Wetlands (2010) 30:1141–1152
DOI 10.1007/s13157-010-0105-z

ARTICLE

Mapping Floating and Emergent Aquatic Vegetation in Coastal Wetlands of Eastern Georgian Bay, Lake Huron, Canada

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Received: 2 October 2009 / Accepted: 14 September 2010 / Published online: 2 November 2010

Abstract Expansion and contraction of floating and emergent vegetation due to fluctuating water levels has a direct impact on the amount of critical fish habitat in the coastal marshes of Georgian Bay, Lake Huron (Canada). Traditional mapping approaches developed for site-specific studies are too expensive to quantify such changes at the scale of Georgian Bay. Here, we use IKONOS images to develop a classification method (process-tree classification (PTC)), an automated, object-based, image-analysis approach that can produce regional maps of wetland habitat for south-eastern Georgian Bay (1466.7 Km). PTC discriminated among six wetland habitat classes (emergent, high-density floating, low-density floating, meadow, water, and rock) in four IKONOS satellite images with a mean accuracy of 87.4%. The PTC was then applied without modification to 17 other IKONOS images collected concurrently in 2002. Based on analysis of 50 randomly chosen wetlands in these images, we estimate that at 2002 water levels, at least 25% of an average wetland (6.5 ha) contains potential fish habitat. Although the PTC developed is specific to the 21 IKONOS images used in this study, the framework is transferable to satellite images acquired in other regions of Georgian Bay, and the approach itself could be applied to other large lakes.

Keywords Great Lakes · Habitat · Remote sensing

Electronic supplementary material The online version of this article (doi:10.1007/s13157-010-0105-z) contains supplementary material, which is available to authorized users.

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Introduction

Wetlands have been globally recognized for their cultural, economic, and ecological value (Brander et al. 2006). Barbier et al. (2008) estimate that 50% of the world's marshes have already been lost or degraded. In North America, close to 70% of the wetlands in settled areas of the Laurentian Great Lakes basin have been lost (Snell 1987), and the remaining are still threatened by human development (Niemi et al. 2007) and declining water levels (Mortsch 1998). In the Great Lakes, coastal wetlands help maintain good water quality, regulate watershed hydrology, and provide essential habitat for a number of organisms, especially Great Lakes fishes that use these marshes for spawning and feeding (Wei et al. 2004), and as shelter from predation (Randall et al. 1996).

Government agencies in both Canada and the U.S. have recognized the need to create a comprehensive wetland inventory as a first step to conserve remaining Great Lakes coastal wetlands (Lawson 2004; Fournier et al. 2007). Ingram et al. (2004) used aerial photographs to delineate most of the coastal marshes of Ontario to create an inventory, but due to incomplete coverage of aerial photography, they were unable to identify all marshes along the eastern and northern shores of Georgian Bay (eastern bay of Lake Huron), where some of the most pristine systems occur (Chow-Fraser 2006; Cvetkovic 2008). The Georgian Bay wetlands have a wide spatial distribution and are rarely road-accessible (DeCatanzaro et al. 2009), making them too time-consuming and expensive to map using traditional ground surveys and aerial photography (illustrated in Wei and Chow-Fraser 2007).

Since coastal marshes are directly connected to open water of lakes, wetland vegetation responds rapidly to changes in water level and water quality (Lougheed et al.

2001; Hudon, 2004; Chow-Fraser 2006). Mortsch and Quinn (1996) predicted that the increase in temperature resulting from a two-fold increase in atmospheric CO_2 could lead to decreased frequency of precipitation and increased evaporation, in turn causing water levels in Lake Huron to drop by as much as 2.5 m from base case. Between 1999 and 2008, water levels in Georgian Bay fluctuated at approximately 50 cm below the long-term average, and this has led to major shifts in the wetland plant community, from emergent and floating vegetation to increased meadow vegetation (Rokitnicki-Wojcik 2009). Because floating, emergent, and submergent vegetation are essential components of fish habitat, wetland managers must be able to identify these critical habitat types and map them. Such maps developed with a method that can be applied consistently would provide wetland managers a means to track changes in fish habitat at regular intervals.

Earlier studies focusing on wetland mapping relied predominantly on two methods: aerial photography, which provides high resolution at a fine spatial scale, or Landsat imagery, which provides low resolution at a coarse spatial scale (e.g., Poulin et al. 2002; Leahy et al. 2005). IKONOS satellite imagery, by comparison, has a much higher spatial resolution than Landsat imagery (1 m pan-sharpened), a wider spatial coverage when compared to aerial photography (~100 km^2 per scene), as well as four distinct spectral bands (red, green, blue, and near-infrared) that are useful for automated classification procedures (Lillesand et al. 2004; Wei and Chow-Fraser 2007).

IKONOS imagery has been used to identify wetlands (Fuller et al. 2005) and to produce vegetation maps from multi-temporal images (Dechka et al. 2002) and pixel-based spectral reflectance (Sawaya et al. 2003). Within a Great Lakes context, Wei and Chow-Fraser (2007) successfully used IKONOS imagery and a maximum-likelihood classification (MLC) to map aquatic vegetation in Fathom Five National Marine Park, Canada, and one wetland in eastern Georgian Bay with accuracies greater than 85%. Although this MLC can provide an accurate wetland-specific classification, the need for local ground truth samples (GTS) limits its application at the regional scale, especially for eastern Georgian Bay, where most wetlands are only accessible by boat.

The MLC used by Wei and Chow-Fraser (2007) is also a pixel-based classification, which may limit its usefulness for classifying wetland systems that have a large degree of variation in pixel values (Fuller et al. 2005). Chubey et al. (2006) and Fournier et al. (2007) have shown that an object-based classification system can yield improved accuracy over traditional pixel-based classification systems because image objects combine spectral properties with additional information provided to the user (e.g., shape, size, area, and mean spectral response) and thus minimize errors induced by local variability in pixel values (Navulur 2007). This image-object-based approach has been used in terrestrial systems (Laliberte et al. 2004; Silva et al. 2008, Zhou et al. 2008), marine systems (Wang et al. 2004), upland coastal habitats (Grenier et al. 2007; Rokitnicki-Wojcik 2009), and riparian marshland (Dillabaugh and King 2008), but to our knowledge has not yet been used to map fish habitat in freshwater coastal wetlands.

