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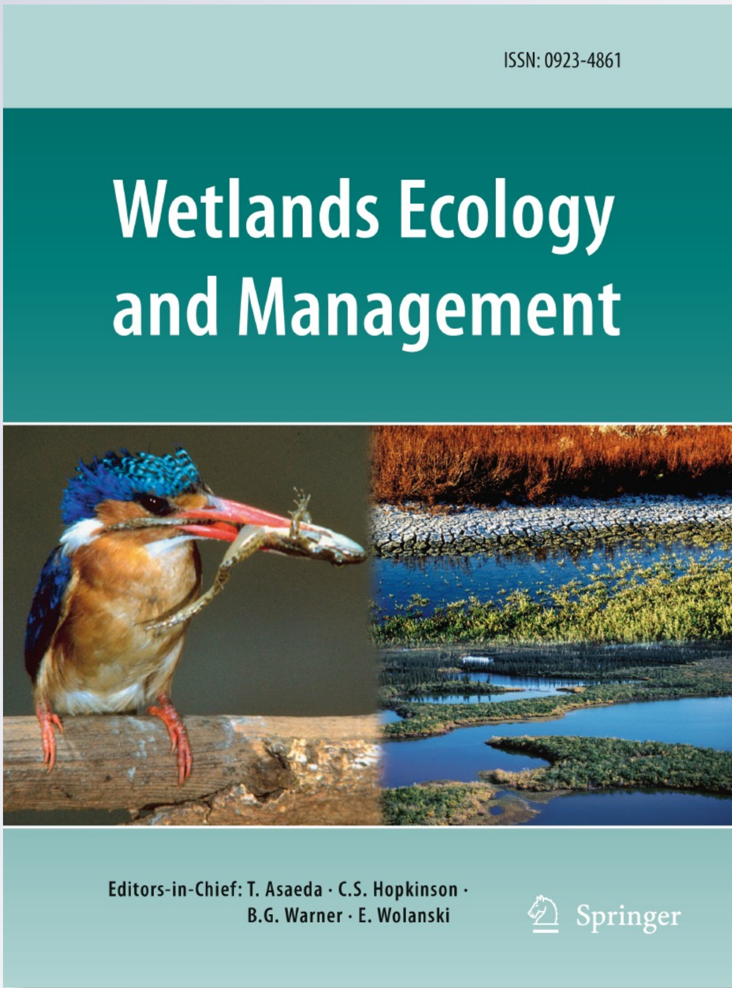
Wetlands Ecology and Management

ISSN 0923-4861
Volume 27
Combined 2-3

Wetlands Ecol Manage (2019)
27:207-221
DOI 10.1007/s11273-019-09655-6



Springer

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https://doi.org/10.1007/s11273-019-09655-6

ORIGINAL PAPER

Hydrogeomorphic modeling of low-marsh habitat in coastal Georgian Bay, Lake Huron

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Received: 2 May 2018 / Accepted: 14 January 2019 / Published online: 9 March 2019

Abstract Potential impacts of global climate change on the amount of low-marsh habitat in coastal wetlands of the Great Lakes are unknown, which may have important implications for the Great Lakes fish community that use such habitat. We developed a generalized linear model that uses only hydrogeomorphic (HGM) features and lake elevations to predict the extent of low marsh in coastal wetlands of eastern and northern Georgian Bay. The McMaster Coastal Wetland Inventory was used as a reference dataset to train the model, while best available data were assembled to create a digital elevation model that was used to derive all HGM features at a lake elevation of 176.17 m (International Great Lakes Datum 1985). The best predictive model included depth, slope, and exposure as HGM variables, yielding an area under the curve (AUC) score of 0.83. We classified the model output into low-marsh and open-water habitat using a threshold value identified by maximizing the true skill statistic. The classified model output had sensitivity and specificity scores of 0.80 and 0.75, respectively, and correctly identified 81% of the low-marsh units present in the reference dataset with an average 60% areal overlap between the model prediction and reference dataset. We applied the model to two external datasets to check model performance, and found the lowest AUC to be 0.79, with associated sensitivity and specificity scores of 0.65 and 0.77, respectively. Applying this model with future water-level scenarios should provide a cost-effective alternative for forecasting changes in the amount of low marsh-habitat in Georgian Bay.

Keywords Coastal wetlands · Georgian Bay · Water levels · Low marsh · Hydrogeomorphology · Modeling

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Introduction

Coastal wetlands in the Laurentian Great Lakes are a valuable habitat type that can support impressive biodiversity and provide important ecosystem services (Brazner et al. 2001; Costanza et al. 1997; Environment Canada 2002; Sierszen et al. 2012). These habitats provide critical habitat for most Great Lakes fish species (Jude and Pappas 1992; Randall et al. 1996; Wei et al. 2004). Low-marsh is the permanently inundated component of coastal marsh that is dominated by submersed aquatic vegetation (SAV) and floating-leaf vegetation that provides habitat for fish throughout the year (OMNR 2014). Despite their great economic and ecological value, much of the coastal wetlands in the Great Lakes basin has been degraded or destroyed due to anthropogenic activities (Environment Canada 2002; Jude and Pappas 1992; Mayer et al. 2004). In Georgian Bay (Lake Huron), there are thousands of coastal marshes (> 8500 ha; Midwood et al. 2012), that have remained largely undisturbed by anthropogenic influences (Cvetkovic and Chow-Fraser 2011). Although incremental human development pressure is an on-going concern, the more recent and immediate concern is that of lake-level conditions, such as the drastic drop in lake levels (Assel et al. 2004) and persistent below-average lake levels that occurred between 1999 and 2014 (data from the Great Lakes Water Level Dashboard; Gronewold et al. 2013), that have threatened the long-term health of the region's coastal wetlands (Fracz and Chow-Fraser 2013; Midwood and Chow-Fraser 2012). Water levels in Georgian Bay can vary naturally by up to 2 m, and are driven in part by quasi-periodic cycles occurring on scales of years to decades (Baedke and Thompson 2000; Hanrahan et al. 2010; Quinn and Sellinger 2006). There remains much uncertainty about the potential impacts of global climate change on these fluctuations, such that there is a broad range of future lake levels predictions (Angel and Kunkel 2010; Lofgren et al. 2002; Mortsch and Quinn 1996). Therefore, scientists must develop approaches to assess how coastal wetlands may respond to changes in lake elevations.

