Landsc Ecol (2024) 39:44
https://doi.org/10.1007/s10980-024-01829-9

RESEARCH ARTICLE

Change detection of wetland vegetation under contrasting water-level scenarios in coastal marshes of eastern Georgian Bay

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Received: 31 May 2023 / Accepted: 26 December 2023

Abstract
Context Global climate change has resulted in extreme water-level (WL) fluctuations in Eastern Georgian Bay (EGB) and has affected its high-quality wetlands. Beginning in 1999, EGB experienced 14 years of extremely low water levels (Period 1), followed by 6 years of rapidly increasing water levels starting from 2014 (Period 2). During Period 1, trees and shrubs invaded the high marsh, but with inundation, they died out and transitioned into the novel Dead Tree (DT) Zone (DTZ) during Period 2.
Objectives We related long-term changes in wetlands vegetation zonation to different levels of anthropogenic impacts and the Vulnerability Index (VI) scores and wetland sensitivity to WL extremes.
Methods We used images acquired in 2002–2003 (IKONOS) and 2019 (KOMPSAT-3 and Pleiades-1A/1B) for four areas (19 wetlands) in EGB with varying anthropogenic impact. We used object-based classification to map land cover in two periods, followed by change detection. We related the percent areal cover of DT in wetlands to corresponding VI scores.
Results We obtained > 85% overall and > 70% DT mapping accuracies. Wetlands with the least anthropogenic impact had the smallest DTZ. Percentage areal cover of the DTZ was significantly and positively correlated with wetland VI. Without exception, the amount of meadow marsh in wetlands was significantly reduced in Period 2.
Conclusions Wetlands with higher VI scores and anthropogenic impact were associated with greater changes in wetland zonation and conversion into DTZ following extremes in water levels. This study provides important insights into how coastal marshes in EGB are responding to extreme water-level fluctuations induced by climate change.

Keywords Eastern Georgian Bay · Water level · Remote Sensing · Wetlands · Zonation

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Introduction

The five Laurentian Great Lakes of North America (Lake Superior, Lake Michigan, Lake Huron, Lake Erie, and Lake Ontario) are among the top 20 largest lakes in the world by volume and area (Herdendorf 1982). Along the extensive shoreline of these large lakes are thousands of coastal wetland complexes (Cvetkovic and Chow-Fraser 2011), formed at river mouths, in deltas and in open and protected embayments, and behind sand and rock barriers (Albert et al. 2005). These wetlands are economically and ecologically important ecosystems that purify water, reduce flooding risks, and provide habitats for diverse communities of plants, reptiles, and fish. Georgian

Published online: 19 February 2024

Bay, the northeastern arm of Lake Huron, covers an area of over 15,111 km^2 and contains over 30,000 islands (Sly and Munawar 1988). With a unique geomorphological setting and a complex shoreline, Georgian Bay provides a home to several thousand wetland units (Midwood et al. 2012; Weller and Chow-Fraser 2019a).

Unlike the degraded coastal marshes of Lakes Erie and Ontario, those in Eastern Georgian Bay (EGB) have been minimally affected by anthropogenic activities (DeCatanzaro et al. 2009; Cvetkovic and Chow-Fraser 2011); however, water-level fluctuations associated with global climate change and human activities are threatening their ecological integrity (Weller and Chow-Fraser 2019b; Montocchio and Chow-Fraser 2021). Lakes Michigan and Huron are hydrologically connected and display synchronous long-term water-level fluctuations that follow ~ 8 and ~ 12 y fluctuation cycles. (Hanrahan et al. 2009). These patterns of water-level fluctuations are essential for maintaining plant biodiversity because higher water levels tend to lead to a higher proportion of open water and the establishment of Submersed Aquatic Vegetation (SAV) communities, while lower water levels tend to lead to a lower proportion of open water and establishment of meadow marsh and emergent vegetation (Keddy and Reznicek 1986; Wilcox and Nichols 2008). Beginning in 1999, however, water levels dropped to extremely low levels and remained low for 14 years (Period 1). Uncharacteristically, this was followed by an abrupt increase in 2014 that has since continued to climb to record high levels in 2020 (Period 2) (Montocchio and Chow-Fraser 2021).

When water levels dropped to extremely low levels during Period 1, previously inundated areas (where SAV and emergent vegetation had been established) became exposed and began to support meadow vegetation and even non-wetland species such as pine trees. When water levels abruptly increased during Period 2, these meadow and terrestrial species became flooded and began to die, forming a novel zone of shrubs and dead trees (DT) along the shoreline. The persistence of this dead tree zone (DTZ) considerably altered the structure and function of these coastal marshes. A survey of fish communities from 2003 to 2019 showed that there had been a change in the fish communities between the two periods of contrasting water levels (Montocchio and Chow-Fraser 2021). In another study, coastal marshes in Georgian Bay that had once supported young-of-the-year muskellunge was no longer suitable as nursery habitat because of a structural change in the SAV community (Leblanc et al. 2014; Leblanc and Chow-Fraser 2017). Further research showed that habitat suitability was related to hydrogeomorphic characteristics of wetlands (slopes, wave exposures, areal extents, and volumes of wetland habitats) that indicated their vulnerability to water-level disturbances; plant communities assessed as being least suitable were found in wetlands with the highest Vulnerability Index (VI) scores (i.e. least resilience to water-level disturbance; Weller and Chow-Fraser 2019b). These results confirm the study by Cvetkovic et al. (2010) that showed the dependence of the fish community on structure and function of the plant community in Great Lakes coastal marshes.

Remote sensing provides one of the best ways to examine temporal changes in plant structure over a large geographic area (Baker et al. 2007; Munyati 2000, 2004). Remote sensing-based change detection uses multitemporal images (images collected in two or more periods) to quantify changes in an area of interest based on changes in the reflectance signature of the land cover (Deng et al. 2008). This could be achieved through direct image reflectance comparison using image subtraction, image ratio, remote sensing-based indices, or image classification approaches (Shaoqing and Lu 2008). In addition, remote sensing methods are also being used to assess many wetlands-related features such as instantaneous water extent, temporal estimates of hydroperiod, soil moisture, water chemistry, and many others (Brisco et al. 2017; Millard and Richardson 2018; Chasmer et al. 2020). Furthermore, investigators have combined this information with topographical data to develop metrics of wetland zonation, hydrology, and connectivity (Crasto et al. 2015; Ameli and Creed 2017; Chasmer et al. 2020).

