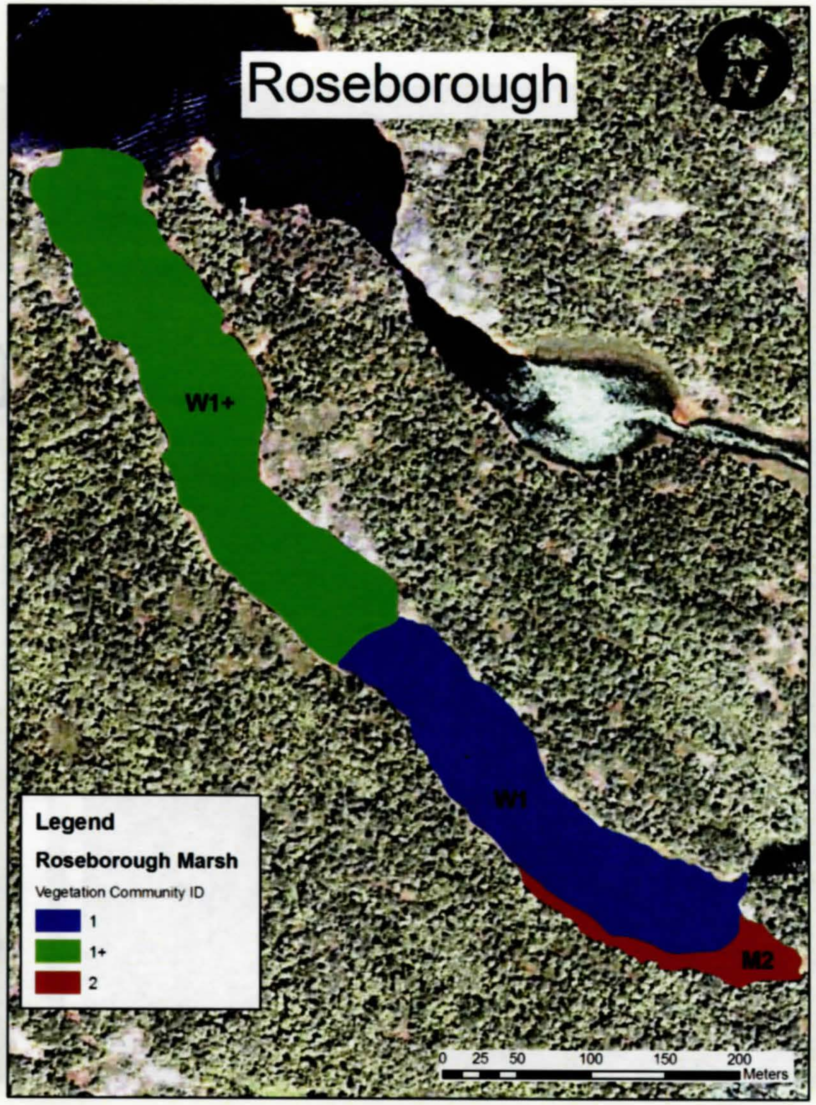

North Bay River
Legend
North Bay River
Vegetation Community ID
1
2
3
4
5
6
7
8
9
10
11
12
13
0 50 100 200 300 400
Meters


Pamplemousse Bay
Legend
0 25 50 100 150 200
Pamplemousse Bay
su W2+
su W2
ne M1
Legend
Pamplemousse Bay Marsh
Community ID
1
2
3
4
Unvegetated
0 25 50 100 150 200

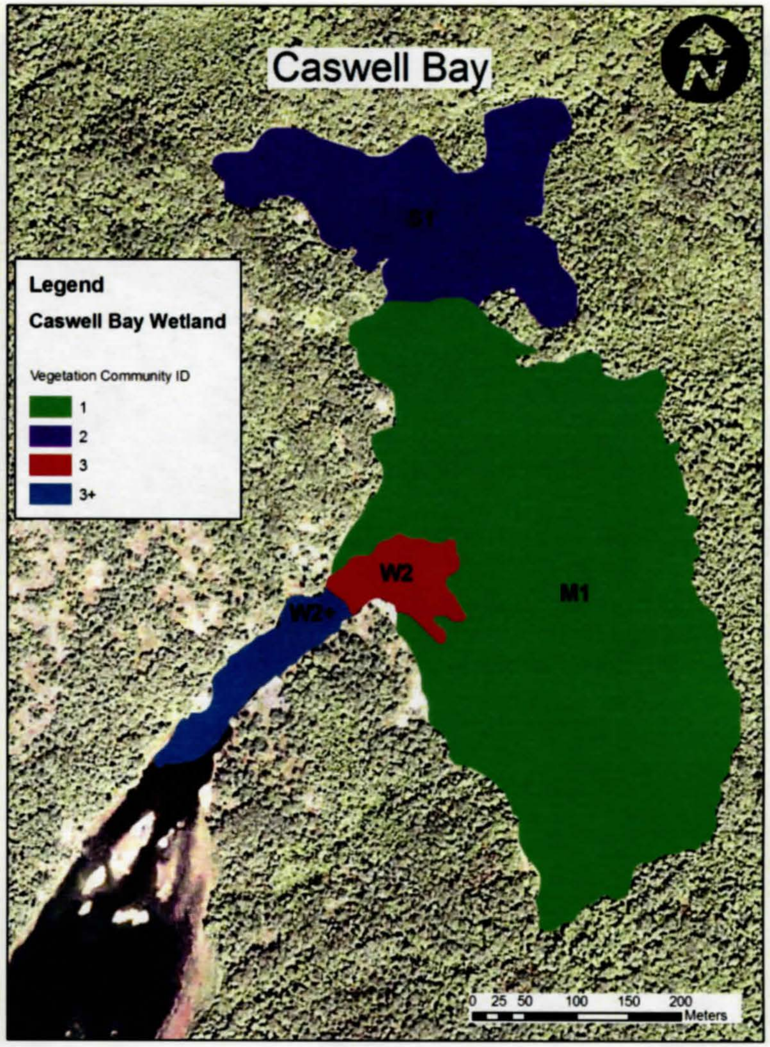

Red Sand Beach
0 25 50 100 150 200
Meters


Red Sand Beach
su W2+
su W2
ne S1
ts S2
Legend
Red Sand Beach Wetland
Vegetation Community IDs
1
2
3
4
5
6
7 Community beyond 2m depth
8 Unvegetated (non-wetland)
0 25 50 100 150 200
Meters