The overall goal of this study is to characterize areal vegetation coverage in south-eastern Georgian Bay. First we develop a regionally applicable classification system that minimizes the need for ground truth samples but produces habitat maps of coastal wetlands with an overall accuracy of at least 85%, which is the level of accuracy achieved in Wei and Chow-Fraser (2007). We next apply this classification and identify the dominant types of vegetation and consequently the composition of fish habitat in these coastal marshes. Since declining water level is one of the most serious threats to pristine Georgian Bay coastal marshes, our results should greatly enhance the ability of environmental agencies to track changes in the amount of fish habitat as water levels fluctuate with climate change. Classification of satellite images acquired at different water-level scenarios could also facilitate development of empirical relationships between areal cover of wetland vegetation and water-level, and these could be used to model how further declines in water levels may affect fish habitat quantity and quality.

Methods

Study Sites

Eastern Georgian Bay, Ontario, Canada contains two distinct geographic regions, the limestone Niagara escarpment in the south-east and the Canadian Shield (granite) along the remainder of the coast. Due to complex local geography, most areas of Georgian Bay are not road-accessible, and are therefore relatively undisturbed by human activities. Marshes that have formed along the coast have retained their naturally low nutrient levels, and are characterized by clear oligotrophic water so long as there is adequate exchange between the bay and the marsh; however, when connectivity with Georgian Bay is restricted, runoff from the Canadian Shield can make the water highly colored with dissolved organic carbon (i.e., dystrophic) (DeCatanzaro 2010). The rocky substrate of the Canadian Shield and exposure to wind and wave action limit the amount of sediment deposition in these wetlands and, as a result, meadow development is very limited. The dominant vegetation types tend to be floating (e.g., *Nymphaea*, *Nuphar*, *Brasenia,* and *Zizania*) and submerged herbaceous vegetation (e.g., many species of *Potamogeton* and *Myriophyllum*, etc.), with a narrow fringe of emergent macrophytes (e.g., *Schoenoplectus* and *Eleocharis*).

We collected samples from 16 wetlands for use in the creation and validation of the classification method in this study. Data from five wetlands were used for creation and 11 for validation. There were six wetlands in Tadenac Bay, six in North Bay, two in Severn Sound, and one each in Go Home Bay and Sans Souci (Fig. 1; Online Resource 1). Tadenac Bay is owned and managed by the Tadenac Club, which has left this property essentially undeveloped since 1896. Wetlands in this bay receive minimal disturbance from human activities. By comparison, many wetlands in the North Bay and Severn Sound in the southern region have been subject to recreational and cottage development (2,340 year round inhabitants, 2006 Census, Statistics Canada) as well as high levels of boat traffic. The Sans Souci and Go Home Bay wetlands were selected because they are associated with intermediate levels of disturbance when compared to the other study sites. Wetlands used in the application (n=50) of the classification were randomly selected from a group of 144 marshes that had been manually delineated by interpretation of IKONOS images covering the entire coast of Georgian Bay from Severn Sound in the south to Parry Sound in the north (Fig. 1; Online Resource 2).

Pre-Processing

IKONOS images were acquired in 2002 by Georgian Bay Forever (formerly Georgian Bay Foundation), an environmental non-profit organization, and licensed to McMaster University. Twenty-one images covered the shoreline continuously from Severn Sound to southern Parry Sound (Fig. 1). For each image, three bands were available in the visible spectrum (red (RE), green (GR), and blue (BL)) and one band in the near-infrared (NIR). The images were cloud-free, collected at approximately 11:30 am on July 1st, 2002 (EST). This date was sufficiently late in the season to ensure majority of the vegetation had matured.

Images were pre-processed by GeoEye (Dulles, VA, U.S. A.) based on a standard, proprietary, geometrically corrected procedure. They were projected into UTM N17 using the WGS84 datum. All four spectral bands were also pansharpened with the 1 m panchromatic band during this preprocessing phase and the resulting bands had 1-m spatial