In the current study, we quantify changes in distribution of wetland habitat classes in four coastal regions of Eastern Georgian Bay (EGB) with different levels of anthropogenic disturbance. We use remote sensing techniques and satellite images acquired in 2002–2003 and in 2019 to map the distribution of wetland habitat classes between extremely low (Period 1) and extremely high (Period 2) water periods, respectively. Since the DTZ is a novel habitat class, we hypothesize that the areal extent of the DTZ would be positively related to the region's VI scores (which would be high if ecosystem resilience were low). Further, we predict that the degree of change in wetland habitats would vary with the degree of human disturbance in the region. This study provides hitherto unreported and important insights into how vegetation in coastal marshes in EGB will respond to extremes in pattern of water-level fluctuations induced by climate change.

Methods

Study sites

The four regions in this study are located along the shoreline of EGB, the eastern arm of Lake Huron which is separated from the main lake by the Bruce Peninsula and Manitoulin Island (Fig. 1). EGB has over 30,000 small islands that form the largest freshwater archipelago (Rokitnicki-Wojcik et al. 2011). This archipelago is both geologically unique, underlain by the Precambrian Shield, and biologically diverse, containing thousands of small pristine coastal marshes, where the anthropogenic impact has thus far been limited to recreational and residential development (Midwood et al. 2012; Weller and Chow-Fraser 2019a). The southernmost region is Severn Sound which includes the town of Honey Harbour, where there is heavy recreational development and has the highest anthropogenic impact among the selected regions. The ten sites in Severn Sound are North Bay, Ojibway Bay, Treasure Bay, Roberts Island, Vennings Bay, Quarry Island, Potato Island, Potato Island (PI) Marsh, Oak Bay, and Green Island. North of Severn Sound is the Tadenac Bay region, which experiences the least anthropogenic impact; this region has been managed for over a century as a protected area for fish and wildlife communities and the sites include Miners Creek, Black Rock, Tadenac, and David's Bay. The two other regions located further north are Franklin Island and Pointe au Baril,

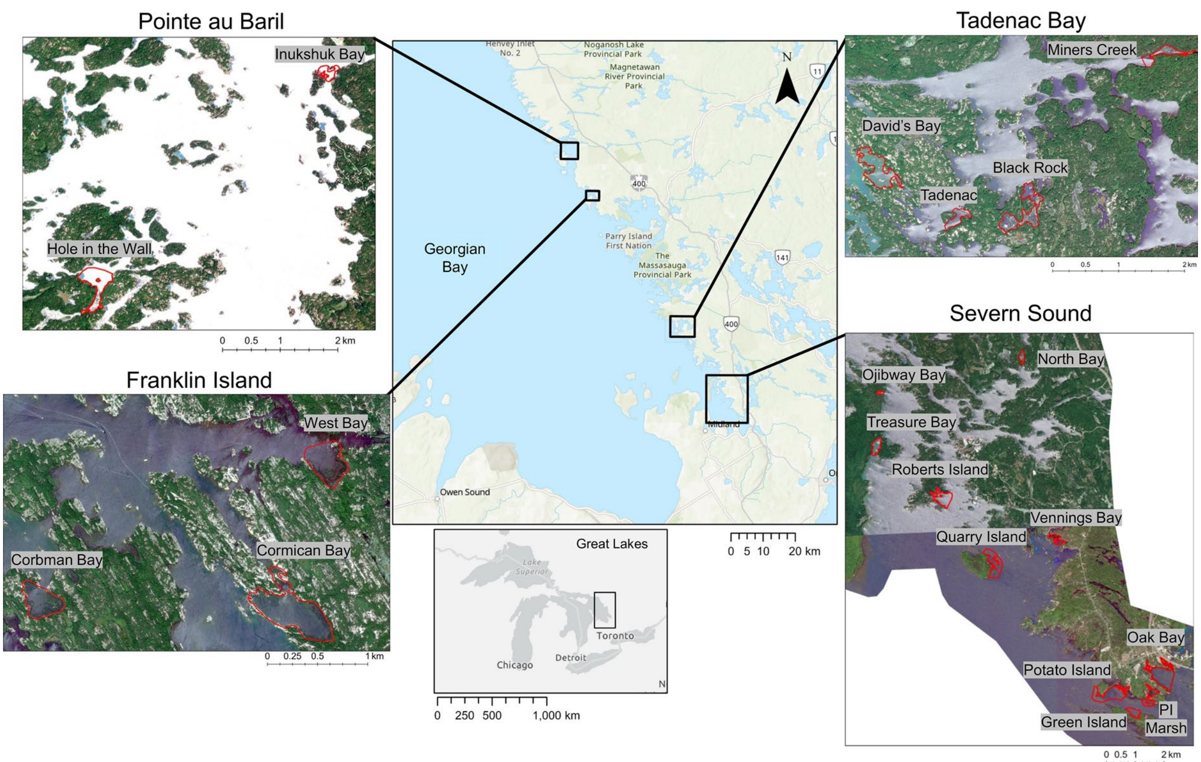


Fig. 1 Study Sites in the four regions

both of which experience intermediate human impact related to cottage development. We selected three wetlands in the Franklin Island region which include Franklin Island, Corbman Bay, Cormican Bay, and West Bay, and two wetlands in the Pointe au Baril region, which includes Hole in the wall, and Inukshuk Bay.

Ground reference data

We used ground truth data from several different sources for this study. Firstly, we conducted fieldwork in the summer of 2021 to collect ground reference data. We recorded geographic coordinates and took photographs of different land cover classes to be used in the image classification and accuracy assessment. Secondly, we used field data collected in EGB between 2003 and 2008 inclusive for various research projects (Chow-Fraser, unpub. data, McMaster University). We also used high-resolution Unmanned Aerial Vehicle (UAV; 4-cm resolution) images collected from 2013 to 2019 for individual wetlands (Chow-Fraser, unpub. images, McMaster University). Lastly, we used aerial photographs (20-cm resolution) collected by the Central Ontario Orthophotography Project (COOP) and South Central Orthophotography Project (SCOOP) in 2016 and 2018 respectively. We visually assessed the UAV and aerial imagery to extract ground reference points for all the land-cover classes considered in the image classification. We also used many ground reference points per region collected as a combination of all sources (further explained under Sect. 'Image classification and accuracy assessment'). In addition, we used wetlands manually delineated by Midwood et al. (2012) as a guide to determine the water level and distribution of wetlands in Period 1.