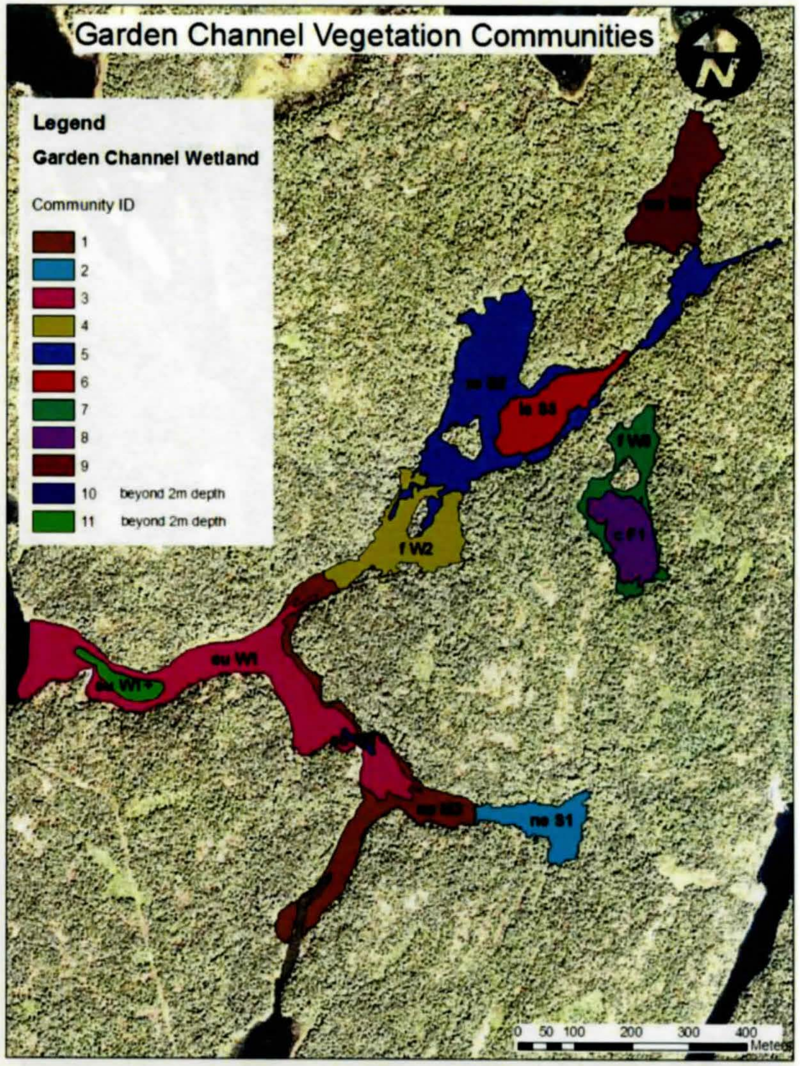

Roseborough
0 25 50 100 150 200
Meters


Roseborough
W1+
W1
M2
Legend
Roseborough Marsh
Vegetation Community ID
1
1+
2
0 25 50 100 150 200
Meters