Past studies have favored use of a hydrogeomorphic (HGM) scheme to classify Great Lakes coastal wetlands (Albert et al. 2005; Ingram et al. 2004; Keough et al. 1999; Minc 1997). Albert et al. (2005) defined coastal wetlands as "lacustrine systems" that are predominantly influenced by lake-level fluctuations and the geomorphic characteristics of the shoreline. Geomorphic characteristics of the shoreline affect how protected or exposed a particular site is to lake processes (e.g. wind waves, ice scour) and those characteristics can themselves be affected by lake level (e.g. exposure of shoals under low water conditions). The HGM classification has been an effective framework because it encompasses many of the major processes that affect coastal wetland distribution and composition. Lake-level fluctuation is a well-documented driver of wetland vegetation diversity (Keddy and Reznicek 1986; Leira and Cantonati 2008; Mortsch 1998; Wilcox and Meeker 1991) and wetland extent (Fracz and Chow-Fraser 2013; Mortsch 1998; Wei and Chow-Fraser 2008). Geomorphic characteristics such as substrate slope (Duarte and Kalff 1986; Duarte et al. 1986) and exposure (Angradi et al. 2013; Fonseca et al. 2002; Keddy 1982, 1984a, b) are important drivers shaping community processes within the wetland. Such wide-spread adoption of the HGM framework for classifying wetlands provides a strong rationale for using HGM variables to model response of coastal wetlands to changing water-level conditions.

The literature has identified several useful HGM predictors, including fetch (Lemein et al. 2017) and geomorphic type (Albert et al. 2005), which were particularly useful for characterizing emergent and meadow vegetation communities throughout the Great Lakes. Water depth and exposure were found to be significant predictors of the cover of SAV (Angradi et al. 2013) in a Lake Superior estuary. Hebb et al. (2013) incorporated water depth into their wetland community modeling, as have Wilcox and Xie (2007). In these cases, HGM features were always considered amongst a suite of other environmental variables like land cover, water quality, or previous vegetation communities.

In this study, we propose to use only HGM features to model the extent and distribution of low-marsh habitat. We will develop this model for the eastern and northern shores of Georgian Bay, Lake Huron, where an existing inventory shows that there are thousands of coastal marshes (Midwood et al. 2012), many of which provide important spawning and nursery habitat for fish (Cvetkovic and Chow-Fraser 2011; Leblanc et al. 2014; Midwood and Chow-Fraser 2012). Given their ecological importance, our goal is to develop a model that can be applied to different water-level scenarios to assess the potential changes to the extent and distribution of low-marsh habitat. While this model will be developed specifically for eastern and northern Georgian Bay, the approach presented herein can be used as a framework for evaluating coastal marshes wherever uncertainty over potential water-level conditions is a management concern.

Methods

Study area

The geographic focus of our modeling efforts extends along the eastern and northern shoreline from Severn Sound in southeastern Georgian Bay to McGregor Bay in the northwest (Fig. 1). This region has remained mostly undisturbed relative to the lower Great Lakes,

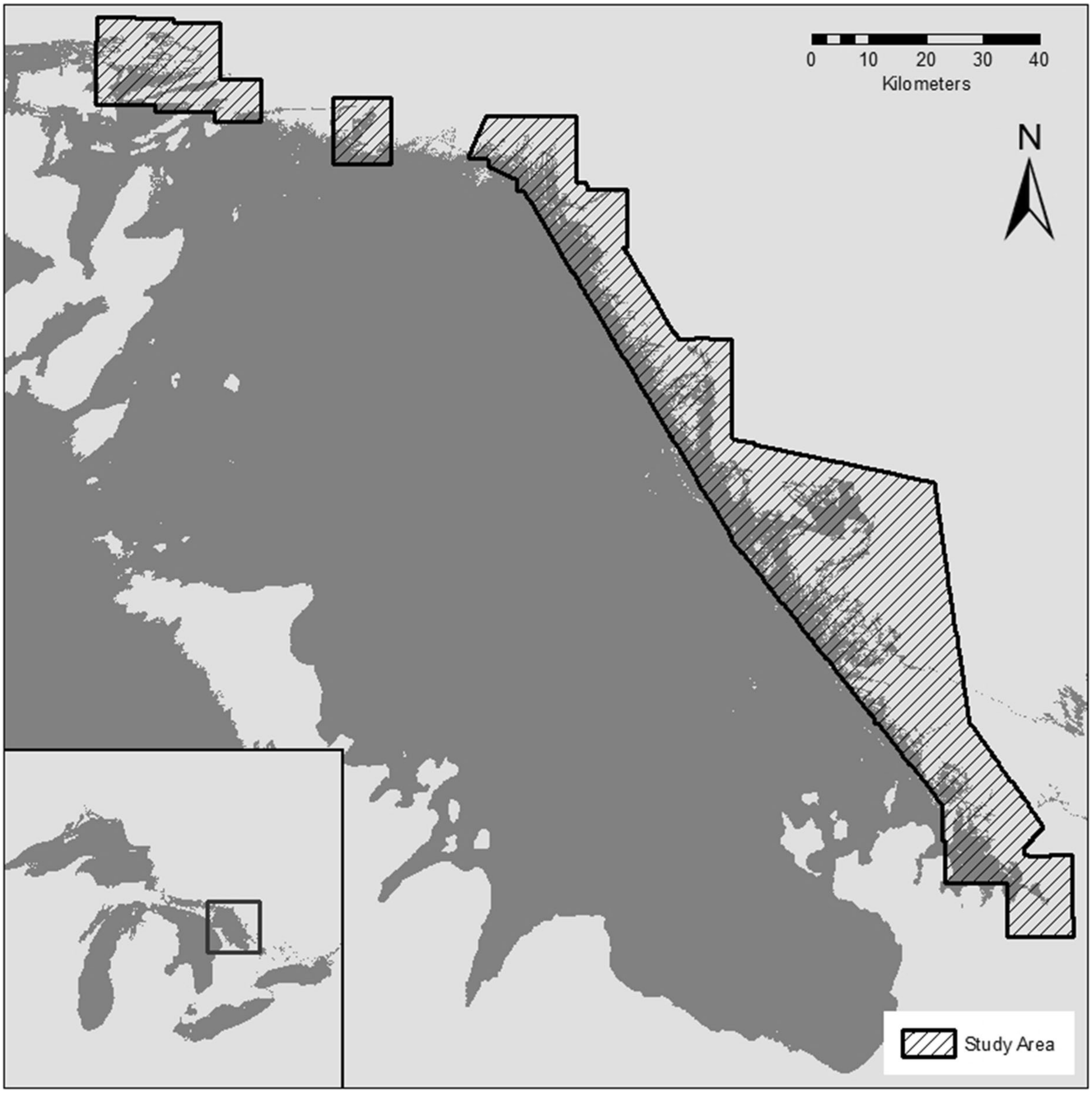

Fig. 1 Location of study area in Georgian Bay (relative to Great Lakes; inset). Cross-hatched study area indicates simplified extent of study area for low-marsh modeling efforts. Areas where insufficient elevation data were available for modeling were removed from the indicated study area

where human impact has been limited to recreational (e.g. cottages, boathouses, marinas) and residential development. The bedrock is primarily granitic Canadian Shield and the coastal zone is characterized by a highly complex shoreline that consists of many small islands and protected embayments that provide habitat for fish, birds, and other wildlife.