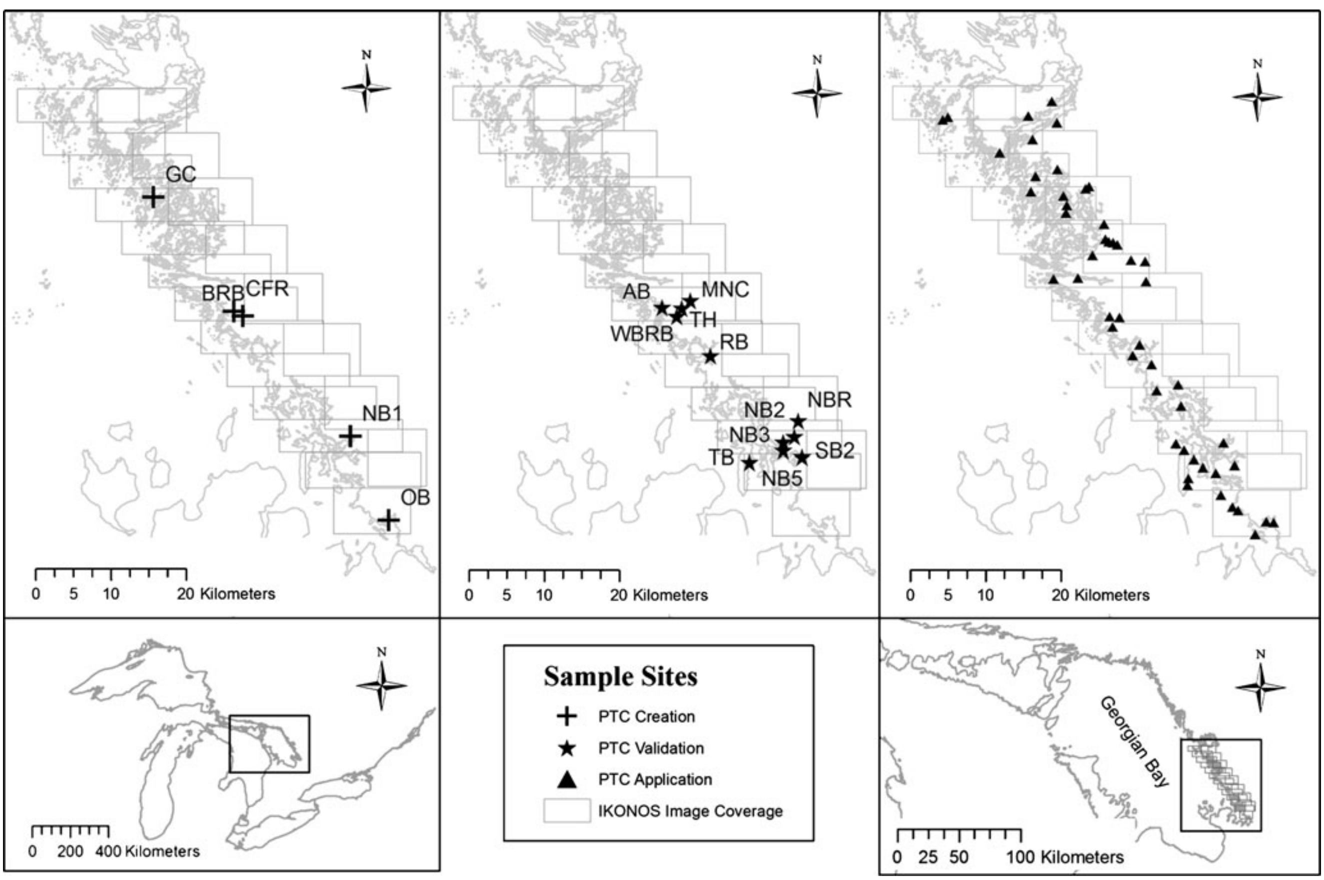

Fig. 1 Map of eastern Georgian Bay identifying coastal wetlands used for creating (*crosses*) and validating (*stars*) the process tree classificaiton (PTC). The PTC was then applied to 50 wetlands located along the south-eastern shore of Georgian Bay (*triangles*). The square boxes outline the coverage of the 21 IKONOS images used in this study

resolution (GeoEye; Dulles, VA, U.S.A.). Sawaya et al. (2003) suggested that images collected during a single pass would share similar spectral properties and could therefore be used for regional mapping purposes. A preliminary comparison of spectral properties among our 21 IKONOS images was conducted by Rokitnicki-Wojcik (2009) and no significant differences were found. Based on this preliminary analysis and the fact that the imagery had been collected contemporaneously, we assume that the spectral properties of ground features in the five images used in this study are representative of features observed in all 21 images and can theoretically be used to create a model applicable to all (see sample image in Online Resource 3).

Image Segmentation

Masking

The PTC was created in Definiens Developer 7.0 software (Definiens®AG, Munchen, Germany). This software uses a decision-tree framework with image objects. Our first step was to isolate the wetland from the surrounding onshore (or upland) vegetation (trees, shrubs) that might share similar spectral properties. We isolated wetland areas using a manually-derived mask layer. A small band of onshore vegetation remained outside of our mask layer to ensure that all wetland vegetation was included; this onshore vegetation will later be identified as meadow vegetation. The lakeward edge of the mask was delineated to include a conservative estimate of submerged aquatic vegetation (SAV) based on SCUBA observations during our field surveys.

Remaining Unclassified

A multiresolution segmentation was used to aggregate the remaining unclassified pixels into image objects. This method employs a user-defined resolution to minimize the average heterogeneity of neighboring pixels. Chubey et al. (2006) used a visual inspection of the image objects created by a multiresolution segmentation to maximize the creation of homogeneous groups. We followed the same process to determine the ideal segmentation parameters. In our final segmentation, we selected the layers associated with the RE, GR, and BL bands with which to create the segmentation. The NIR band was excluded due to its coarser pixel size.

We selected a scale factor of 10 within which the heterogeneity would be minimized. This means that large-homogenous regions would be grouped together to form objects greater than 10 m^2 while small heterogeneous regions would be grouped together into objects smaller than 10 m^2. The color or shape of the input pixels can be used to help identify objects based on composition and degree of homogeneity of neighboring pixels. Since information in our imagery was derived from spectral or color data, there is no expectation that our classes would be predicted based on shape such as agricultural fields or land plots. As such, we opted to use color as the main determinant in our segmentation. We set the influence of shape to 10% and color was used for the remaining 90%.

Training/Testing Sample Selection

During 2007 and 2008 (June to August inclusive), we collected GTSs in 15 of the 16 wetlands (none were collected in Roseborough Bay). In each of the 15 wetlands, all homogeneous ground cover with an area >4 m^2 were sampled for meadow vegetation ("M"), emergent vegetation ("E"), high-density floating vegetation ("HD"; >50% coverage within the quadrat), low-density floating vegetation ("LD"; <50% coverage), rock ("R"), and water ("W") (see Online Resource 1). On average, 26 GTS were collected per wetland. Samples of water and rock were not always collected at each site since these two classes are easily recognizable in imagery. Portions of the 2002 IKONOS images for Tadenac Bay and North Bay were printed off and used in the field to manually delineate all coverage types in 13 wetlands. For three of our wetlands (Garden Channel, Roseborough Bay and Oak Bay), maps were drawn by hand in the field, showing the distribution of aquatic vegetation within the wetlands. Since there had been a 5- to 6-year difference between image acquisition and GTS collection, we did not rely on a direct overlay of the GTS when selecting sample objects (SO). Instead, the GTSs were used to help guide the selection of representative SOs in the IKONOS images (Wei and Chow-Fraser 2007). The use of representative points allowed us to use a comparatively small number of GTSs (n=385) and maps to collect a larger number of SOs (n=1845; Online Resource 4).