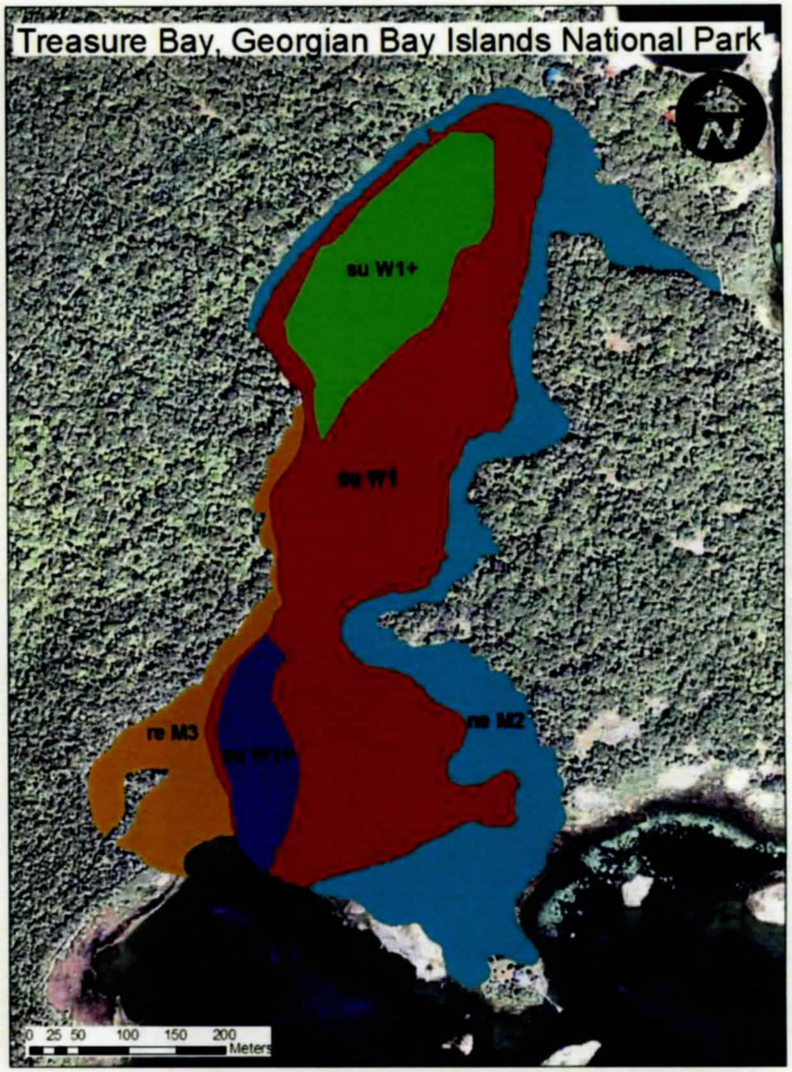
Small Terrestrial



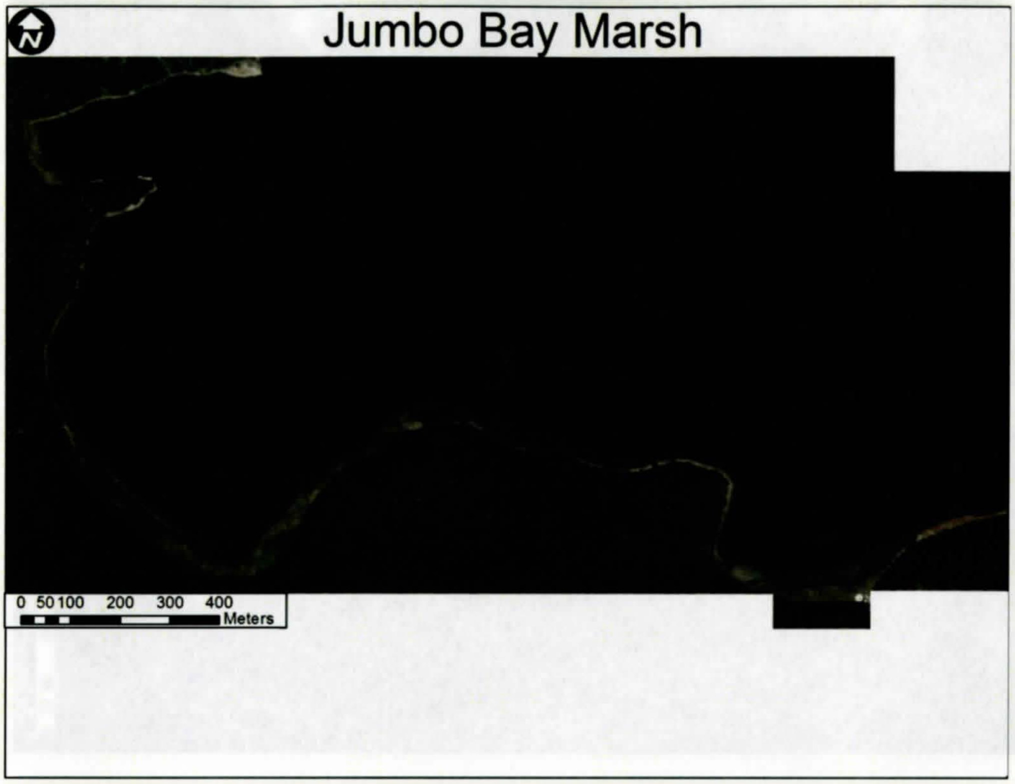

Garden Channel
0 50 100 200 300 400
Meters

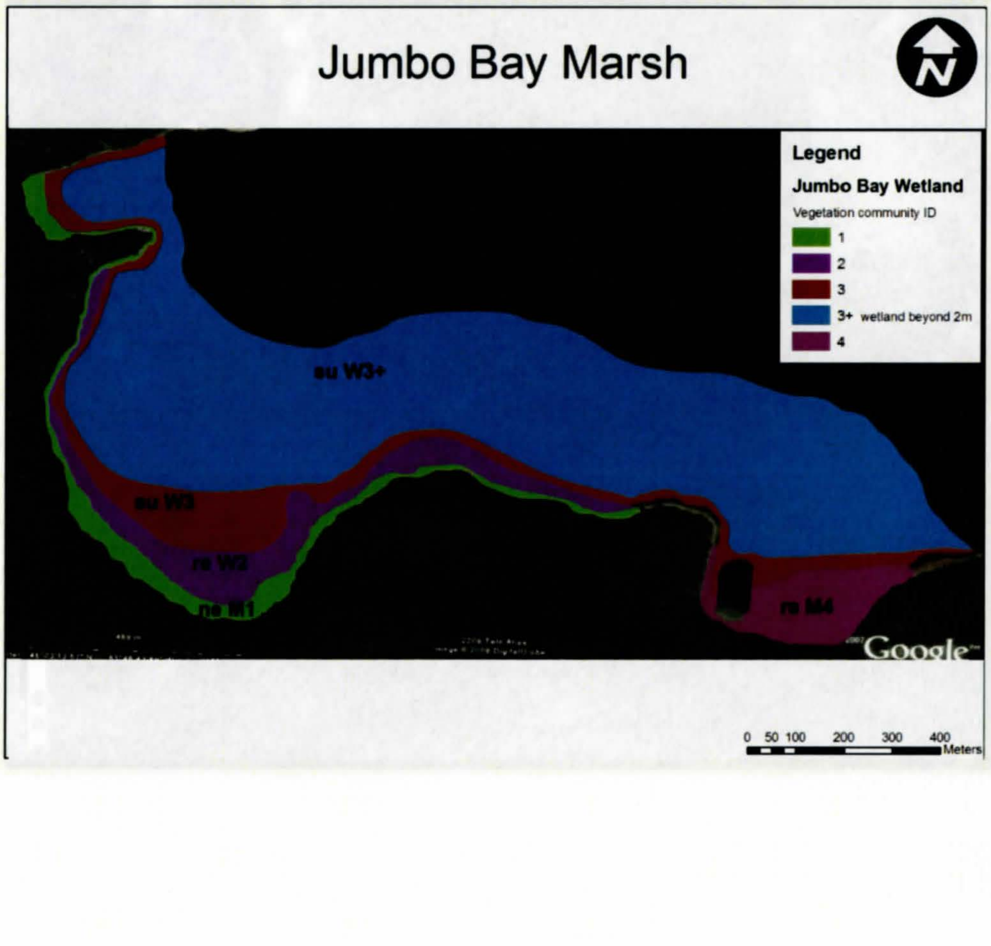

Garden Channel Vegetation Communities
Legend
Garden Channel Wetland
Community ID
1
2
3
4
5
6
7
8
9
10 beyond 2m depth
11 beyond 2m depth
0 50 100 200 300 400
Meters