Lake levels in Georgian Bay fluctuate regularly by up to 2 m between extreme highs and lows, but between 1999 and 2014 there was a prolonged period of stable, low water levels that hovered near record lows. Notable low-water periods also occurred in Georgian Bay in the 1960s and 1930s; only the 1930s-period was characterized by a lack of interannual fluctuation similar to the recent low-water period, but was several years shorter. Between 2015 and 2017, lake levels rebounded to above-average levels, with the result that many coniferous trees and perennial shrubs that established in the wet meadow zone during the prolonged drawdown period began to occupy low-marsh habitat and slowly perished (Boyd 2017).

Hydrogeomorphic parameters

For our modeling, we chose three parameters based on their well-established relationships with wetland vegetation: water depth, substrate slope, and wave exposure. Since data for these parameters are not available for the entire region of interest, we had to derive them from a digital elevation model (DEM) that we assembled for Georgian Bay, using the best available elevation data in terms of both coverage and resolution. The DEM was built by importing and manipulating relevant spatial data in ArcMap 10.5 (ESRI, Redlands, California). These data included navigation charts produced by the Canadian Hydrographic Service (CHS), which were used to derive elevation data below the low water chart datum of 176.0 m (all elevations are referenced to the International Great Lakes Datum 1985). The vertical and horizontal positional accuracy (95% confidence interval) for the hydrographic survey data within our study area was at least 0.5 m and 5 m, respectively (CHS 2013). Although navigation charts ranged in scale from 1:200,000 (i.e. full Georgian Bay chart) to 1:1200 (e.g. narrow channels), the majority of the study area was derived from 1:20,000 scale charts. Depth soundings, depth contour lines, and the shoreline elevation from each chart were converted to elevation values in meters above sea level (International Great Lakes Datum (IGLD) 1985). Elevation data derived from the charts were sequentially stacked from the coarsest to finest scale, with the finer-scale elevation data replacing the coarser-scale elevation data where the chart footprints overlapped. We used the Ontario Provincial DEM v3.0 (OMNR 2013) as the source for all elevation data above 176.0 m. The horizontal and vertical accuracy of the input data for our study area was at least 5 m and 2.5 m, respectively (OMNRF 2016).

We interpolated the Georgian Bay DEM using the Topo to Raster function in ArcMap 10.5 (based on the ANUDEM program; Hutchinson 1989) by pooling all elevation data extracted from the CHS navigation charts and the Provincial DEM. Input elevation data were identified as spot (i.e. point elevations) or contour where appropriate. The hydrology option was set to “Enforced” and the number of iterations set to 50. All other input parameters were left as defaults. Due to the volume of elevation data and geographic extent of the DEM product, we interpolated the final DEM as a series of 10 km^2 tiles with a 1 km overlap with all neighboring tiles. All tiles were then mosaicked together to form the completed Georgian Bay DEM (GB-DEM) with a pixel size of 10 m. Any areas with missing or insufficient elevation data were identified and excluded from further analyses. Within the context of our wetland habitat modeling, the scope and accuracy of the GB-DEM was sufficient. A depth of 2 m is typically accepted as a lakeward boundary for coastal marshes (Albert et al. 2005; Keough et al. 1999; OMNR 2014) so we expected the majority of low-marsh habitat to occur between the 0-m (i.e. shore) and 2-m depth contours. The 0.5-m vertical accuracy of the hydrographic survey permits sufficient estimates of elevation below 176.0 m. The steep nearshore morphology of the study area is such that with a 10-m resolution DEM the differences in elevation between adjacent cells often exceeds the 2.5-m vertical accuracy in the topographic survey data. This still allows for sufficient capacity to estimate elevation and delineate contours relative to the working resolution of the GB-DEM.

We used the GB-DEM to derive all HGM feature layers: depth, slope, and exposure. The depth layer was calculated by subtracting the elevation value from our target lake level. We derived the slope layer using the average maximum technique (Burrough and McDonell 1998) through the Slope tool in ArcMap 10.5. To develop the exposure layer, we used a 32-point direct fetch measurement as the basis for wave exposure, similar to the 16-point direct fetch measurement used by Keddy (1982). From a given point on the water’s surface, 32 bearing lines were drawn from the point until they intersected land, starting at North (0°) with 11.25° spacing between bearings. The sum of the lengths of all 32 bearing lines was used as a wave exposure metric for that point; this calculation was performed with a custom-built tool in ArcGIS 10.5. The time-intensive computations could not be performed for all points within the study area. Instead, we selected a subset of representative sample locations to capture the variation in wave exposure values and interpolated between these points. Since

Midwood (2012) found negligible amount of low marsh vegetation (i.e. SAV) below 5-m, we first bounded the study area to only water depths between the shoreline and the 5-m contour and then placed a sample point at the center of all spatially distinct 0 – 5 m depth zones within the study area. Sample points were placed around the perimeter of all islands to account for their ability to block incoming waves. Four points were placed around islands with perimeters < 500 m and eight around perimeters > 500 m. Finally, we iteratively filled the remaining study area with sample points until we achieved a maximum distance of 500 m between adjacent points. This threshold was a suitable compromise that allowed us to capture the regional variation in fetch without spending excessive time on computations. We calculated the 32-point direct fetch value at each point and then interpolated between them using a triangulated irregular network, which was then converted to a raster layer with the same resolution and cell alignment as the GB-DEM. This was used as our wave exposure layer for the study area.