Sample Analysis

Using a combination of GTS and field-derived maps for five wetlands (Black Rock Bay, Coffin Rock, Garden Channel, Oak Bay and North Bay 1), we selected 1,076 SOs that corresponded to the six habitat classes in the IKONOS images: "E" (n=192), "LD" (n=141) "HD" (n=202), "M" (n=230), "R" (n=158), and "W" (n=153) (Online Resource 4). We exported the mean values of IKONOS bands (RE, GR, BL, and NIR) as well as NIR divided by RE, hue, intensity, and saturation associated with each SO. The hue, saturation, intensity (HSI) transformation for hue represents a gradient of color among the IKONOS bands. HSI transformation for saturation used in this study is an expression of the maximum level of intensity in either the RE, GR, and BL spectrum, minus the minimum intensity level in the same bands, divided by the original maximum value. Finally, the HSI transformation for intensity uses the largest value in either the RE, NIR or NIR/RE bands (Schowengerdt 1997; Definiens 2007). For each feature an ANOVA was performed in SAS JMP IN 5.1 (SAS Institute, Cary, North Carolina, U.S.A.) to determine if there were significant differences in the value of the feature among the six habitat classes. Once significance was established, we used a Tukey-Kramer analysis to identify differences among the ground-cover classes (data not shown). While this technique provided us with distinct SO properties for water (mean NIR <250) and rock (RE, GR, BL saturation <0.23), the remaining four vegetation classes shared too many similar properties for them to be separated solely on the basis of spectral responses. Hence, the Tukey-Kramer analysis was only used as a starting point to identify potentially separable features for vegetation classes. In order to identify the four vegetation classes, we selected new samples from GTSs and a field-derived map from a single wetland, Black Rock Bay (“E” (n=37, “LD” (n=16), “HD” (n=92), “M” (n=20), “R” (n=70), “W” (n=31); Online Resource 4). For most features, there was a considerable amount of overlap among all vegetation classes. For our final classification, we selected the feature that provided the least amount of overlap and then used relational features to refine the classification.

Process Tree Creation

The process tree was created in a hierarchical manner such that the input IKONOS image bands could be substituted for in any of the 21 images (Fig. 2). In the first step of the classification, we identified image objects that corresponded to “W” and “R”. An SO was assigned to “W” if it had a mean digital value of ≤250 in the NIR band. We classified the object as “R” when the saturation value of the HSI transformation had a mean value <0.23. We grouped the vegetation classes “E” and “LD” into a category called “wet” vegetation when the HSI transformation for intensity was <0.007. The remaining vegetation (“HD” and “M”) was grouped together as “dry” vegetation. The next step was to separate the “dry” and “wet” vegetation into their constituent classes. “E” was separated from “wet” vegetation when the HSI transformation for hue was >0.8. The remaining “wet” vegetation was classified as “”LD vegetation. “M” was separated from “Dry” vegetation when the mean digital number in the blue band was <380. The remaining SOs were classified as HD vegetation.

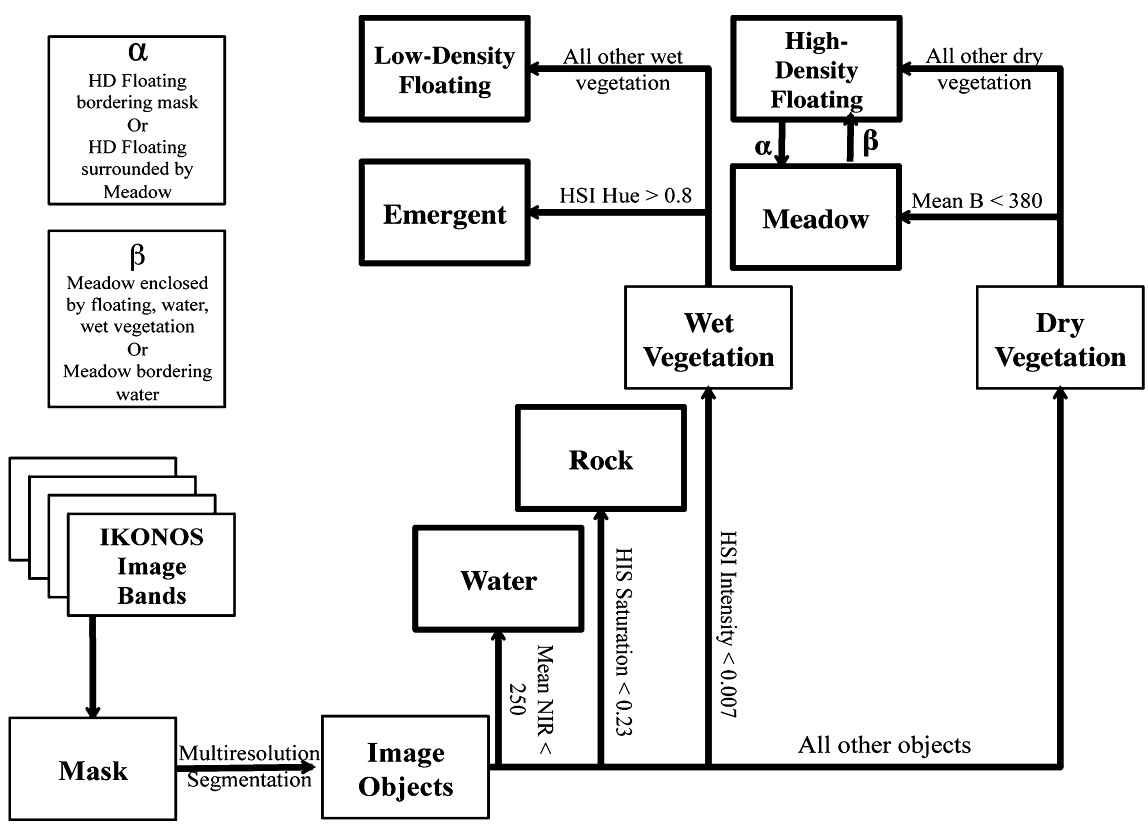

Fig. 2 Flow chart illustrating the steps in the Process Tree Classification (PTC). Small text next to each arrow indicates the feature(s) that were used to separate the image into six different land cover classes

Non-spectral class separation features or "relational" features were also used to correct for misclassifications. Objects identified as "M" that were completely surrounded by water or other aquatic vegetation ("HD", "LD", or "E") were assigned to the "HD" class. Conversely, "HD" was converted to "M" if it was in contact with the mask or if it was surrounded by other meadow classes.