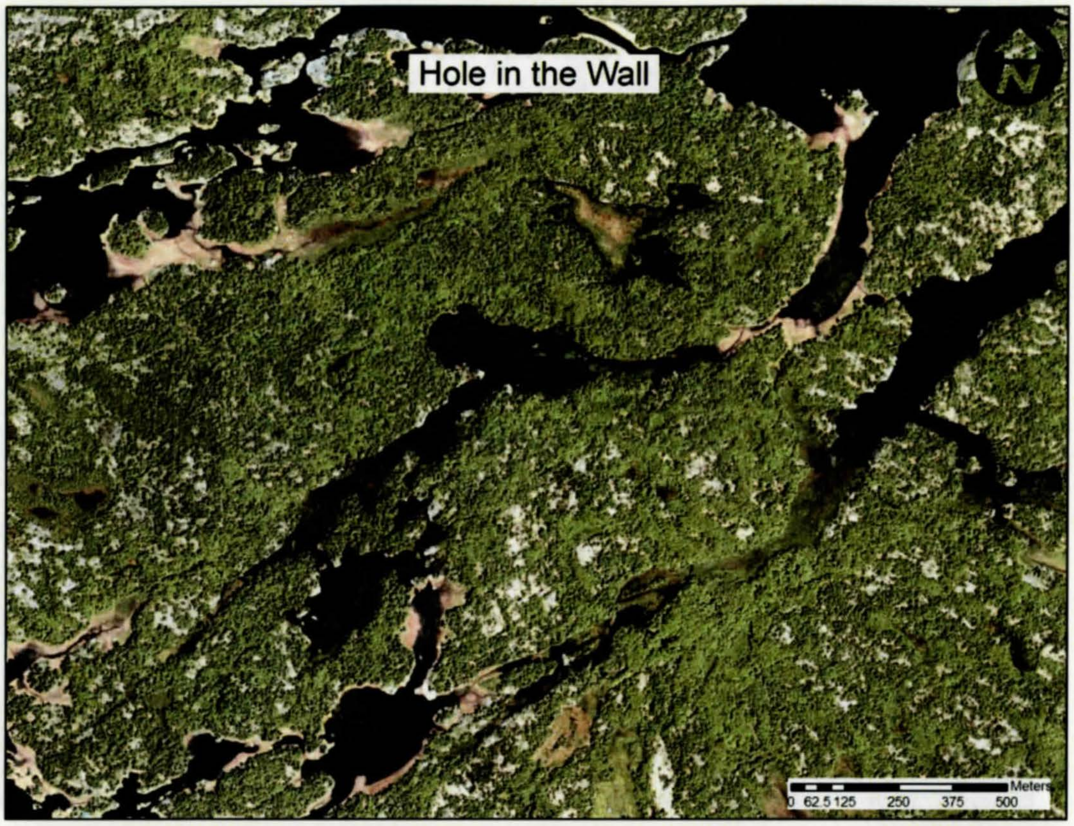

Treasure Bay, Georgian Bay Islands National Park
N
0 25 50 100 150 200
Meters

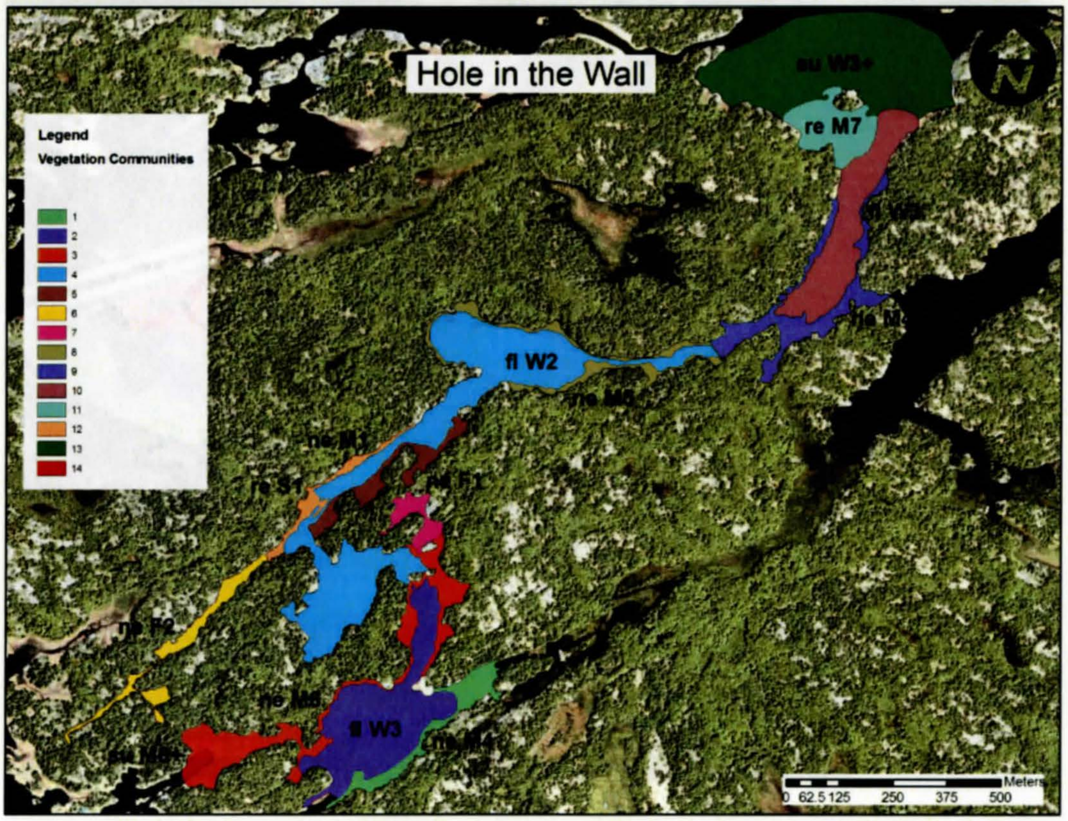

Treasure Bay, Georgian Bay Islands National Park
N
su W1+
su W1
re M3
re M2
0 25 50 100 150 200
Meters