Model development and evaluation

The McMaster Coastal Wetland Inventory (MCWI; Midwood et al. 2012) is a geodatabase of coastal wetland habitat in eastern and northern Georgian Bay, digitized manually from IKONOS and Quickbird satellite images acquired between 2002 and 2009, during a period of sustained low water levels with a calculated mean monthly water level of 176.17 m (SE = 0.05) across the image acquisition dates. The coastal marsh habitat was classified as low marsh, high marsh and upstream wetlands. Low marsh consists of the permanently inundated portion of the wetland and is dominated by SAV, floating-leaf, and emergent vegetation types. High marsh is the seasonally-inundated part of the wetland and was bounded by the shoreline and the forest edge (i.e. "wet meadow" or "meadow marsh"). Upstream wetlands are those with a direct hydrological connection to Georgian Bay that occur with 2 km from the shoreline (e.g. beaver impoundments). We used the low marsh layer as our training dataset to develop the model, and converted the inventory file to a 10-m raster, coincident with the GB-DEM. We took the entire extent of low-marsh habitat in the MCWI (Fig. 1; study area) and then removed any areas where the bathymetric data were insufficient or missing. Due to the typically dystrophic nature of coastal areas in eastern and northern Georgian Bay, the lakeward extent of the low marsh zone in the MCWI could not be accurately determined from the satellite imagery (Midwood et al. 2012), instead using visible characteristics and shape of the wetland to estimate the lakeward boundary of the low-marsh zone. To address possible overestimates of the areal extent of low marsh we restricted the remaining study area to water depths between shore and 5 m deep, since that is the maximum depth at which we would expect to find SAV in Georgian Bay (Midwood 2012). Hereafter we will refer to the area entrained by the shoreline to the 5 m depth contour as the "coarse study area". We then determined the distribution of slope and wave exposure values and the upper 95th quantile for all remaining low-marsh areas. These values were used as thresholds to remove any outlying low-marsh areas. The depth, slope, and exposure cutoffs were used to delineate areas that were deemed to be suitable for development of low marsh; hereafter, we will refer to this as the "effective study area", which can be further divided into low marsh or open water. Two-thirds of the classified low marsh and open water served as the training dataset, while the remaining third served as the test dataset.

We set our lake level to 176.17 m because that was the calculated mean monthly lake level when the imagery used to delineate the MCWI wetlands was acquired. We calculated the HGM feature values for every cell in the training dataset and used those as predictors in a series of generalized linear models run in JMP 13.0.0 (SAS Institute Inc., Cary, NC) to predict the probability of a location supporting low marsh or open water. The generalized linear model consists of a random component, a systematic component, and a link function (Quinn and Keough 2002). Since we had classified the training dataset into two habitat types (low marsh = 1, open water = 0), we used a logit link function that is used for modeling binary data. We used each HGM feature as a single predictor and each possible combination of features for a total of seven different model runs. The generalized linear models calculated the probability that low-marsh habitat was present at a particular location.

We used a receiver operating characteristics (ROC) plot to rate each model's performance since it provided a threshold-independent evaluation (Fielding and Bell 1997), that is, the discrimination between open-water and low-marsh habitat was not biased by the threshold used to differentiate between these classes (Deleo and Campbell 1990). The ROC plot consists of the sensitivity (true-positive fraction) plotted against 1 minus specificity (false-positive fraction) for all possible threshold values (Fielding and Bell 1997). The area under the curve (AUC) of the ROC plot is used as an index of overall model performance, regardless of threshold (Deleo 1993), where 0.5 indicates that the model performance is comparable to random (i.e. an event has a 50% chance of being correctly classified) and an AUC of 1.0 indicates that the model performs perfectly (i.e. 100% chance of an event being classified correctly).

We selected the best-fitting model based on the AUC values from the ROC plots. For the best-fitting model, we found the threshold value that maximized the true skill statistic and used that threshold to classify our model output into low-marsh or open-water habitat categories. The true skill statistic is calculated as the sensitivity plus specificity minus 1 for a given classification threshold, where values can range from − 1 to 1. We used this metric to select a classification threshold because it maximizes both our true positive and true negative classification rates and is independent of prevalence (Allouche et al. 2006), which was important since our low-marsh habitat category made up only a small portion of our overall dataset. We used a confusion matrix to evaluate the performance of the classified model output. We validated the model using the test dataset using the AUC score for the unclassified model output and a confusion matrix for the classified output. We then pooled the test and training datasets and repeated the AUC and confusion matrix evaluations on the full reference dataset (i.e. the effective study that was classified as low marsh or open water based off the MCWI).

Two large embayments in eastern Georgian Bay were excluded from the study area because of gaps in the bathymetric data available from the CHS navigation charts, Tadenac Bay and Sturgeon Bay (near Pointe au Baril, ON). Both embayments were mapped as part of the MCWI (Midwood et al. 2012) so reference habitat information was available. We constructed DEMs for each site using the same methods as for the GB-DEM, but substituted the bathymetric data from the CHS navigation charts with bathymetric data collected from an off-the-shelf sonar unit (e.g. Lowrance HDS7 or comparable; horizontal accuracy approx. 3 m, vertical accuracy approx. 30 cm) for unrelated survey work. We continued to use the Ontario Provincial DEM v3.0 (OMNR 2013) as the source of our elevation data above 176.0 m. All HGM feature layers were derived in the same manner as for the GB-DEM, and the MCWI reference data were limited to the same depth, slope, and exposure thresholds as the effective study area. We ran the best-fitting model with the HGM data from each embayment and evaluated the model performance and classified output using the same methods described above.

For the full dataset (i.e. test and training) we used a confusion matrix to evaluate the classified output from the best-fitting model within the effective study area. We included an additional category, “excluded”, to denote any areas that had slope or wave exposure values above the 95th quantile and that had been removed while creating the effective study area. We made this evaluation relative to the coarse study area to evaluate how the model performed in response to the cutoffs in slope and wave exposure. We maintained the 0–5 m boundary of the coarse study area because that threshold was based on empirical field observations (Midwood 2012). We then overlaid categories from the confusion matrix over the study area to visually assess the accuracy of the classification and to look for possible reasons to explain errors. Since low-marsh habitat class had such low prevalence in the dataset, we were more concerned with omission errors (i.e. false exclusion) than with commission errors (i.e. false inclusion).

In addition to the pixel-based evaluation of the classified model output, we also assessed the ability of our model to identify units of low-marsh habitat (i.e. spatially distinct patches of low marsh) in the effective study area. We considered it a “match” when some portion of a reference low-marsh unit was classified correctly by the model. For each match, we calculated the percentage reference unit that was correctly classified. Using multiple cutoffs of minimum area, we calculated the sensitivity (i.e. fraction of correctly identified low-marsh units) and mean overlap (i.e. percentage reference low-marsh unit that was correctly classified) to evaluate if there is a minimum low-marsh unit that must be used to achieve acceptable model performance.

Results

Model development and evaluation

Once we removed areas with insufficient bathymetric data and further excluding areas deeper than 5 m, we obtained 3619 ha of low-marsh habitat and 37,092 ha of open water. The effective study area, however, which is restricted to the upper 95th quantile of slope (7.096%) and wave exposure (71,464 m), contained 3259 ha of low-marsh habitat and 13,964 ha of open water.