Image Data

High-resolution IKONOS images and high-accuracy wetland inventory products were already available for Period 1 (Midwood et al. 2012). The IKONOS satellite images (3.2 m multispectral and 0.82 m panchromatic) were provided by Georgian Bay Forever (formerly Georgian Bay Foundation) and was operated by MAXAR Technologies Inc. launched in September 1999 and was decommissioned in March 2015 (Satellite Imaging Corporation 2022a). IKONOS images that cover the study area were collected in 2002 and 2003 (Table 1). We used Red, Green, blue, and Near InfraRed (NIR) bands in our image classification. These images had been pre-processed and pan-sharpened to 1 m resolution by the image provider (Midwood and Chow-Fraser 2010).

Given that the IKONOS satellite was retired in 2015, and there was insufficient time for wetlands to exhibit detectable changes in vegetation zonation by 2015, we had to use other sensors, recognizing that this would limit our ability to use index-based change-detection techniques. We were able to use high-resolution images from a single sensor for three regions (Pleiades1A/1B; 2 m multispectral and 50 cm Panchromatic 0.5 m pansharpened resolution), and the KOMPSAT-3 (2.8 m multispectral and 0.7 m pansharpened resolution) for the remaining (Table 1). Pleiades is composed of two satellites, Pleiades-1A (2 m multispectral and 0.5 m panchromatic) and Pleiades 1B (2 m multispectral and 0.5 m panchromatic) and were launched in December 2011 and 2012 respectively. These are owned by AIRBUS Defence and Space and are still functioning (Satellite Imaging Corporation 2022b, 2022c). KOMPSAT-3 is owned by the Korean Aerospace Research Institute (KARI) and was launched in May 2012 and was decommissioned in May 2022 (eoPortal 2022; Satellite

Table 1 Satellite image information

Site	Period 1		Period 2	
	Satellite	Image acquisition Date	Satellite	Image acquisition Date
Tadenac Bay	IKONOS	07-03-2002	Pleiades-1B Pleiades-1B	06-21-2019 06-27-2019
Franklin Island	IKONOS	06-25-2003	KOMPSAT 3	07-07-2019
Pointe au Baril	IKONOS	06-25-2003	Pleiades-1B	07-14-2019
Severn Sound	IKONOS	07-03-2002	Pleiades-1A Pleiades-1B	06-21-2019 06-27-2019

Imaging Corporation 2022d). Both KOMPSAT-3 and Pleiades-1A/1B Images consist of Blue, Green, Red, and NIR bands. We performed radiometric and atmospheric correction (ENVI QUAC correction) to these images and pansharpened using the Nearest Neighbour Diffused Pansharpening (KOMPSAT-3 to 2.8 m and Pleiades-1A/1B to 0.5 m) with ENVI 5.5 (L3Harris Geospatial 2020) prior to image classification. Since there was a displacement between the images collected for Periods 1 and 2, we used image-to-image georegistration in ArcGIS Pro to produce an exact overlap between corresponding IKONOS and KOMPSAT-3 or IKONOS and Pleaides-1A/1B images. Pleiades and KOMPSAT had very similar spatial resolutions and spectral bands (blue, green, red, and NIR). We further performed geometric corrections for UAV, SCOOP, and COOP images which were sources of ground reference data.

Image classification and accuracy assessment

For all study sites, we created separate independent sets of classification and validation points using multiple sources (explained under Section 'Ground reference data') for the images collected in Periods 1 and 2. For image classification, we included 6 land cover classes in both time Periods: i) emergent, meadows or shrubs (EMS), ii) floating vegetation (FV), iii) open water (OW), iv) rocks and barren land (RBL), v) submersed aquatic vegetation (SAV), and vi) trees (T). For Period 2, however, we added vii) the dead tree zone (DTZ) as an additional land cover class. Initially, we tried to map emergent, meadow and shrubs as three separate classes, respectively, but due to high confusion among these individual classes, we combined them into a single one (i.e. EMS). Similarly, we considered rocks and barren land as separate classes initially but then combined them into a single one (RBL). We used approximately 30% of the total reference points for the accuracy assessment and we selected these points manually to ensure that the points are uniformly distributed. The total number of reference points varied for the four sites due to differences in available ground reference data for each area, distribution of each class across the landscape, and the areal cover of the image (Table 2). We used a minimum of 5 locations for both classification and accuracy assessment for each class and each study site. For both periods and all study sites, we conducted object-based image classification with the random forest classifier followed by the accuracy assessment using Quantum GIS (QGIS) 3.16.16 (Semi-automatic Classification (SCP), dzetsaka: Classification Tool, and Orfeo Toolbox (OTB) 8.1.0 plugins).

Table 2 Total number of training and validation points used in image classification and validation

Site	Period	Training data	Validation data
Tadenac Bay	Period 1	90	41
	Period 2	120	51
Franklin Island	Period 1	57	28
	Period 2	88	45
Pointe au Baril	Period 1	312	120
	Period 2	152	65
Severn Sound	Period 1	226	97
	Period 2	441	181

Data analysis

After image classification, we used both QGIS and ArcGIS Pro for further data analysis. First, we used the COOP 2016 and SCOOP 2013 Digital Elevation Models (DEM) (Ontario Ministry of Natural Resources 2015, 2017) to extract the water level corresponding to dates of acquired images (Government of Canada 2019). Then we visually inspected the satellite images used for the image classification along with UAV images (depending on the availability) to manually edit the water level extracted from the DEM. We created a 10-m buffer around the shoreline of each wetland and used it to clip the classified images acquired for the two periods. For Period 1, we used the McMaster Wetlands Inventory by Midwood et al. (2012) to determine the shoreline. We then converted the clipped wetland classification layers to raster (resolution of the corresponding Period 2 image for both periods) and used the SCP plugin in QGIS to conduct the change detection.