Image Classification

The PTC (Fig. 2) was used to classify all coastal wetlands in the 21 IKONOS images that were >2 ha in size (the minimum size for a wetland to be evaluated in the Ontario Wetland Evaluation System (OWES, OMNR 1993)). The RE, GR, BL, NIR, and NIR/RE bands along with a mask layer, were used for the classification. All classified files were exported into a GIS for further analysis.

Validation

We used maps and ground control points to select a unique set of SOs in 11 independent wetlands to validate the accuracy of the PTC (Fig. 1 ; Online Resource 4). Since we used samples to select representative objects, we were once again able to use a small number of GTSs and maps to collect a larger number of SOs. We calculated user- and producer-accuracy as well as the Kappa statistic to test overall and class-specific accuracies. The user-accuracy represents the ratio of correctly classified objects in a class to the total number of objects assigned to that class. By comparison, the producer-accuracy represents the ratio of correctly classified objects in a class to the actual number of ground-truth objects for that class. The Kappa statistic, ranging from 0 to 1, represents the expected agreement between ground truth and classification results, after accounting for the fact that some of the agreement will happen purely by chance (Congalton 1991). Although there is no consensus in the remote sensing community concerning acceptable Kappa thresholds, Kappa values greater than 0.80 are preferred, but values from 0.5 to 0.79 are still reasonable (Cohen 1960).

Application

In total, 144 wetlands (>2 ha in size) were identified in the IKONOS imagery that cover the shoreline from Severn Sound to Parry Sound. We used the PTC to classify all 144 wetlands and then imported areal cover associated with all six habitat classes into ArcMap 9.2 (ESRI Inc., Redlands, California, U.S.A., 2006). To illustrate how this approach can be used to estimate quantity of habitat classes at a regional scale, we randomly selected 50 of the 144 wetlands (see Fig. 1) to estimate fish habitat. As an estimate of generic fish habitat, the "E", "LD", and "HD" classes were merged together to form what we will call "visible fish habitat" (VFH), which does not contain habitat containing SAV. By combining VFH with an estimate of open water containing SAV, we produced an estimate of "potential fish habitat" (PFH). We feel that applying the approach to 35% of the wetlands would be sufficient for demonstrating the usefulness of our approach. Total time spent on the application and areal assessment of these 50 wetlands, excluding time spent on the creation of the PTC, was approximately 6.5 h (eight min per wetland); however, this time may vary according to users' familiarity of the software and prior experience with classification.

Results

The overall accuracy for our 11 wetlands was 87.4%. For each wetland, with the exception of West Black Rock Bay, Alexander Bay, North Bay River, and Treasure Bay, the overall accuracy was greater than our minimum benchmark accuracy of 85% (Table 1). An example of a classified wetland can be found in Fig. 3. The overall Kappa statistic for the wetlands ranged from 0.75 to 1.00, with the majority of the sites above 0.8. Only Alexander Bay and North Bay River had Kappa values below 0.8 (0.75 and 0.76 respectively). "W" had the highest overall class accuracy (Kappa=0.96), with 98.5% of image objects identified correctly. While accuracies associated with "R" and "M" were higher, "HD" was only slightly lower (92.4%, Kappa=0.89; 93.9%, Kappa=0.96; 88.4%, Kappa=0.91, respectively); "E" and "LD" had the lowest overall accuracies (77.9%; Kappa=0.71 and 74.6%; Kappa=0.72, respectively).

The Kappa statistic was used to evaluate the PTC and to determine the degree to which our classification accuracy occurred purely by chance. The majority of our sites fell within either the "excellent agreement" category suggested by Cohen (1960; 0.8–1.0) or the "almost perfect agreement" category suggested by Landis and Koch (1977; 0.81–1.00). Alexander Bay and North Bay had Kappa values <0.8 (0.75 and 0.76, respectively), still within the "reasonable agreement" category of Cohen (1960; 0.5–0.79) or "substantial agreement" category of Landis and Koch (1977; 0.61–0.80).

Of the 50 wetlands (mean size 6.6±7.9 ha; Online Resource 2) randomly selected from the inventory of 144 wetlands distributed along the shoreline of south-eastern Georgian Bay from Severn Sound to Parry Sound (Fig. 1), the most common type of vegetation coverage was "LD" (1.1 ha,±71.3 ha), followed by "E" (0.32±70.38 ha), "HD" (0.23±70.42 ha) and "M" (0.18±70.33 ha). In terms of fish habitat, we calculated that on average, the coastal wetlands

Table 1 Error matrix for the 12 wetlands used to test the accuracy of our process tree. Kappa is expressed as a value from 0 to 1. The label "N/A" means that for a specific wetland, no features of that class were present