We used our training data subset to run seven different generalized linear models, one for each permutation of the depth, slope, and wave exposure predictors (Table 1). For every model run, all predictor variables were negatively correlated with the probability of a location supporting low-marsh habitat. The best-fitting model with respect to the AUC scores was the full model that included depth, slope, and wave exposure as predictor variables (AUC = 0.831). This was followed closely by the depth-slope model with an AUC score of 0.825. Of the models with only a single predictor variable, the depth-only model performed best, followed by slope-only, then wave-exposure-only. The AUC score of 0.7627 for the depth-only model indicates that there is a 76% chance that the model will correctly classify a given point within the effective study area as low-marsh habitat, and is a good overall fit. Slope-only also performed well at 0.7095. Exposure-only fared much poorer with an AUC of 0.5697, indicating it was a weak predictor of low-marsh presence within the effective study area boundary. The performance of the single-predictor models provides a sense of the relative importance of each of the variables.

The equation for the full model is as follows:

$$P(LM) = \frac{1}{1 + Exp(-(0.94271 - 0.97224(D) - 0.42310(S) - 1.5013 \times 10^{-5}(E))}$$

where P(LM) is the probability of low-marsh habitat occurring at a given location, D = depth, S = slope, and E = exposure. For this model, the true skill statistic was maximized at a P(LM) value of 0.203,

Table 1 Predictor coefficients (± SE) and performance metrics for the seven generalized linear model runs with the training dataset

Parameters	Intercept	Depth	Slope	Exposure	AUC	Rank
All	0.94271 (± 6.036 × 10^{-3})	− 0.97224 (± 3.151 × 10^{-3})	− 0.42400 (± 1.773 × 10^{-3})	− 1.50 × 10^{-5} (± 1.6547 × 10^{-7})	0.8306	1
Depth-slope	0.62952 (± 4.924 × 10^{-3})	− 1.00638 (± 3.162 × 10^{-3})	− 0.39424 (± 1.712 × 10^{-3})	NA	0.8250	2
Depth-exposure	− 0.01752 (± 4.568 × 10^{-3})	− 1.03345 (± 3.138 × 10^{-3})	NA	− 7.29 × 10^{-6} (± 1.55 × 10^{-7})	0.7673	3
Depth	− 0.14162 (± 3.748 × 10^{-3})	− 1.04886 (± 3.134 × 10^{-3})	NA	NA	0.7627	4
Slope-exposure	− 0.04430 (± 5.103 × 10^{-3})	NA	− 0.48001 (± 01.762 × 10^{-3})	− 2.19 × 10^{-5} (± 1.57 × 10^{-7})	0.724	5
Slope	0.55675 (± 3.721 × 10^{-3})	NA	− 0.43794 (± 1.689 × 10^{-3})	NA	0.7095	6
Exposure	− 1.17352 (± 3.603 × 10^{-3})	NA	NA	− 1.44 × 10^{-5} (± 1.48 × 10^{-7})	0.5697	7

Models were evaluated and ranked from the area under the curve (AUC) value derived from their respective ROC plots

Table 2 Performance of best-fitting model with different datasets

Dataset	AUC	Overall	Sensitivity	Specificity	TSS
Training	0.831	0.755	0.799	0.745	0.544
Test	0.831	0.756	0.801	0.745	0.546
Full GB	0.831	0.755	0.800	0.745	0.545
Sturgeon Bay	0.785	0.739	0.654	0.765	0.419
Tadenac Bay	0.849	0.800	0.766	0.807	0.573

Training and test datasets were randomly selected subsets, 2/3 and 1/3 respectively, of each habitat type (low marsh and open water) from the effective study area dataset. Area under the curve (AUC) of the ROC plot for respective model runs was used as threshold-independent evaluation of the model performance. Model outputs were classified into open water and low marsh based on a threshold value of 0.203. Overall performance (total correct classification), sensitivity (true positive fraction), specificity (true negative fraction), and true skill statistic (TSS) were derived from confusion matrices

indicating that any cell with a value equal to or larger than the threshold was classified as low marsh and any smaller value was classified as open water. Based on the classified output of the full model, there are 10,152 low-marsh units (i.e. spatially distinct patches of wetland habitat), comprising a total area of 6166 ha within the effective study area.

The model output for the test, training, and full Georgian Bay dataset all had very similar sensitivity and specificity values of approximately 0.80 and 0.75, respectively (Table 2). Consistency in the performances of the training and test datasets justified recombining them into the full Georgian Bay dataset for subsequent evaluations of model performance. For both of the external datasets (Sturgeon Bay and Tadenac Bay), the model performed comparably to the full Georgian Bay dataset. Model performance for Tadenac Bay was marginally better than that for the full Georgian Bay dataset, and even though the model performed poorest in Sturgeon Bay, it still received an AUC score of 0.785 (Table 2). Sensitivity of the classified model output was lowest for Sturgeon Bay; based on visual assessments, this can be attributed to the consistent underestimation of the lakeward extent of low marsh, and not to errors associated with classifying low-marsh units.

The model faithfully reproduced the MCWI reference layer (Table 3), correctly classifying 80% of the low-marsh habitat and 75% of the open-water area in the effective study area. Applying the slope and wave exposure thresholds excluded 23,128 ha of open water from the effective study area, but also 360 ha of low-marsh habitat. The model could not accurately discriminate between open water and low marsh along the lakeward boundary of correctly classified low-marsh units, and this resulted in both omission and commission errors (Fig. 2). Some low-marsh habitats were also misclassified along deep channels (natural or dredged) bordering wetlands and in nearshore areas where true elevations were higher than indicated by the GB-DEM. The latter resulted in some low-lying areas being misclassified as low marsh that were in reality high-marsh habitat, which should not have been excluded from the effective study area. Approximately

Table 3 Confusion matrix of the classified output of the best model (i.e. depth, slope, exposure) of the full Georgian Bay dataset within the effective study area

		Full model		
		LM (6165.87)	WTR (11,057.28)	EXCL (23,488.30)
Effective study area (17,223.15)	LM (3259.11)	2605.89 [0.80]	653.22 [0.20]	360.14 [NA]
	WTR (13,964.04)	3559.98 [0.25]	10,404.06 [0.75]	23,128.16 [NA]

Area of each class (*LM* low marsh, *WTR* open water, *EXCL* excluded) is reported in hectares (round brackets) and as a proportion of the reference class (square brackets). The excluded class indicates the area of low marsh and open water in the reference dataset that was in the 0–5 m depth zone but above the 95th quantile for slope and wave exposure. *NA* not applicable