We sorted the data according to three anthropogenic disturbance levels: High (Severn Sound wetlands), Moderate (Pointe au Baril and Franklin Island wetlands), and Low (Tadenac Bay Wetlands). We then determined if there were significant differences in percent DTZ among the three anthropogenic levels. Since the data were not normally distributed, we performed Kruskal–Wallis H test followed by the Mann–Whitney U test with IBM SPSS Statistics 28.0.1.0. We also used the same non-parametric tests to compare significant differences in percentage areas of land-cover classes that had changed between low and high water levels, and significant differences in percentage areas that had changed to the DTZ for all land cover classes. We extracted the mean VI scores for each wetland in this study using the data calculated in Weller and Chow-Fraser (2019b) for EGB. We then correlated percentage areal cover of the DTZ against VI scores. VI scores range from 0 to 1, with 1 indicating that wetlands are highly vulnerable to sustained water levels due to relatively low substrate slope (see Weller and Chow-Fraser 2019b for complete explanation).

Results

We obtained over 85% overall accuracy for all sites for the two time periods with the object-based classification using the Random Forest classifier. We also obtained over 70% users' and producers' accuracies for the DTZ in Period 2 (Table 3).

Overall, we observed the greatest shift in shoreline for wetlands located in the Franklin Island region and the least for wetlands in the Tadenac Bay region, although on a per unit area basis, the largest DTZ was observed in the Severn Sound region, and the smallest in the Tadenac Bay region (Fig. 2). The areal cover of DTZ differed significantly among the regions when they were sorted by disturbance levels (Kruskal–Wallis H test; $P < 0.05$); in pairwise comparisons (Mann–Whitney U test), areal extent of DTZ in the Tadenac region (lowest disturbance level) was significantly lower than that in the Pointe au Baril and Franklin Island regions (moderate disturbance level; $P = 0.014$) and lower than that in the Severn Sound region (highest disturbance; $P = 0.048$). We did not find any significant differences in areal cover of DTZ between the sites experiencing moderate and highest disturbance.

Table 3 Accuracies for overall classification and for the DTZ. There was no DT in Period 1

Site	Period	Overall Accuracy (%)	Accuracy of DTZ classification	
			Users' Accuracy	Producers' Accuracy
Tadenac Bay	Period 1	92.0	–	–
	Period 2	89.4	100.00	75.23
Franklin Island	Period 1	92.6	–	–
	Period 2	92.9	74.84	80.73
Pointe au Baril	Period 1	95.8	–	–
	Period 2	92.0	88.88	74.37
Severn Sound	Period 1	98.6	–	–
	Period 2	97.3	96.69	91.53

We found a general reduction in the EMS class from Period 1 to Period 2, and these were all statistically significant for Tadenac Bay (P=0.043), Franklin Island (P=0.049) and Severn Sound (P=0.049); since there were only 2 sites in Pointe au Baril, no statistical comparisons could be made, but the average percentage area of EMS during the low water-level period was triple that during the high water-level period (Fig. 3). The percentage area of RBL also declined over the study period, with a significant decrease in the Tadenac Bay region (P=0.034). By contrast, open water generally increased during Period 2, although these differences were not statistically significant (Fig. 3). There was inconsistency in the response of the SAV, with a significant increase in the Franklin Island region (P=0.05), which was mirrored by an increase in Pointe au Baril region; however, there was an overall reduction in percentage area of SAV in Period 2 for wetlands in the other two regions, although they were not statistically significant. We found DT in all regions during Period 2, with mean percentage area of the DTZ ranging from a low of 1.24% in Tadenac Bay to high of 6.67% in Severn Sound (Fig. 3). Appearance of the DTZ was accompanied by a reduction in mean percent areal cover of EMS from Period 1 to Period 2 (Fig. 3). For three regions (Tadenac, Pointe au Baril and Severn Sound), mean percentage areal cover of FV also decreased from Period 1 to Period 2, but none of these changes were statistically significant.

There were no clear effects of anthropogenic disturbance on land-cover changes between Periods; however, conversion of EMS to DT was highest in all regions except for Tadenac, and mean conversion percentage increased from the region with lowest to the region with highest disturbance level (Fig. 4). Similarly, the conversion rate of T to DT increased along the disturbance gradient, while the conversion from SAV-DT was significantly lowest for the Tadenac