Wetland	Accuracy Method	Class Meadow (%)	High-Density Floating (%)	Low-Density Floating (%)	Emergent (%)	Rock (%)	Water	
West Black Rock Bay	Producer	92.6	59.6	81.9	53.3	100	97.2	
	User	82.8	100	49.5	86.7	84.4	99.0	
	Kappa	0.92	0.59	0.80	0.51	1.00	0.96	
							Overall Accuracy (%)	82.3
							Average Kappa	0.80
Treasure Bay	Producer	77.3	83.9	79.7	71.3	100	95.4	
	User	66.5	32.8	89.2	80.4	100	100	
	Kappa	0.75	0.83	0.77	0.69	1.00	0.89	
							Overall Accuracy (%)	81.4
							Average Kappa	0.82
Miners Creek	Producer	100	100	98.4	100	N/A	95.5	
	User	100	100	100	98.3	N/A	100	
	Kappa	1.00	1.00	0.98	1.00	N/A	1.00	
							Overall Accuracy (%)	99.2
							Average Kappa	1.00
Thunder Bay	Producer	100	N/A	89.4	80.8	80.5	100	
	User	98.1	N/A	86.5	86.8	100	100	
	Kappa	1.00	N/A	0.88	0.79	0.80	1.00	
							Overall Accuracy (%)	92.2
							Average Kappa	0.89
Alexander Bay	Producer	100	N/A	52.8	36.4	90.2	100	
	User	100	N/A	15.7	100	100	98.6	
	Kappa	1.00	N/A	0.49	0.34	0.90	1.00	
							Overall Accuracy (%)	79.4
							Average Kappa	0.75
Roseborough Bay	Producer	100	100	78.0	93.0	83.0	97.2	
	User	95.0	100	86.0	85.0	100	99.0	
	Kappa	1.00	1.00	0.77	0.92	0.82	0.90	
							Overall Accuracy (%)	93.0
							Average Kappa	0.90
North Bay 2	Producer	100	89.3	66.6	59.0	100	100	
	User	75.1	82.9	90.6	59.7	100	100	
	Kappa	1.00	0.88	0.63	0.57	1.00	1.00	
							Overall Accuracy (%)	85.3
							Average Kappa	0.85
North Bay 3	Producer	94.6	94.3	74.2	100	98.2	100	
	User	100	71.0	94.1	100	100	100	
	Kappa	0.94	0.94	0.73	1.00	0.98	1.00	
							Overall Accuracy (%)	93.9
							Average Kappa	0.93
North Bay 5	Producer	100	100	79.6	98.0	53.2	100	
	User	98.3	100	86.0	78.0	100	100	
	Kappa	1.00	1.00	0.77	0.98	0.53	1.00	
							Overall Accuracy (%)	91.1
							Average Kappa	0.88

Table 1 (continued)

Wetland	Accuracy Method	Class: Meadow (%)	High-Density Floating (%)	Low-Density Floating (%)	Emergent (%)	Rock (%)	Water	
North Bay River	Producer	95.4	100	68.3	38.2	N/A	95.0	
	User	57.5	83.4	64.6	68.0	N/A	100	
	Kappa	0.95	100	0.65	0.36	N/A	0.86	
							Overall Accuracy (%)	77.0
							Average Kappa	0.76
South Bay 2	Producer	100	100	47.2	63.0	100	98.6	
	User	100	94.1	63.4	78.9	100	91.6	
	Kappa	1.00	0.99	0.42	0.61	1.00	0.97	
							Overall Accuracy (%)	86.4
							Average Kappa	0.83
All Wetlands	Producer	96.4	91.9	74.2	72.1	89.5	98.1	
	User	88.5	84.9	75.1	83.8	98.3	98.9	
	Overall	92.4	88.4	74.6	77.9	93.9	98.5	
	Kappa	0.96	0.91	0.72	0.71	0.89	0.96	
							Overall Accuracy (%)	87.4

in south-eastern Georgian Bay contained 1.6 ha (±2.0 ha) of VFH, representing 25% of the total wetland area. The wetland masks we created contained a conservative estimate of SAV, and we determined that each wetland contained approximately 6.3 ha (±7.7 ha) of PFH. Assuming that the 50 wetlands that were randomly sampled are representative of all 144 wetlands, we estimate that approximately 230.4 ha of VFH and 907.2 ha of PFH existed in coastal wetlands of the southern half of Georgian Bay during 2002.

Discussion

This is the first time that an approach based on image objects has been used to map aquatic vegetation in Great Lakes coastal wetlands. The PTC represents an accurate and regionally applicable approach to map coastal marsh habitat, especially useful for assessing the Great Lakes fish community. Using a combination of spectral and relational image object features, we are now able to identify and quantify fish habitat in eastern Georgian Bay wetlands. Vegetation is known to have higher reflectance in the NIR spectrum, compared to the visible spectrum. Conversely, water has low reflectance in both the visible spectrum and the NIR (Swain and Davis 1978). Following an initial segmentation process, we identified open water where there were low levels of reflectance in the NIR spectrum. Water had the highest accuracy at the class level largely due to naturally high absorption in the NIR that limited confusion with other classes.

Eastern Georgian Bay and the coastal wetlands along its shore are located on the Canadian Shield, a large, ancient, granitic rock formation extending across central Canada. Rock is therefore prevalent in many of our wetlands, but probably not as pertinent a feature to classify in other Great Lakes coastal wetlands. Because there is a high reflectance in the three bands of the visible spectrum (RE, GR, and BL) associated with this land-cover feature, there were very low values for the HSI saturation transformation, and consequently, there was minimal confusion with other land-cover classes, and "R" was the second most accurately classified feature.

Scmidt and Skidmore (2003) were able to use hyperspectral data to discriminate among vegetation classes to the species level in salt-marshes. This was likely achievable because of a greater number of bands with narrower bandwidth in their study. By comparison, the four bands of the IKONOS imagery in this study only allowed for a modest degree of separation. Two of our vegetation classes ("E" and "LD") were mixtures of both vegetation and water and this combination allowed for an accurate separation of this "wet" vegetation from "dry" vegetation. Vegetation typically has high reflectance in the NIR spectrum but, when vegetation is combined with water, this reflectance is diminished; therefore "wet" vegetation was classified when there were lower values in the HSI intensity transformation.