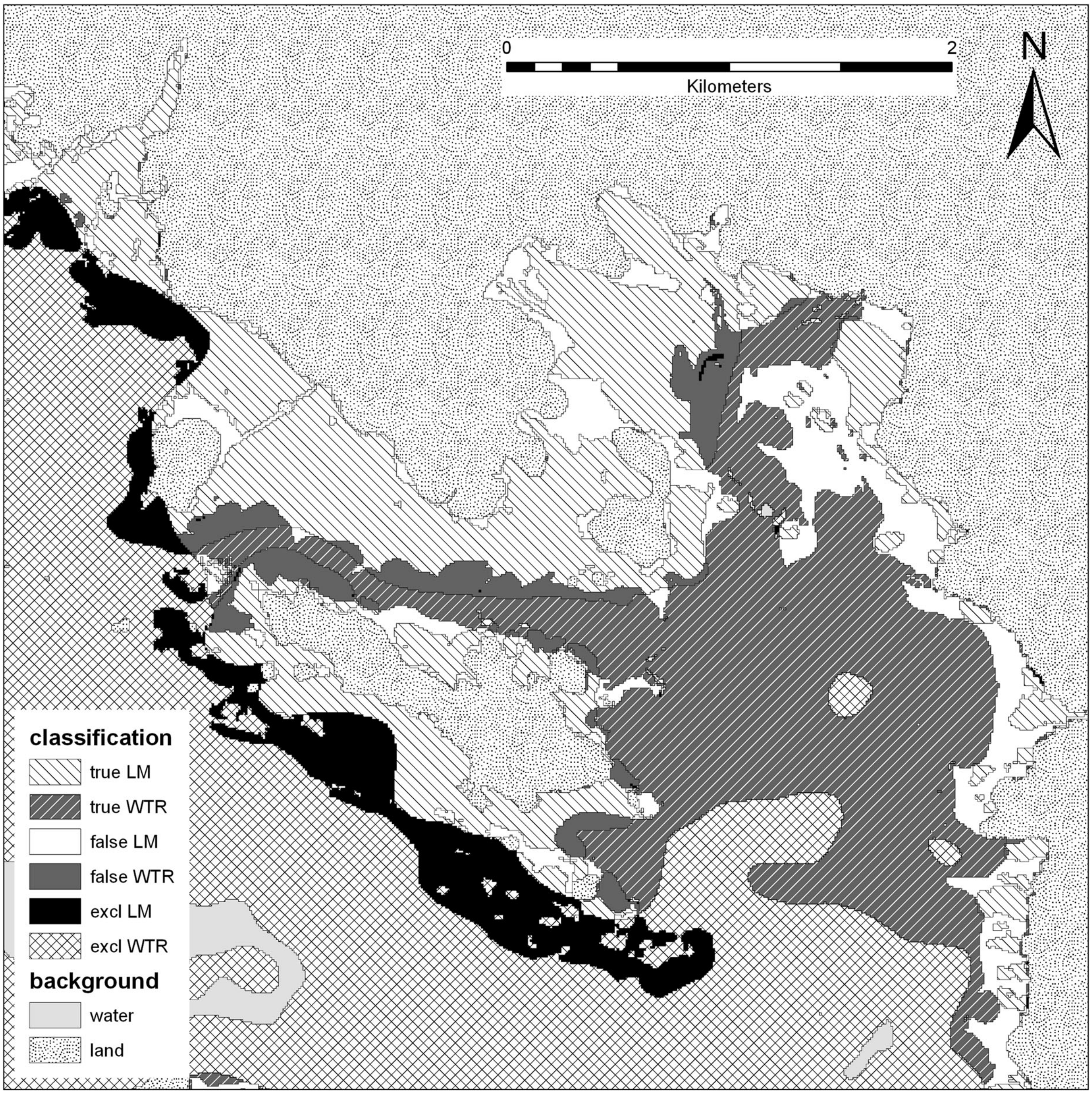

Fig. 2 An area in southeastern Georgian Bay that is representative of the typical classification successes (true) and failures (false) of the model in predicting the presence of low marsh (LM) and open water (WTR) relative to the reference dataset. Excluded (excl) categories indicate LM and WTR that were present in the reference dataset but outside the effective study area of the model

10% of the low-marsh area in the coarse reference dataset had been incorrectly excluded from the effective study area, which included very steep areas along the shoreline. In these areas, nearshore slopes had been overestimated in the GB-DEM due to resolution limits, such that a tall cliff face adjacent areas with a gradual nearshore slope appeared as a very steep slope. This typically resulted in omission of fringing wetland that is frequently found in such geomorphic settings. Similarly, we found that exclusion of low-marsh due to the wave exposure cutoff was largely attributable to the resolution of the GB-DEM. In southeastern Georgian Bay, there are areas with relatively high wave exposure but the water is relatively shallow in the nearshore (< 2 m) and often contain many shoals and rocks that can attenuate wave exposure; however, since these features occur at a spatial scale that is finer than our DEM can resolve, the calculated exposure for these areas tended to be overestimated and led to misclassification of low-marsh habitat as open water.

The MCWI reference dataset contained 2840 low-marsh units within the effective study area (mean ± SE: 1.42 ha ± 0.23). The model correctly identified 81% of the reference low-marsh units with a mean overlap of 60%, when no minimum low marsh size threshold was applied. The model sensitivity and mean overlap improved as the minimum area threshold for low marsh units increased (Table 4). When only low-marsh units larger than 1.0 ha were considered, the model sensitivity was nearly 100% (only one fringing wetland occurring along a steep channel had been missed) with mean areal overlap of 74%.

Discussion

Overall, our full model performed remarkably well, yielding AUC scores of 0.785–0.849 for model runs with all datasets, including two independent datasets (Table 2), and acceptable performance of the classified model output (Table 3). Further, its ability to correctly identify low-marsh units from the reference dataset was strong, correctly identifying over 99% of low marsh units from the MCWI that were larger than 1.0 ha (Table 4; for reference, with the 10 m resolution of the GB-DEM a 0.1 ha low-marsh unit was the equivalent of 10 pixels). The performance of the model at that scale is relevant since Midwood et al. (2012) found that the average low marsh unit in eastern and northern Georgian Bay had an area of 1.4 ha, and the Ontario Wetland Evaluation System indicates that provincially significant wetlands must be > 2 ha in size, either as a single wetland or a complex consisting of functionally-grouped set of smaller wetlands (OMNR 2014). Based on a simple visual assessment of the predicted low marsh area (i.e. Fig. 2), the model capably differentiated between low-marsh and open-water habitat types. In cases where the model overestimated the lakeward extent of the low marsh area compared with the MCWI, we confirmed that the predicted extent was generally consistent with field observations (J.D. Weller, pers. obs).

Despite the promising model performance, there were still notable classification errors: the exclusion of 360 ha of low-marsh habitat from the effective study area, and the misclassification of 653 ha of low marsh and 3560 ha of open water (Table 3). The most commonly misclassified area was along the lakeward edge of low marsh areas, but this is largely attributable to the nature of the reference dataset. The habitat types in the MCWI (Midwood et al. 2012) were manually delineated from satellite imagery and the lakeward extent of the low marsh zone was delineated without the benefit of bathymetric data. As pointed out by Midwood et al. (2012), a set of heuristic rules had been used to estimate the lakeward boundary of the low marsh zone based on the morphology of the site and observable wetland characteristics. These differences in ruleset is one of the main reasons for the lower areal estimate of low marsh in the MCWI relative to our model output.