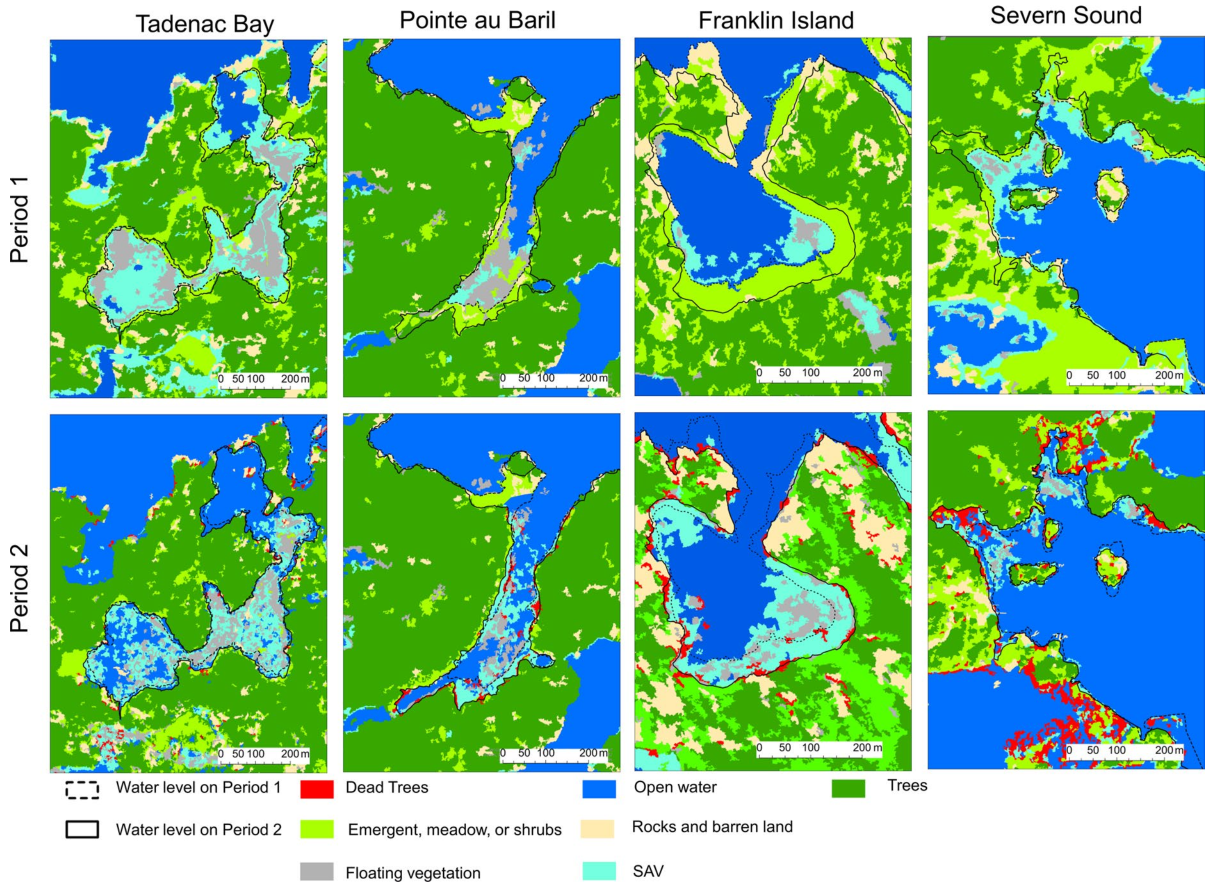


Fig. 2 Comparison of land cover classes in wetlands between Periods 1 (low water levels) and 2 (high water levels). From left to right are Black rock (Tadenac Bay), Hole in the Wall (Pointe au Baril), Corbman Bay (Franklin Island), and Roberts Island (Severn Sound) wetlands

Bay region. Although the conversion rate for the other land-cover classes to DT was not significantly related to the disturbance levels, when we regressed the percent areal cover of DT against corresponding VI scores for each wetland, we found a significant positive relationship ($R^2=0.569$, P value = 0.0004; Fig. 5). Overall, DT and VI were lowest in Tadenac Bay, while those associated with Severn Sound were highest, and those associated with Pointe au Bail and Franklin Island were intermediate.

Discussion

Due to recent technological advancements, use of remote sensing-based classification and change-detection techniques have become popular in landscape ecology. Availability of high-resolution images has reduced the amount of field sampling required compared to traditional site-level methods, making it possible to examine changes in vegetation over large spatial scales and over long time periods. We have adopted such an approach to examine long-term changes in wetland vegetation in coastal marshes of EGB. The mapping accuracy of such an approach is highly dependent on the spatial resolution of the satellite images used, especially when complex land-cover classes (with fine features) are considered. Pansharpening (or panchromatic sharpening) methods can be used to increase image resolution of satellite imagery. In the current study, we used Nearest Neighbour Diffused pansharpening to increase detection of the DTZ along the shoreline of EGB. This technique fuses pixels of low-resolution multispectral bands with those

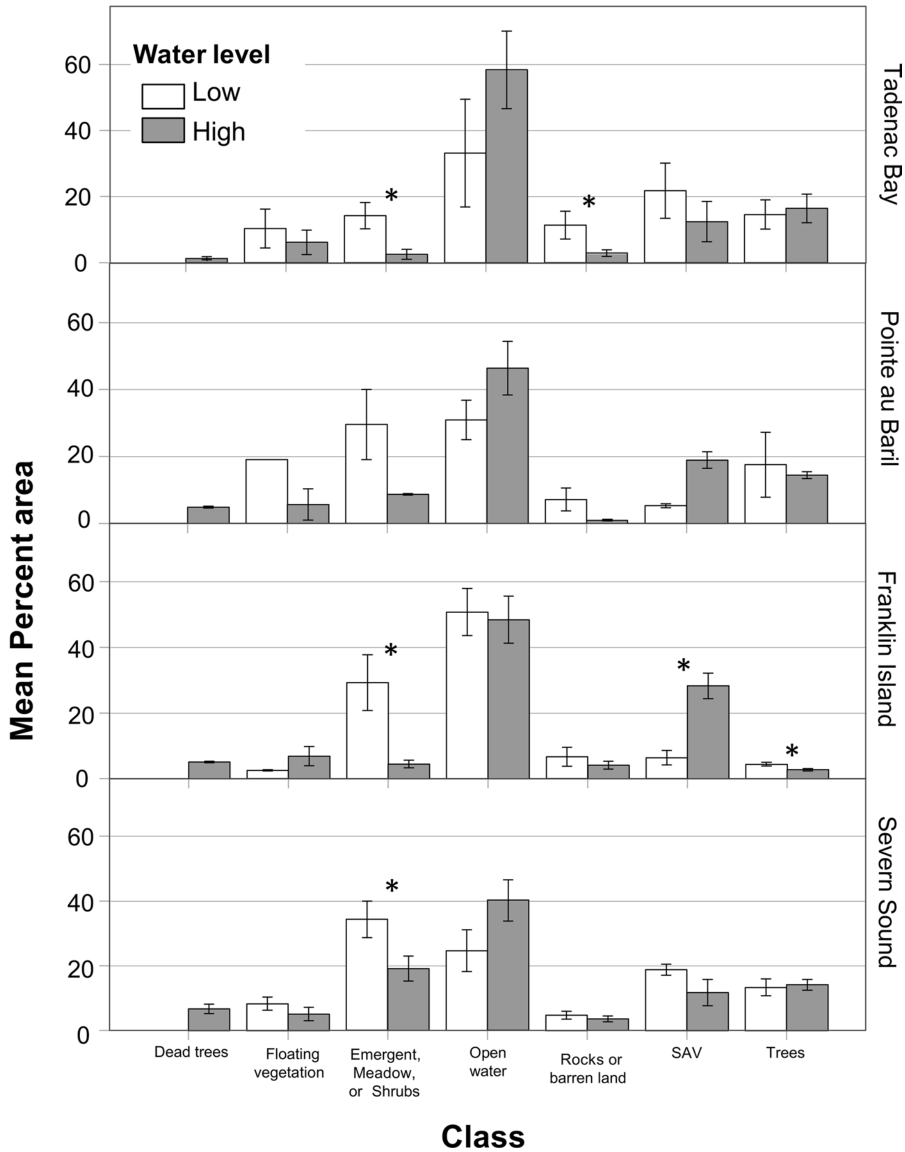
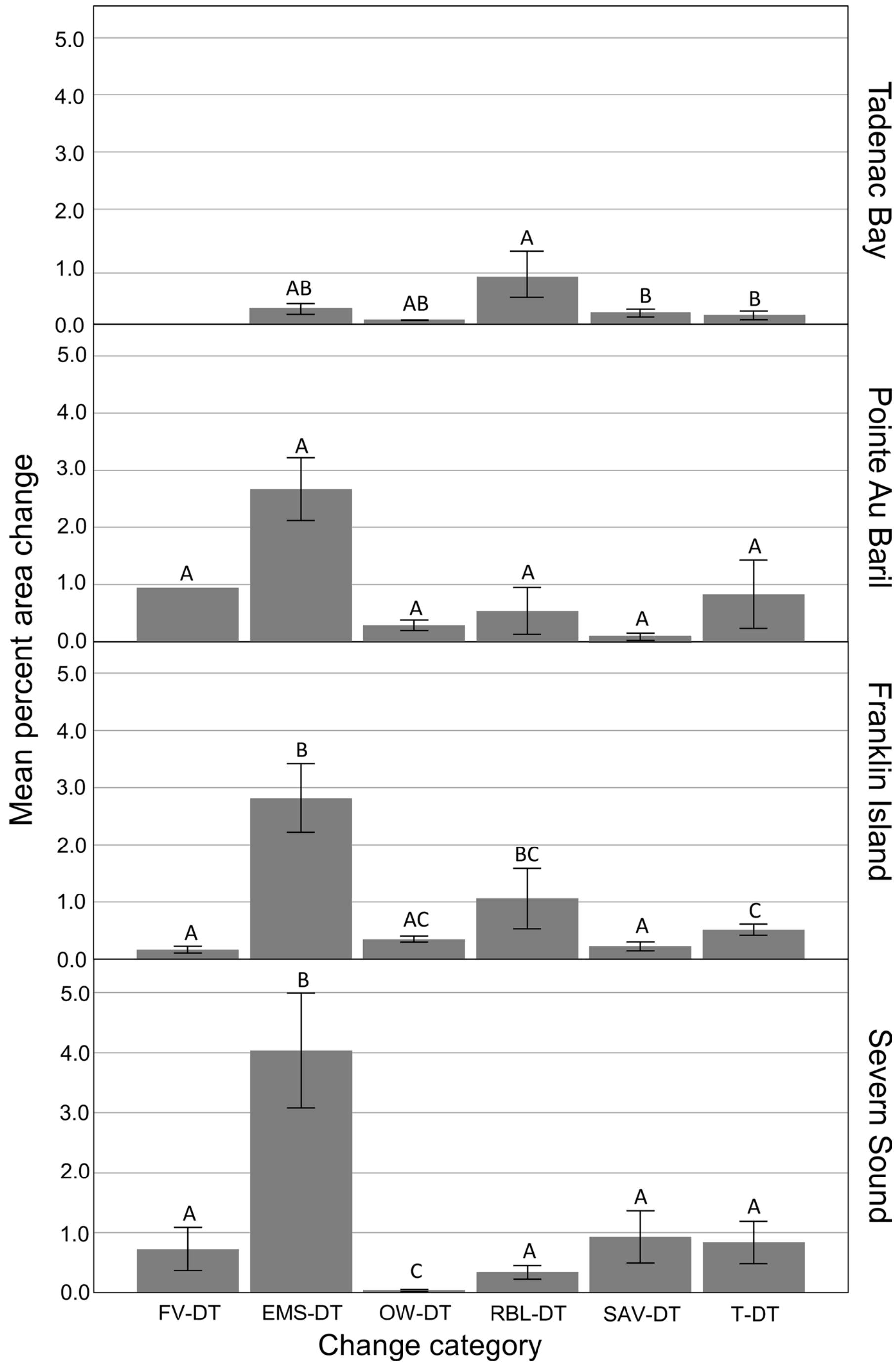