Ullah et al. (2000) compared spectral reflectance in three different species of emergent vegetation and found that *Schoenoplectus* spp. (the dominant emergent species in Georgian Bay) had the lowest reflectance. They also noted

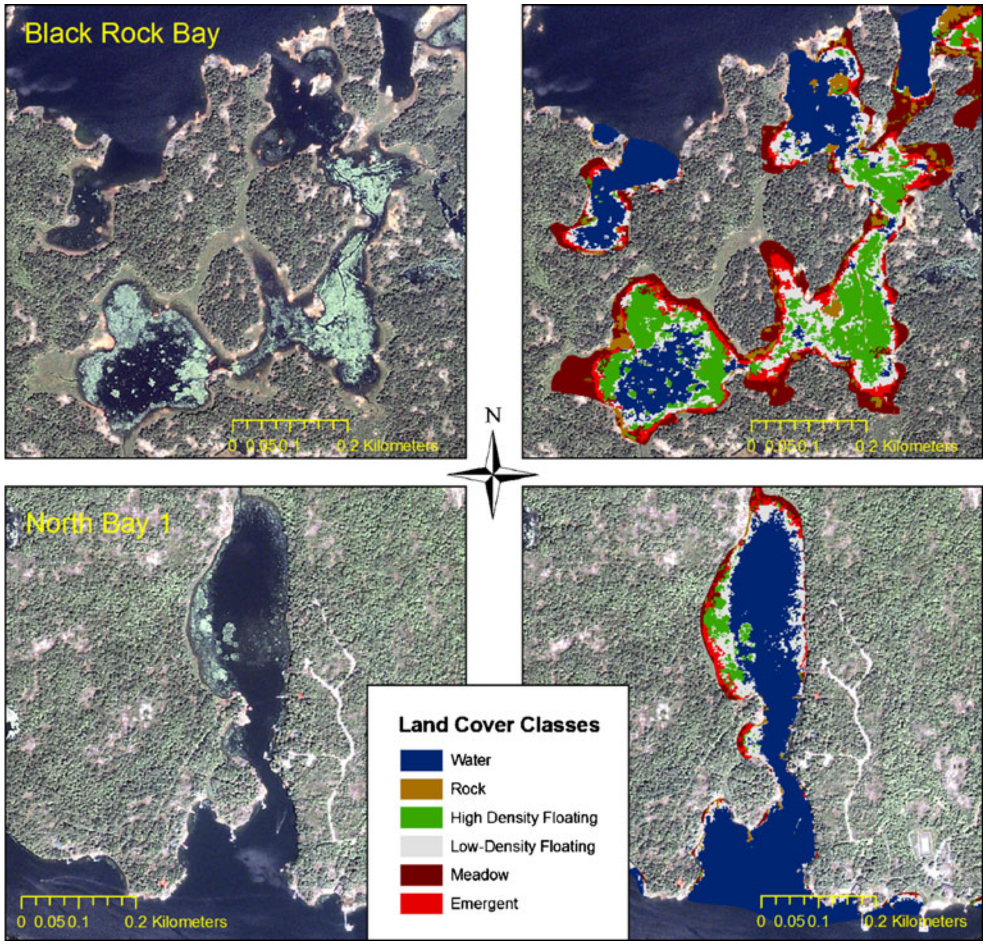

Fig. 3 Comparison of **a** original IKONOS image with **b** classified image using **PTC** method. Red=emergent vegetation, green=dense floating vegetation, grey=sparse floating vegetation, maroon=meadow vegetation, blue=water and brown=rock. This image was taken in July 2002 of the Tadenac Bay region of eastern Georgian Bay

that vertical vegetation (emergent) decreased spectral interference from substrates since long stems can block or intercept electromagnetic radiation from reaching or reflecting off the substrate. We used this differential influence of the substrate (water in the case of "wet" vegetation) to isolate "E" from "LD" vegetation. Due to a greater influence of water in "LD" vegetation, we classified image objects as "E" when there was a high HSI hue transformation. The "LD" and "E" vegetation classes had the lowest overall accuracy. The majority of the error in their classification was due to confusion with the other "wet" vegetation type, which we attribute to the mixture of both water and vegetation and discuss in more detail later.

We considered both "M" and "HD" vegetation to be "dry" vegetation. This is despite the presence of water in "HD" (defined as >50% vegetation coverage) because the dense vegetation made this type of aquatic vegetation more spectrally similar to "M" than to either "E" or "LD". In preliminary analyses, we tried to use the NIR/RE ratio to further separate "HD" from "M" classes since we anticipated that meadow vegetation would have a higher ratio due to greater vegetation density and less influence from water. Unfortunately, this approach did not prove useful, and instead, we were able to separate out "M" using low values in the BL band.

Overlap in spectral signature, especially between "HD" and "M" classes, made it necessary to use additional logic-based features to correct for any misclassifications that arose during spectral separation. Based on our knowledge of wetland zonation, we know that wetlands progress lakeward from terrestrial vegetation (not inundated), to meadow vegetation ("M"; seasonally inundated), to aquatic vegetation (permanently inundated; "HD", "LD" and "E"), and finally to open water ("W") with submerged aquatic vegetation (SAV). The transitional zone from meadow to aquatic vegetation is usually dominated by "E", and as water depth increases, "LD" and "HD" begins to take over. We have visited dozens of wetlands in Georgian Bay, and we rarely observe open water bordered by meadow vegetation without the presence of a transitional aquatic zone. It is equally rare for us to find dense floating patches mixed with meadow vegetation. Finally, we know that meadow vegetation does not exist in patches surrounded by any other habitat classes within the aquatic zone or in isolation without contact with the mask layer. We were able to use this type of logic to create rule sets that could correct for misclassifications of the various land-cover classes.

Using a combination of spectral and relational features, the PTC was able to separate our six classes with an overall accuracy greater than the benchmark of 85% that we had set out as a goal for this study. Four of the 11 wetlands did not meet our target overall accuracy of 85% (i.e., Alexander Bay, North Bay River, West Black Rock Bay and Treasure Bay; see Table 1). In all cases, the low accuracy associated with "LD" and "E" classes decreased the overall accuracy for these wetlands. The lowest overall accuracy was found for North Bay River (77%). This site was also associated with low user accuracy, which was attributed to a higher incidence of "E" being misclassified as "M". This site was one of the few wetlands which contained *Typha* spp. (cattails), which is atypical for other wetlands in Georgian Bay (Croft and Chow-Fraser 2007). Although this species is clearly emergent vegetation, it is known to have higher reflectance in all four IKONOS bands compared with *Schoenoplectus* spp. (bulrushes; Ullah et al. 2000), which is the more typical dominant emergent plant in Georgian Bay wetlands. It is probable that the presence of *Typha* spp. in parts of the emergent zone increased reflectance and caused the incorrect classification.