Exclusion of 360 ha of low marsh corresponding to the effective study area accounted for nearly 10% of the total low-marsh area from the MCWI, which was already a small component of the total dataset. These

Table 4 Ability of the model to identify low marsh units ("Match" = correctly classify some portion of a low-marsh reference unit), with the mean proportion of overlapping area for matched units and the fraction of correctly classified units from the reference dataset

LM unit size (ha)	# of units in MCWI	# of matches	Mean proportion overlap (± SE)	Sensitivity
All	2840	2294	$0.60 \pm 7.96 \times 10^{-3}$	0.81
> 0.1	1441	1374	$0.67 \pm 7.96 \times 10^{-3}$	0.95
> 0.2	1072	1035	$0.68 \pm 9.17 \times 10^{-3}$	0.97
> 0.5	622	615	$0.71 \pm 1.10 \times 10^{-2}$	0.99
> 1.0	389	388	$0.74 \pm 1.28 \times 10^{-2}$	1.00

Multiple minimum area cutoffs were included to evaluate model performance at different spatial scales exclusions are the result of overestimated slopes immediately along the shoreline in areas where the resolution of the GB-DEM was not sufficient to accurately capture the true landscape structure. Although this was a pervasive issue throughout the study area given the rocky nature of the landscape, mostly narrow bands of shoreward low-marsh habitat were excluded. Omission errors due to inflated exposure as a result of the inability of the GB-DEM to detect shoals in the shallow region of southeastern Georgian Bay (see Fig. 2) will not be corrected until a finer-scale elevation data set becomes available. We acknowledge that the scale of evaluating these HGM features is important (Duarte and Kalff 1990) but incorporating different scales of HGM data into this modeling effort was beyond the scope of this study.

Many management agencies operationally define the lakeward extent of coastal wetlands to be the 2 m depth contour (Albert et al. 2005; Keough et al. 1999; OMNR 2014). In this study, we explicitly applied a 5-m depth limit because we wanted to ensure our region of interest included all depths where aquatic vegetation could potentially colonize. Even so, our classified model output predicted a total 6166 ha of low marsh, of which 6141 ha was in water < 2 m deep. In fact, < 0.4% of our total predicted low-marsh habitat occurred in depths outside the accepted lakeward extent; therefore, the model predictions are consistent with the generally accepted criteria for the lakeward boundary of coastal wetlands. Even though the total area of low-marsh habitat predicted by the model is nearly double that of the MCWI, we believe this to be an underestimate of its lakeward extent because the model was trained with a conservative dataset. Sonar logs collected from a set of coastal wetlands that were surveyed in southeastern and northern Georgian Bay (J.D. Weller unpublished; see Fig. 3) support this observation, with SAV extending further lakeward than the predicted low-marsh extent.

Our model does not take into account lake-level fluctuation and assumes a static lake level. Water-level fluctuations are a key feature of Great Lakes coastal wetlands (Environment Canada 2002) and the role that water-level fluctuation plays in coastal wetland processes is well documented (Keddy and Reznicek 1986; Leira and Cantonati 2008; Mortsch 1998; Wilcox and Meeker 1991). Our model attempts to predict extent of low marsh, as a general habitat category, and we do not attempt to predict any level of community composition or structure within that habitat area. Further, our training dataset (MCWI; Midwood et al. 2012) was delineated from imagery captured at least 3 years into a period of sustained low water levels. Assuming there is a 2 to 3 year lag time for wetland communities to respond to a shift in water levels (Gathman et al. 2005; Quinlan and Mulamoottil 1987; Wilcox and Nichols 2008), the wetland community should have responded to the new water level conditions by the time the imagery had been acquired. We assume that our training dataset is representative of a low-marsh community that had adjusted to the stable water-level regime and in which different vegetation classes occupied their "optimal" depth range. Although the scope of the present paper did not permit it, inclusion of prior hydrographic conditions in the model would be a worthwhile refinement for future consideration.

We restricted our model evaluations to the best-fitting model, which was the full HGM model. Our depth-slope model performed nearly as well as the full-model, with AUC scores of 0.825 and 0.8306, respectively (Table 2). This is a computationally simpler model without sacrificing much in terms of performance. Deriving the wave exposure layer was by far the most computationally demanding process. An exposure threshold is still necessary to delineate the effective study area, but a reduced exposure layer could be derived that simply aimed to classify areas as above or below the exposure threshold. The exposure-only model had an AUC of 0.5697, indicating that it was only marginally better than random as a predictor of low-marsh habitat within the effective study area. Nevertheless, the value of the exposure layer was in delineating the region of interest that contained potential low-marsh areas. The majority of 23,128 ha of open water that were excluded from the effective study area (Table 3) can be attributed to applying the wave exposure threshold.

Inventories of coastal wetland are required to evaluate how these habitats may change over time and this HGM modeling approach is a practical way to address current data gaps and limitations. Large-scale efforts to inventory wetland habitat typically rely on remotely-sensed imagery (i.e. aerial or satellite imagery) to identify and delineate wetland areas (Bourgeau-Chavez et al. 2015; Ingram et al. 2004; Midwood and Chow-Fraser 2010; Midwood et al. 2012). While this is certainly an effective approach,