Large Aquatic

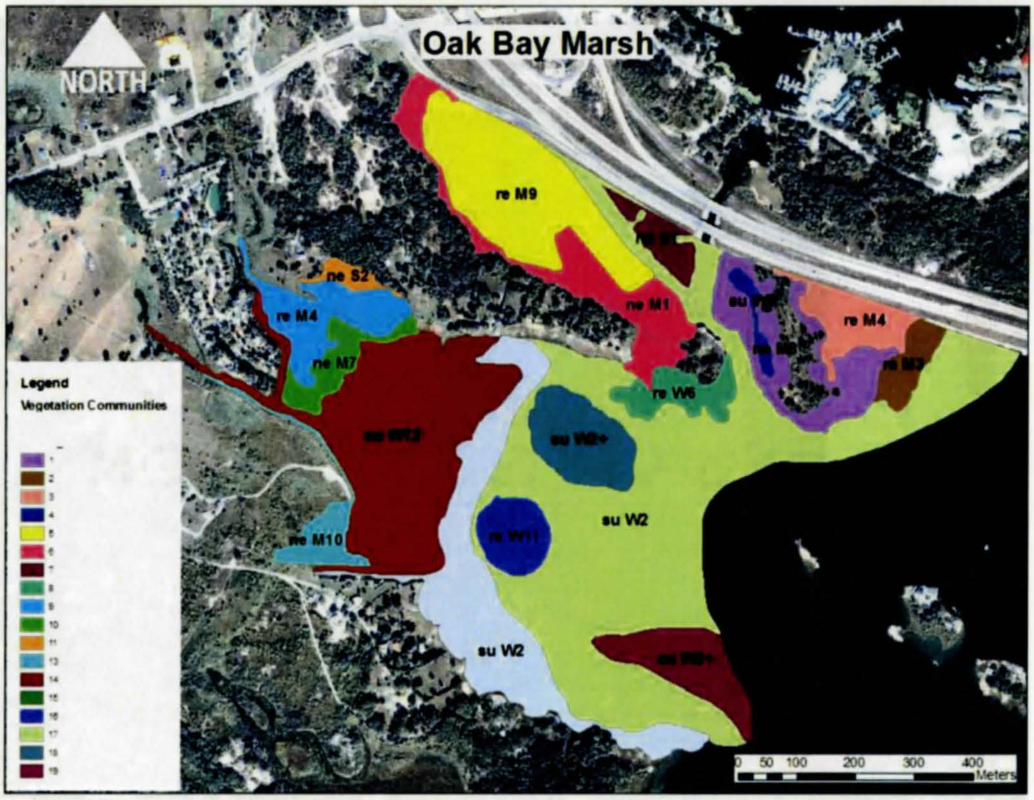




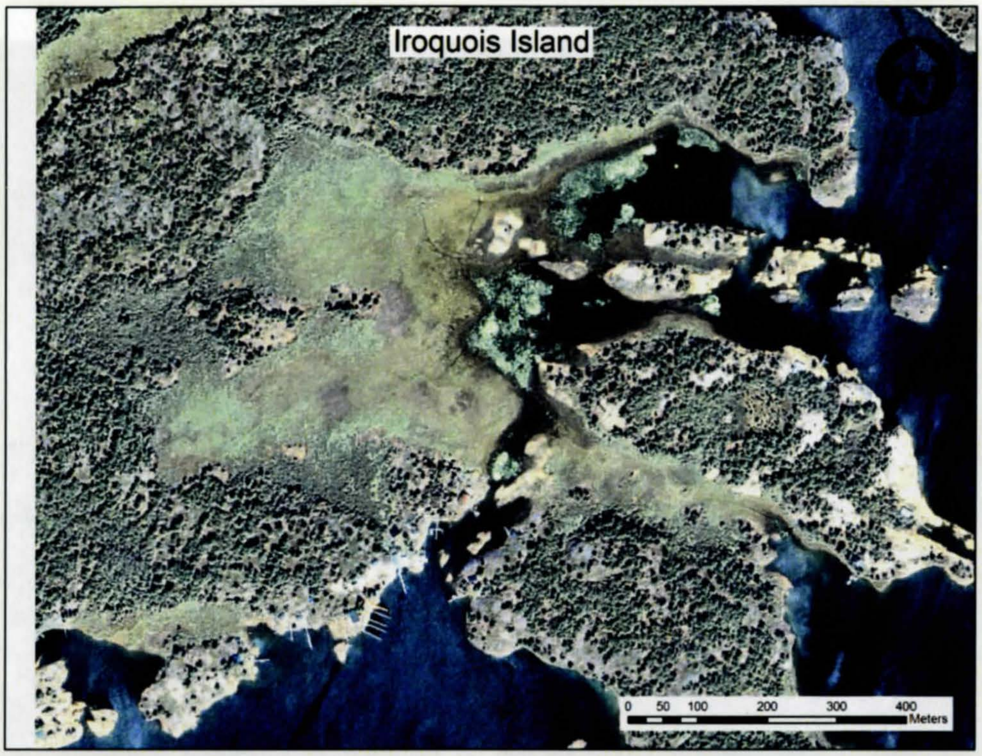

Hole in the Wall
Meters
0 62.5 125 250 375 500

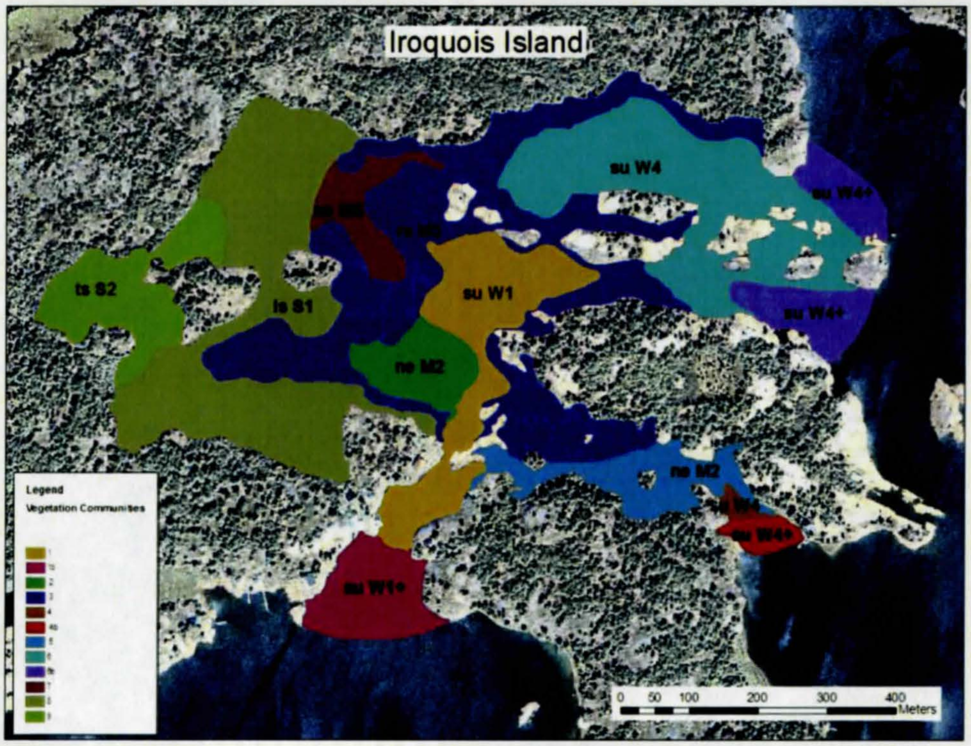

Hole in the Wall
Legend
Vegetation Communities
re M7
fl W2
fl W3
Meters
0 62.5 125 250 375 500