While there was some variation among sites in terms of both overall accuracy and Kappa values, the PTC in general performed extremely well for four of the classes, but only moderately well for "E" and "LD". Dillabaugh and King (2008) also had low accuracy when classifying emergent vegetation. Since it occurs in a transitional zone, emergent vegetation shares spectral properties with both onshore and aquatic vegetation. In this study, the similar spectral properties of "LD" and "E" prevented accurate discrimination of these two classes. We could have improved our overall accuracy by keeping these two classes together in the "wet" vegetation class, but, since these two vegetation types represent distinct types of fish habitat (Cvetkovic 2008), we opted to keep them separate. Incorporation of bathymetric data or a digital elevation model (DEM) into the PTC should decrease confusion between these two classes. This combination of spectral data with water depth would allow a more precise classification since our field observations indicate that emergent vegetation is typically found in shallower water than are low-density floating vegetation. Even though "M" and "HD" are already associated with high accuracies, the DEM may also improve the discrimination between these vegetation classes.

In this study, we were not able to map SAV, which is a large portion of fish habitat. In the clear waters of Fathom Five National Marine Park, Wei and Chow-Fraser (2007) were able to map SAV. In a preliminary study, we found that the dystrophic waters of eastern Georgian Bay prevented us from accurately mapping SAV using IKONOS imagery. We have observed, however, that SAV tends to be found in most open-water areas immediately adjacent to "LD" or "HD" vegetation, and extend lakeward to at least 5-m depth. Since many fish species are dependent on SAV for spawning and nursery habitat (Randall et al. 1996), it is important that future mapping efforts incorporate this component so that total potential fish habitat can be quantified for Georgian Bay.

To map aquatic vegetation in this study, we utilized IKONOS satellite imagery. This satellite launched in 1999 and was one of the first satellites to provide fine-resolution multispectral data. In the intervening years, other satellites have been launched that offer finer-resolution (Quickbird) and a greater number of multispectral bands (WorldView-2). Although these new satellites may offer better discrimination among wetland vegetation classes, availability of archived images makes IKONOS an attractive option, when agencies are interested in tracking long-term changes in vegetation cover at the regional scale.

Hardisky et al. (1986) first documented the need for a rapid, cost-effective approach to map coastal wetlands nearly 25 years ago. Because of pressures from human development, the majority of mapping efforts by Canadian environmental agencies in the 1990s have focused on wetlands of Lakes Erie and Ontario (Ball et al. 2003), leaving unmapped the most pristine coastal wetlands in remote areas of eastern Georgian Bay. Using the PTC, we have mapped a subset of some of the larger wetlands (>2 ha) in the southern half of Georgian Bay in order to establish a baseline for vegetation coverage during a period of sustained low water levels. If these maps are updated at regular intervals, we can begin to develop a relationship between water level and aquatic vegetation coverage. This relationship will help managers take actions to cope with a forecasted decline in water level of up to 2.5 m by 2050 (Mortsch and Quinn 1996). From field surveys conducted between 2002 and 2006, we know that these Georgian Bay wetlands contain some of the most diverse fish and macrophyte communities in the Great Lakes basin (Croft and Chow-Fraser 2007; Seilheimer and Chow-Fraser 2007), and an emerging concern is that lower water levels could lead to loss of fish habitat and a subsequent decline in the fishery.

Since fish are known to associate with different densities of vegetation (Jude and Pappas 1992; Jacobus and Webb 2005) as well as different morphological forms (Dibble et al. 1997; Cvetkovic 2008), we have mapped "E", "HD", and "LD" vegetation separately. These are important fish habitat classes, accounting for 25% of the average wetland in this region. We estimated a total of 230.4 ha of VFH and 907.2 ha of PFH, and these data could be used in conjunction with fish community surveys to develop species-area relationships for fish species in coastal wetlands of Georgian Bay. Future investigations should use this approach to identify wetlands that may be vulnerable to biodiversity loss when they become diminished in size because of human or natural disturbance.

Coastal wetlands in south-eastern Georgian Bay has high biodiversity, but the average size is small (8.7 ha) compared with wetlands in Lake Erie (15.9 ha) and Lake Superior (39.2 ha) (Ingram et al. 2004). While these wetlands are small, there are many more of them. For instance, there are 568 wetland units in the south-eastern shoreline of Georgian Bay alone, compared with only 881 for the whole of Lake Ontario (Ingram et al. 2004). It would have been too costly and difficult to map the many small wetlands in Georgian Bay using the traditional approach involving field-truthing and aerial photography, and may explain why the inventory prepared by the Great Lakes Coastal Wetland Consortium omitted many of these (Midwood et al. unpub. data). We speculate that these small wetlands are important to the fish community of Georgian Bay because the oligotrophic nature of these wetlands (DeCatanzaro et al. 2009) may force the fish community to forage by constantly migrating from wetland to wetland. Hence, small proximate wetlands may function as alternate habitats for metapopulations of fish, and this hypothesis should be properly addressed in future studies.

Wei and Chow-Fraser (2007) demonstrated that broad vegetation groups in wetlands can be separated using a pixel-based method, provided the plants have unique spectral properties. We have extended their research to utilize a process tree classification to accurately map broad vegetation groups over a large region using an object-based approach and involving minimal field surveys. This regionally applicable PTC can provide biologists with a tool to rapidly map wetland vegetation and characterize coastal fish habitat. In view of the anticipated drop in water level in the Great Lakes due to global climate change, we encourage environmental agencies to adopt this or similar methods to continue to map wetlands in Georgian Bay to track losses and gains in fish habitat.

Acknowledgments This study could not have been carried out without funding and access to IKONOS imagery provided by Georgian Bay Forever (GBF). We thank the Georgian Bay Association (GBA), especially Mary Muter, who helped us gain access to the coastal wetlands and generously provided their cottages for us to stay in. Other funding for this research came from the Ontario Ministry of Natural Resources and the Natural Sciences and Engineering Research Council of Canada. We thank Maja Cvetkovic, Daniel Rokitnicki-Wojcik, Lyndsay Smith, Henry Heiser, and Anhua Wei for helpful suggestions and comments, and everyone in the Chow-Fraser lab who helped collect field data.

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