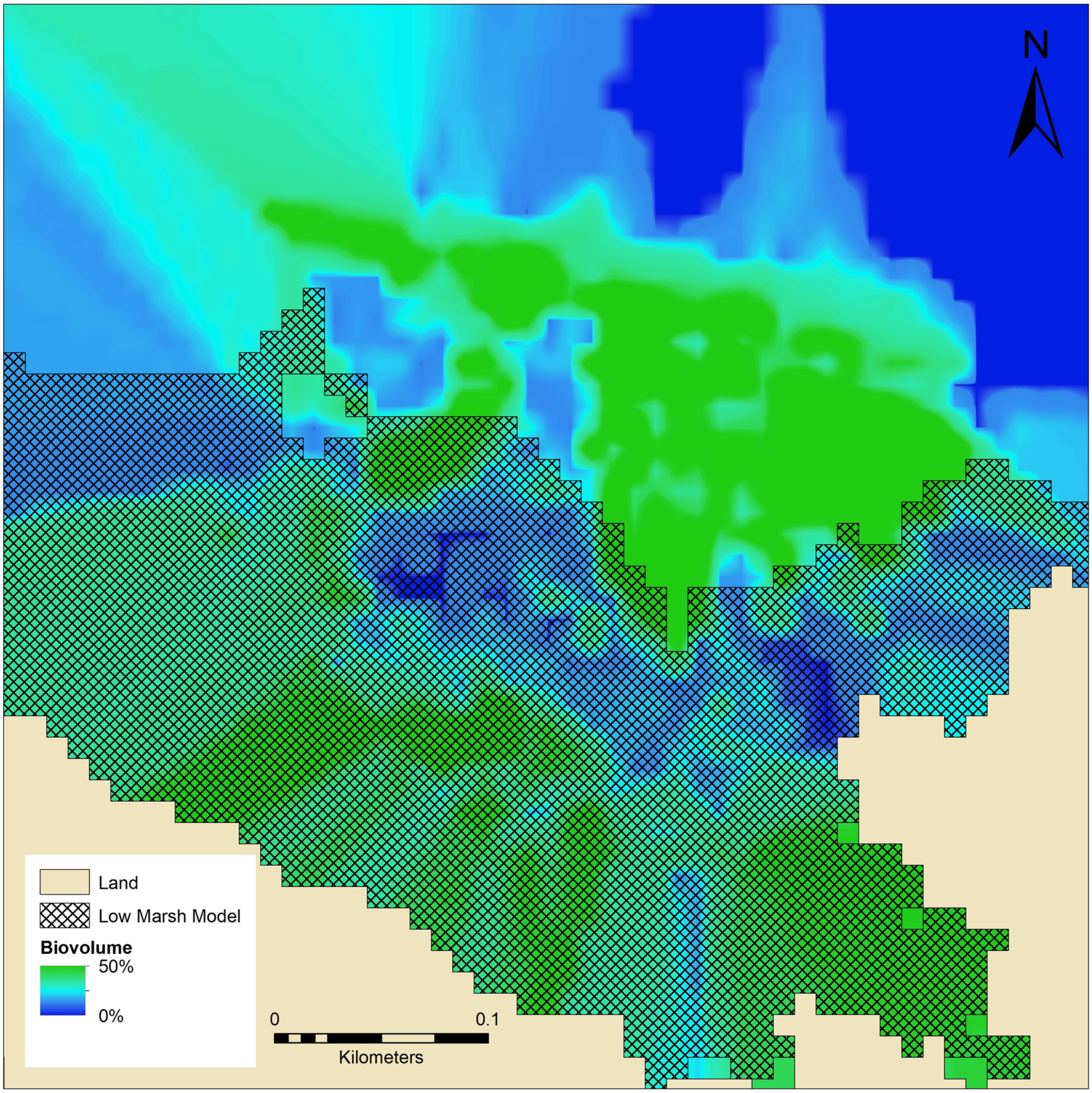

Fig. 3 Comparison of modeled low marsh (hatched area) to aquatic vegetation data collected using sonar at a lake level of 176.75 m. Sonar data is expressed as biovolume (percent of the water column occupied by aquatic vegetation), where 0% is bare substrate and 25–50% approximates moderate density aquatic vegetation. The model underestimates the lakeward extent of the low marsh vegetation and does not capture the patchiness of aquatic vegetation within the wetland

the spatial and temporal extent of the inventory is limited by available imagery. Given that it is not always possible to access suitable images to reflect past and future conditions outside the range of recently observed conditions, our HGM modeling approach only requires a suitable training dataset and an appropriate DEM. This approach was particularly well-suited to our Georgian Bay study area because of limited anthropogenic impact and the fact it is underlain by weather-resistant Canadian Shield. As such, we are confident that our GB-DEM is an acceptably accurate representation of the true elevation of the area for upwards of several decades into the past or future. This approach may be less appropriate in areas where the landscape is subject to change on a much smaller timescale (e.g. dredging, shifting sand bars) or would require additional calibration of the DEM.

Data availability was certainly the most significant obstacle to overcome in this study, and we would qualify our efforts as a "best-possible" effort for Georgian Bay. The Ontario Provincial DEM v3.0 more than met our requirements for spatial scale, but lacked desirable resolution. In contrast, the resolution of the CHS data was an improvement over the comparable open-source bathymetric data but the coverage was not comprehensive. The Georgian Bay archipelago contains thousands of islands and shoals and in many areas, a comprehensive bathymetric survey is not possible. The morphological complexity of the landscape relative to the resolution of available elevation data is certainly a challenge inherent with this modeling approach, as highlighted by the abrupt and irregular changes in elevation that occur in a granitic landscape like Georgian Bay. This can be addressed through the collection of improved elevation datasets, which is a long-standing need identified by other researchers studying Great Lakes coastal wetlands (Ciborowski et al. 2009; Hebb et al. 2013; Ingram et al. 2004).

In this paper we detailed the development and validation of our low-marsh model, but a comprehensive application of the model to eastern and northern Georgian Bay across a range of lake levels is found in Weller and Chow-Fraser (2018). The authors mapped the extent and distribution of low-marsh habitat at five lake levels (175.5–177.5 m, 0.5 m intervals) spanning the range of historically observed conditions. They found that low-marsh area was largest under low lake levels (176.0 m), but tradeoffs between area and volume of low-marsh habitat may have important implications for fish habitats. Weller and Chow-Fraser (2018) did not consider any novel lake level conditions (i.e. extreme highs or lows) since projections over the next century are generally within the historically observed range (Angel and Kunkel 2010; Lofgren et al. 2002), but there is no operational limitation in applying the model to novel lake levels. In the case of our Georgian Bay study area, the different vertical accuracies of the elevation data used to develop the GB-DEM (i.e. above or below 176.0 m) had implications for interpreting the model outputs. The coarser elevation data above 176.0 m resulted in larger commission errors under high lake levels (i.e. 177.0–177.5 m) which were addressed by applying several mask layers to improve the low-marsh habitat maps.

Lake levels play a key role in shaping coastal wetlands habitats. The uncertainty about future lake levels necessitates a means to predict and evaluate how coastal wetlands may respond to these novel conditions. The HGM modeling approach that we have demonstrated in this paper should satisfy that need and serve as a jumping-off point for more refined analyses.

Acknowledgements With regards to the DEM developed for this project, it was produced by McMaster University based on Canadian Hydrographic Service charts and/or data, pursuant to CHS Direct User Licence No. 2016-1121-1260-M. The incorporation of data sourced from CHS in this product shall not be construed as constituting an endorsement by CHS of this project. This product does not meet the requirements of the *Charts and Nautical Publications Regulations, 1995* under the *Canadian Shipping Act, 2001*. Official charts and publications, corrected and up-to-date, must be used to meet the requirements of those regulations. This work was supported in part through an Ontario Graduate Scholarship for Dan Weller and a research contract from Environment and Climate Change Canada. We appreciate the comments from two anonymous reviewers whose input improved the quality of this manuscript.

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