Fig. 3 Changes of all landcover classes from Period 1 to Period 2 (Error bars are 1SE. * indicate a significant change of % area cover between Low and High water levels for the corresponding land cover classes)

of high-resolution panchromatic bands, while simultaneously preserving the spectral information (Amro et al. 2011). Despite the slight spectral distortion that may result (Amro et al. 2011), this technique has been used in visual interpretations (e.g. Google Earth) and as a preliminary step for higher-level processing such as mapping crops, landcover monitoring, anomaly detection (Du et al. 2013; Gilbertson et al. 2017; Qu et al. 2017; Vivone et al. 2021) and for wetland mapping in other parts of the world (Lin et al. 2015; Gao et al. 2016; Kaplan and Avdan 2018).

Following pansharpening, we tested several pixel-based and object-based classification techniques and object-based random forests classifier gave us an overall accuracy of 85% for all sites (i.e. users' and producers' accuracies), and relatively high accuracies for individual land-cover classes, especially for the DT class. We were thus able to quantify changes in wetland vegetation in contrastingly low and high water levels spanning a period of almost two decades. Similarly, Ibarrola-Ulzurrun et al. (2017) tested the use of pansharpened methods for mapping vegetation and tested several pixel-based and object-based image classification approaches. They reported higher mapping accuracy levels with the Bayes classifier applied following an object-based classification approach.

Fig. 4 Percentage change of land cover classes in Period 1 that were converted to DT in Period 2 (Error bars are 1SE. Bars with the same letters (A, B, C) in each panel indicate that mean percent areas are not significantly different within the site)



Use of images collected from a single sensor would have increased our mapping accuracy and offered us an opportunity to test index-based change-detection techniques; however, obtaining high resolution, cloud-free images from one sensor over the 17-y period of the study was not possible. Use of images acquired from the same kind of sensors was extensively explored with satisfactory results in previous studies (Wan et al. 2018; Chastain et al. 2019; Woodcock et al. 2020). Images with similar spectral and spatial resolutions provided capability to track the full range of landscape patterns while finer resolution