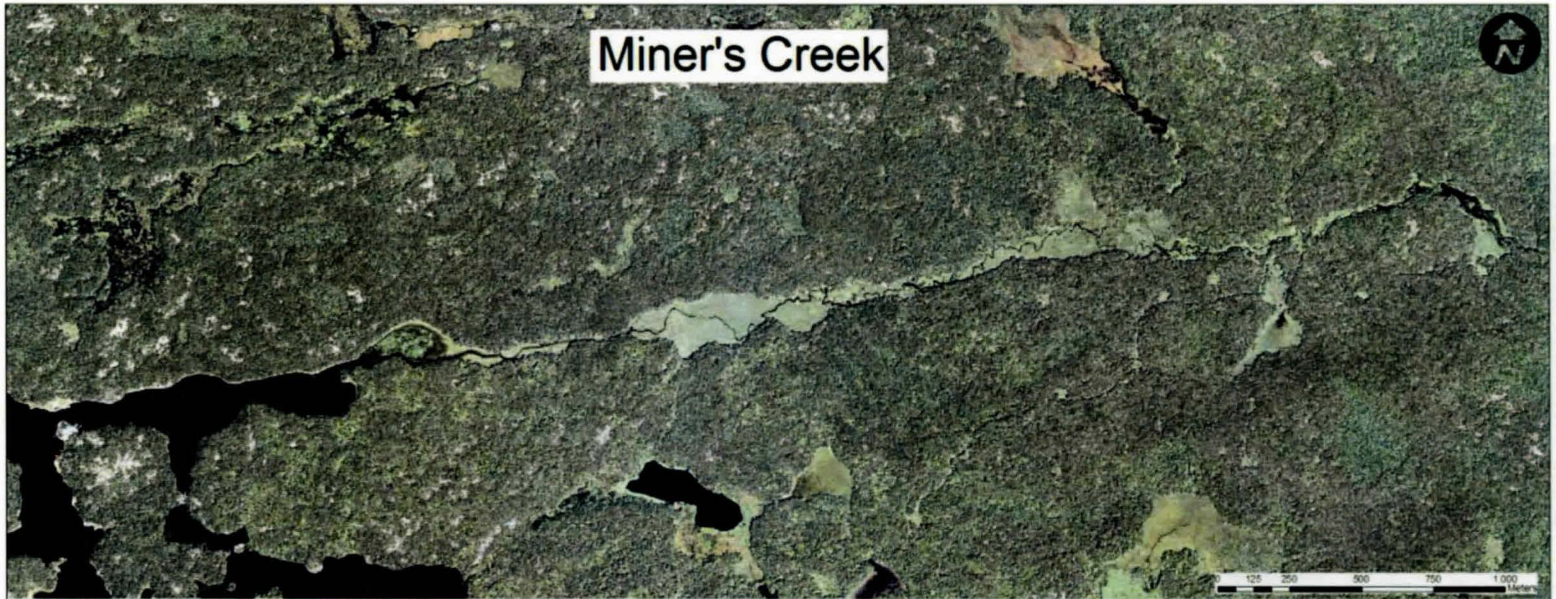

Oak Bay Marsh
NORTH
0 50 100 200 300 400
Meters

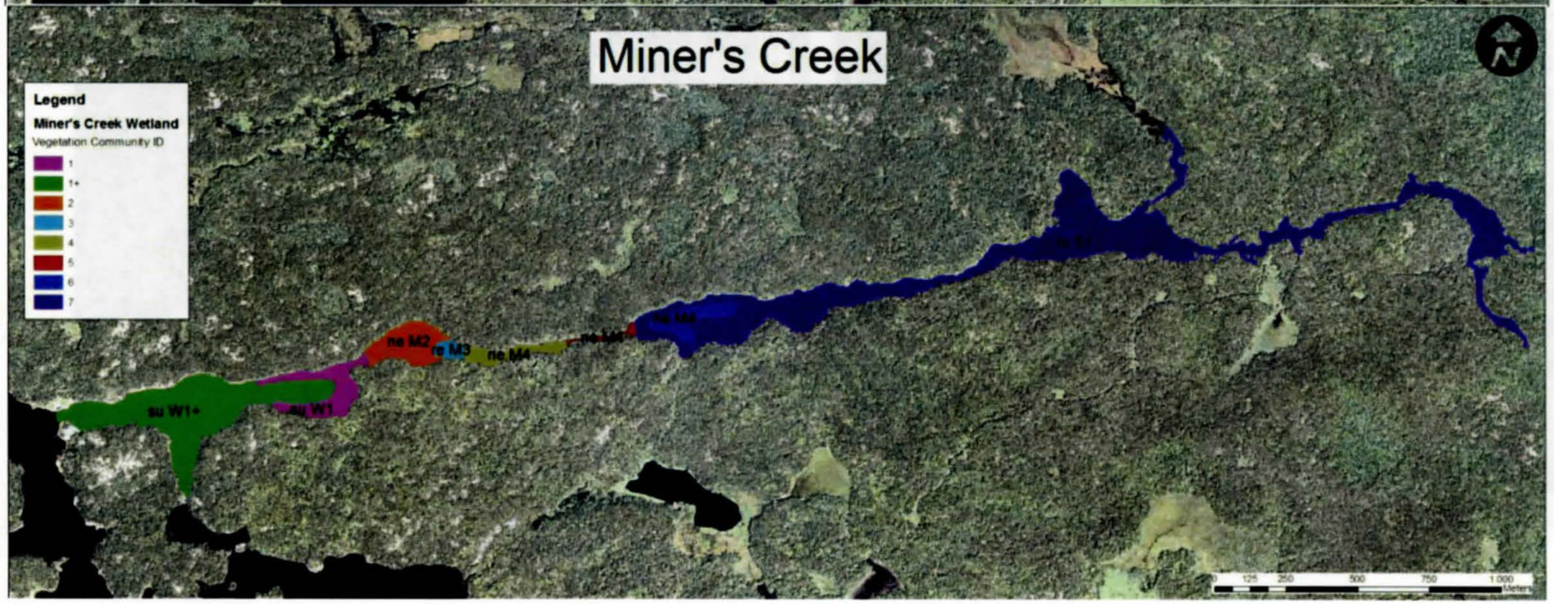

Oak Bay Marsh
NORTH
re M9
ne M1
ne S2
re M4
ne M7
re W6
re M4
su W8+
su W2
ne M10
re W11
su W2
Legend
Vegetation Communities
0 50 100 200 300 400
Meters