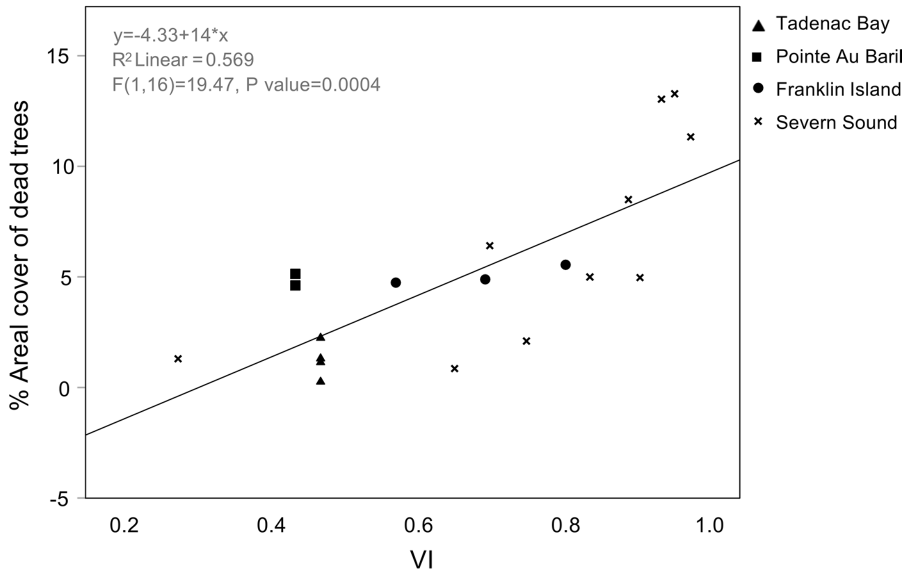


Fig. 5 Linear regression of % area cover of dead trees with Vulnerability Index (VI) scores of wetlands in the four regions

images reduced the errors associated with spatial heterogeneity, longer time gaps, and finer-scale changes (Gao et al. 2015). Furthermore, the use of classification-based change-detection methods can provide accurate change information that is not affected by external factors such as atmospheric interferences (Asokan and Anitha 2019). Classification-based change detection is directly affected by the classification accuracy levels, but since we used a large amount of ground reference data for both classification and validation, we were able to minimize this error (Asokan and Anitha 2019). When class level classification accuracies are considered, we encountered some unavoidable misclassifications among trees and EMS classes because of their similar vegetation signals; there were similar confusion between RBL and FV classes due to their high reflectance values. These misclassifications, however, only occurred occasionally and therefore they did not have a considerable level of affect on the conclusions.

The extent and structure of coastal wetlands at EGB are primarily controlled by water levels of Lake Huron. Extreme water-level changes mediated by climate change significantly affected the vegetation communities as well as wildlife habitats. Midwood and Chow-Fraser (2012) concluded that the sustained water levels between 1999 and 2009 created more homogeneous wetland habitats in Tadenac Bay and Severn Sound that resulted in a net loss of suitable fish habitat in these regions. They also reported a significant decline in species richness following 6 years of sustained low water levels and homogeneous fish communities between 2003 and 2009 for 84 wetland complexes. Based on these observations, Leblanc et al. (2014) hypothesized that sustained low water levels reduced the suitability of nursery habitat for age-0 muskellunge in coastal marshes of Severn Sound, and predicted that a return to high water levels would restore suitability of the nursery habitat. Results in this study, however, show that even after 7 years of increasing lake levels in Lakes Michigan and Huron, the habitat structure in coastal wetlands had not been restored, primarily because the zone of dead trees and shrubs that established during the 14 years of extreme low water levels are still standing in 1-2 m of water in 2021 and have prevented the proper re-establishment of the aquatic vegetation community (i.e. Emergent, Submergent and Floating vegetation).

Keddy and Campbell's (2020) Twin Limit Marsh Model predicted how vegetation in north temperate coastal marshes would respond to different water levels. Their model assumes that marsh will colonize newly-exposed sediments within a year, and that within 4 years of flooding, the inundation would kill marsh plants and create open water or aquatic vegetation. They also assumed that most temperate woody plants are killed by just one year of continuous flooding, but that a few can survive 2 to 3 years (their Table 1). Even though their model was able to explain the vegetation zonation in Lakes Erie and Ontario, it is not applicable to coastal marshes of EGB, where inundation of the wet meadow zone (EMS) for 7 successive years has not resulted in dead trees and shrubs falling down nor re-establishment of the SAV. Our results are also different from the small but immediate expansion of SAV into the wet meadow noted by Smith et al. (2021) for Lake Ontario coastal marshes that experienced 2 years of extremely high water levels (2017 and 2019) following a relatively stable period of water-level fluctuations between 2009 and 2016. The unique pattern of water-level fluctuations in EGB (Lake Huron) over the past 2 decades, together with the unique wetland geomorphology have led to a novel response by the vegetation community that cannot be explained by considering hydrographical data collected in the past century, or by observations obtained from other Great Lakes.

Despite obvious differences in development of the DTZ, we also observed similarities in how the meadow zone generally shrinks in response to high water levels due to the intolerance of meadow marsh species to prolonged flooding (Keddy and Reznicek 1986). The negative relationship between areal cover of emergent and meadow vegetation and water levels has been well established for Lake Ontario wetlands (Wilcox et al. 2005; Chow-Fraser 2005; Wei and Chow-Fraser 2008). Although we expected this to be upheld for coastal marshes of EGB, there were regional differences (i.e. lowest percentage EMS in the Tadenac Bay region and highest in the Severn Sound region), and further research should be conducted to determine if these differences are related to substrate slope and/or human activities.

There is currently no published literature on how the newly-created zone with dead trees and shrubs is used by fish and wildlife, although we are doubtful they provide the same ecosystem services as the zone of aquatic vegetation that existed prior to the period of anomalous water-level changes. This “novel” habitat has not been reported in Georgian Bay or elsewhere along the Laurentian Great Lakes coastline. Similar phenomena, however, had been observed in marine, brackish water, and near-sea freshwater wetlands due to climate-mediated sea level rise (Grieger et al. 2020). In the estuarine coastal wetlands, trees have been replaced by marsh vegetation due to increased water levels, leaving a zone of dead terrestrial trees and shrubs, which are referred to as ‘ghost forests’ (Kirwan and Gedan 2019). Such ghost forests are studied in different regions of North America including the Florida Gulf coast, Albemarle Pamlico Peninsula of North Carolina, tidal freshwater forests in South Carolina, Georgia, and Louisiana, and many other regions of the USA and the St. Lawrence estuary in Canada (Robichaud and Bégin 1997; Conner et al. 2007; Raabe and Stumpf 2016; Kirwan and Gedan 2019; Martinez and Ardón 2021). Kirwan and Gedan (2019) found no such studies conducted outside of North America; they suggested that such land conversions may affect both the composition and the function of wetlands because invasive species such as *Phragmites australis* and *Schinus terebinthifolius* can colonize these new habitats and reduce the amount of potential wildlife habitat including those for at-risk species (Smith 2013; Langston et al. 2017). There is a great need to continue monitoring these new habitats of EGB, both with respect to vegetation composition and usage by wildlife, since at-risk turtle species are known to use coastal marshes in EGB (DeCatanzaro and Chow-Fraser 2010; Markle and Chow-Fraser 2014).

Even though water-level changes had been the same across the EGB, we observed that sites with higher anthropogenic disturbance experienced greater habitat conversion. Coincidentally, the significant positive relationship between percentage area of the DTZ and VI confirms Weller and Chow-Fraser’s (2019b) observation that wetlands in the Severn Sound region where wetlands are shallower with gentle slopes, had higher vulnerability to sustained low water levels than those in the Tadenac Bay region, where wetlands are deeper with steeper slopes. In addition to the gentle slopes, Severn Sound also experiences the greatest human impact related to recreational and cottage development and the highest amount of boat traffic, due to its closer proximity to populated urban centers of southern Ontario. Therefore, this area is associated with a high level of buildings, roads, and marina development. These anthropogenic impacts (increased densities of roads, docks, and buildings along the shoreline) may exacerbate the impact of higher vulnerability to water-level extremes and prevent wetlands from recovering from disturbances. In contrast, Tadenac Bay, the least human disturbed site appeared to have been more resilient to water-level disturbances and exhibited the least amount of vegetation change between time periods.

Following 14 years of extreme low water levels, at least some emergent, meadow, and shrub classes had been converted into dead trees in all four regions during Period 2. In addition, we observed a reduction in areal cover of floating vegetation and a decrease in SAV in the Severn Sound and Tadenac bay sites. Floating vegetation, emergent, and SAV provide the most important fish habitats and therefore, reduction of these classes should have an adverse effect on wetland fish communities (Midwood and Chow-Fraser 2010). It would have been ideal to map emergent vegetation as a separate class. Unfortunately, dense emergent vegetation had higher confusion with the meadow and shrub vegetation while sparse emergent vegetation had higher confusion with the open water. Therefore, we had to combine emergent vegetation with the meadow and shrubs class. However, we were able to map SAV as an individual class, and thus delineate a large portion of fish habitats to a satisfactory level. Loss of SAV habitat in Severn Sound was due to conversion of SAV to DTZ, not because the wetland was no longer suitable for SAV (gradual slopes provide more suitable conditions for SAV than do steeper slopes; Duarte and Kalff 1986), but because the trees and shrubs did not relinquish their foothold, some having been established in the wetland for 15 + years. Further studies should be conducted to examine the impact of this habitat loss on the wetland fish communities in Severn Sound.

Conclusions

Our study explored the changes in wetland vegetation as a response to extreme water level fluctuations in EGB. We successfully mapped wetlands in four selected regions during periods of extremely low and extremely high water levels using object-based image classification of multispectral images collected by multiple sensors. We calculated the amount of six land-cover classes in wetlands that were converted into DT from Period 1 to Period 2. Our results suggest that among the four regions, Severn Sound, the site with the highest VI score to water-level disturbances and that experienced the highest amount of anthropogenic disturbance, exhibited the greatest conversion to DT. The lowest areal cover of DT was associated with Tadenac Bay, the site with the lowest VI score and least anthropogenic disturbance, suggesting that these wetlands were more resilient to water-level changes. Two other regions with moderate levels VI and moderate anthropogenic disturbance level, Franklin Island and Pointe au Baril, had intermediate levels of DT cover. We observed a significant positive relationship between percentage DTZ and VI scores, and since VI reflects hydrogeomorphic characteristics primarily related to substrate slope, we suggest that regions with lower slopes are more susceptible to changes caused by extreme and prolonged water level fluctuations. The higher VI scores were also associated with higher anthropogenic impact presumably because these areas are more desirable for recreational development. It was not possible for us to explore how the creation of DTZ affected the ecology of the transformed wetland in this study; however, the DTZ was created at the expense of emergent, meadow and shrub vegetation, and should affect habitat use by aquatic species such as wetland fish, birds, amphibians, and reptiles. Future studies should focus on understanding the interaction between water levels and changes in zonation on the ecology of fish and wildlife that depend on these important coastal systems.

Our study is the first to explore changes in wetland habitats due to sustained low water levels followed by extremely high water levels in EGB. We provide important insights into how high-quality wetlands in this region may respond to further water-level fluctuations in the future and how they may respond to climate change. Since published literature predicting how marsh vegetation should respond to flooding and de-watering have assumptions that should not be applied to our wetlands, we caution against using data from other Great Lakes to forecast impacts of climate change on the vegetation community of Georgian Bay coastal marshes. We therefore recommend that our approach be used to map and conduct change-detection for the remaining regions of the entire Georgian Bay coast so that the impact of climate-induced water-level anomalies on ecosystem functions of coastal marshes can be documented. The maps we have produced in this project should be used to identify a gradient of change with which further research can be conducted to determine how fish and wildlife are using the novel dead-tree habitat.

Acknowledgements The authors would like to thank the Georgian Bay Great Lakes Foundation (GBGLF) and the

Mitacs Elevate postdoctoral fellowship for providing financial support, and Ms. Mary Muter, Chair of GBGLF for advice and logistical support. We also thank Dr. Dan Weller for sharing VI data and Dr. James Marcaccio for drone image acquisition. Access to original IKONOS image data was provided by Georgian Bay Forever (formerly GBA Foundation) for this project. We also thank all present and past Chow-Fraser lab members for collecting field data over the years, especially S. McNair, M. Croft, J. Midwood, D. Rokitnicki-Wojcik, J. Marcaccio, L. Boyd, D. Weller, and D. Montocchio.

Author contributions All authors contributed to the study conceptualization and design, data analysis, investigation, and resources. All data curation, image processing and data extraction, spatial data analysis, and original manuscript preparation by Prabha Amali Rupasinghe. Supervision, project administration, funding acquisition, and manuscript reviewing and editing by Patricia Chow-Fraser. All authors read and approved the final manuscript.

Funding This research is funded through MITACS Accelerated program in partnership with Georgian Bay Great Lake Foundation, and the Natural Sciences and Engineering Research Council of Canada Discovery Grant.

Data availability The datasets generated during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests The authors have no relevant financial or non-financial interests to disclose.

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