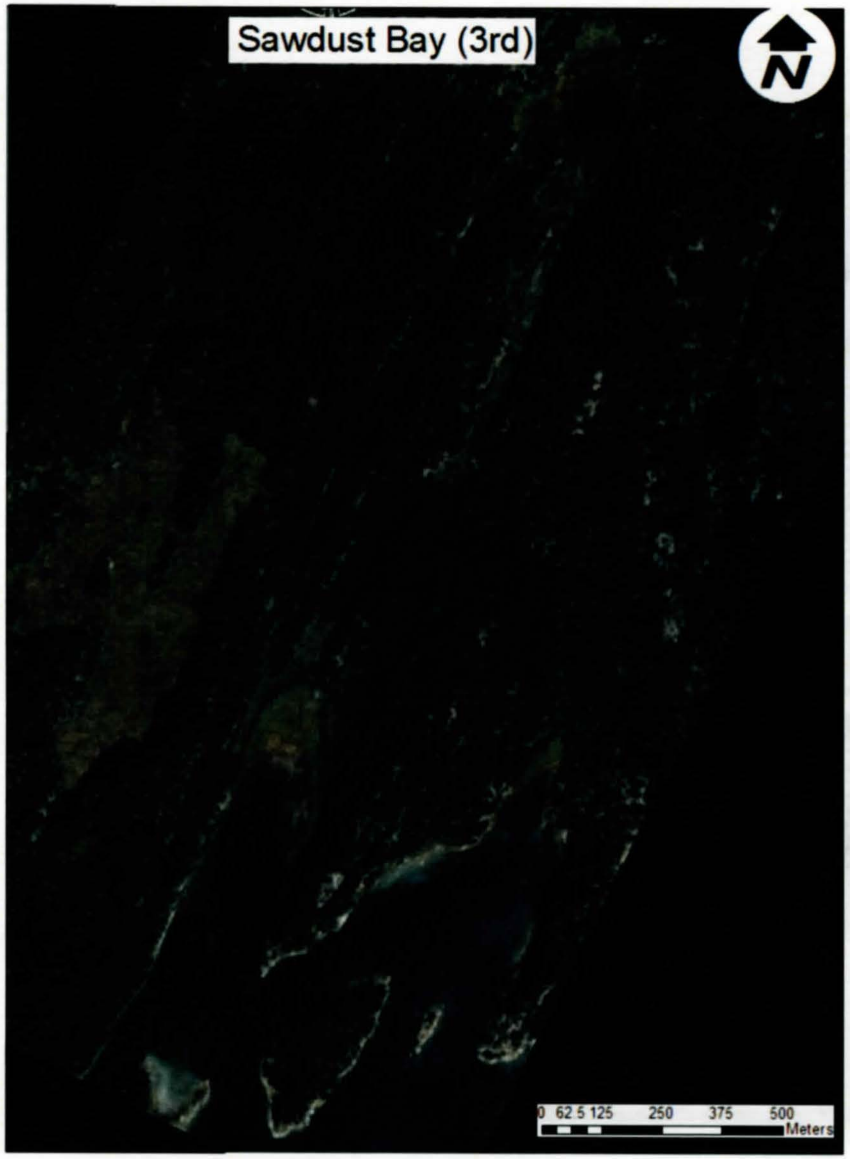
Large Terrestrial

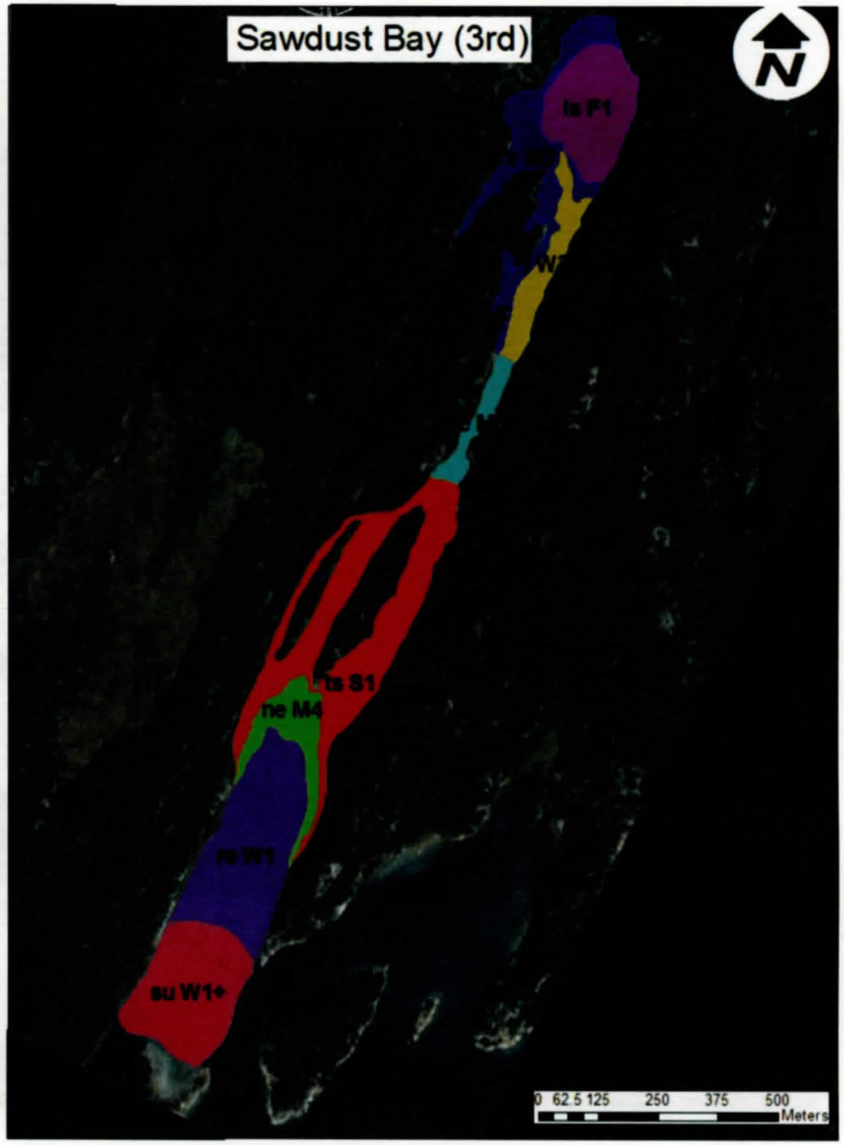


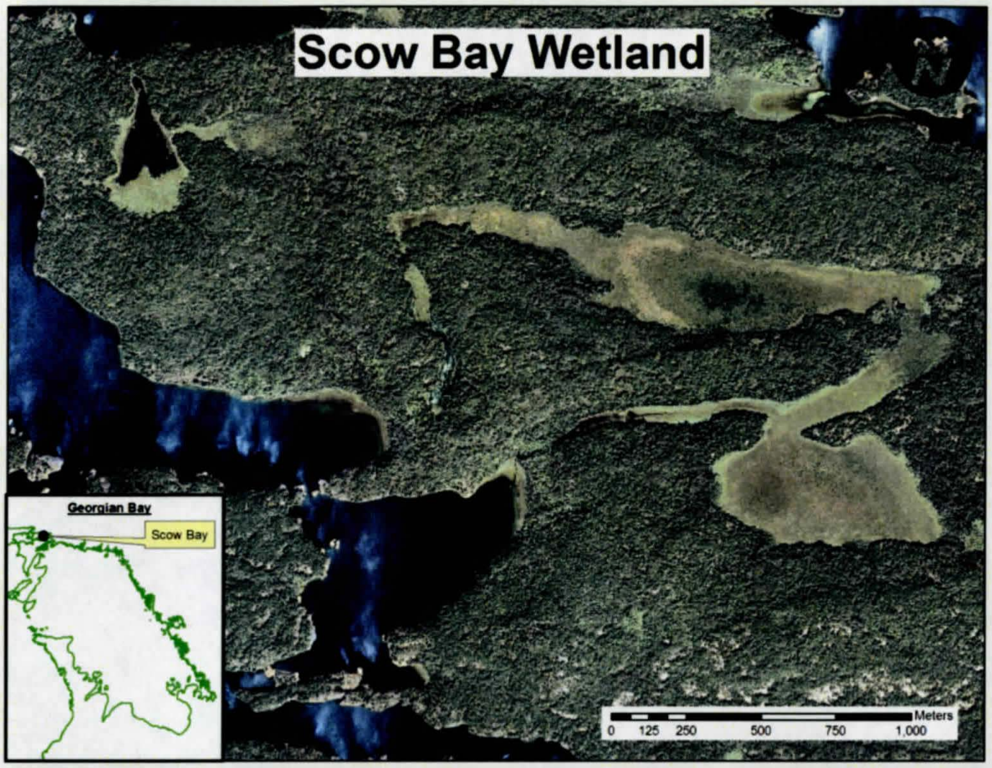


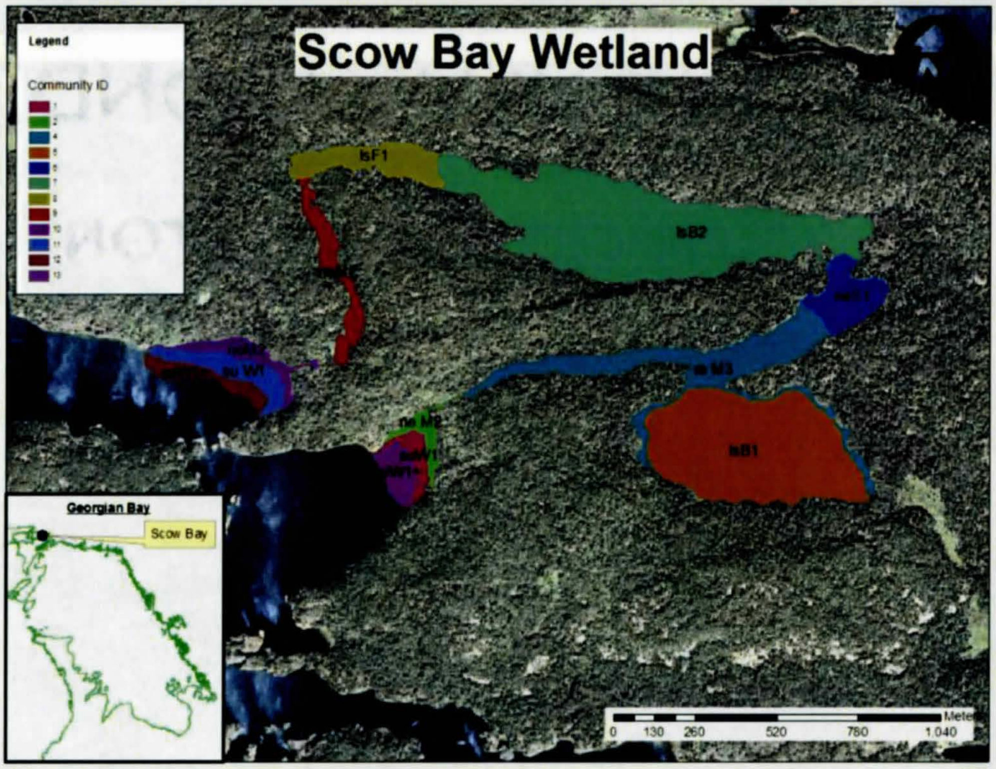

Miner's Creek


Miner's Creek
Legend
Miner's Creek Wetland
Vegetation Community ID
1
1+
2
3
4
5
6
7
su W1+
su W1
ne M2
re M3
ne M4


Sawdust Bay (3rd)
N
0 62.5 125 250 375 500
Meters


Sawdust Bay (3rd)
N
ls F1
ts S1
ne M4
su W1+
0 62.5 125 250 375 500
Meters


Scow Bay Wetland
Georgian Bay
Scow Bay
Meters
0 125 250 500 750 1,000


Scow Bay Wetland
Legend
Community ID
lsF1
lsB2
lsB1
Georgian Bay
Scow Bay
0 130 260 520 780 1,040