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Transferability of object-based rule sets for mapping coastal high marsh habitat among different regions in Georgian Bay, Canada

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Abstract Coastal wetlands of eastern and northern Georgian Bay, Canada provide critical habitat for a variety of biota yet few have been delineated and mapped because of their widespread distribution and remoteness. This is an impediment to conservation efforts aimed at identifying significant habitat in the Laurentian Great Lakes. We propose to address this deficiency by developing an approach that relies on use of high-resolution remote sensing imagery to map wetland habitat. In this study, we use IKONOS satellite imagery to classify coastal high marsh vegetation (seasonally inundated) and assess the transferability of object-based rule sets among different regions in eastern Georgian Bay. We classified 24 wetlands in three separate satellite scenes and developed an object-based approach to map four habitat classes: emergent, meadow/shrub, senescent vegetation and rock. Independent rule sets were created for each scene and applied to the other images to empirically examine transferability at broad spatial scales. For a given habitat feature, the internally derived rule sets based on field data collected from the same scene provided significantly greater accuracy than those derived from a different scene (80.0 and 74.3%, respectively). Although we present a significant effect of ruleset origin on accuracy, the difference in accuracy is minimal at 5.7%. We argue that this should not detract from its transferability on a regional scale. We conclude that locally derived and object-based rule sets developed from IKONOS imagery can successfully classify complex vegetation classes and be applied to different regions without much loss of accuracy. This indicates that large–scale mapping automation may be feasible with images with similar spectral, spatial, contextual, and textural properties.

Keywords Transferability · Object-based rule sets · Habitat · Wetland · Landscape · Georgian Bay · IKONOS

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Introduction

Habitat identification is an important goal for wetland managers, researchers, and policy makers in the creation of sound conservation and management practices. Landscape level mapping using remote sensing has long been a source of identifying and quantifying specific habitats such as wetlands. Remote sensing of wetlands for habitat identification has been extensively studied using a variety of sensors and mapping techniques (Ozesmi and Bauer 2002); however, the recent emergence of object-based approaches to image analysis has now allowed for the development of multiple-image classifications

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and the potential for automation of habitat mapping. Here we evaluate the use of an object-based approach to map coastal high marsh habitat in eastern Georgian Bay, Ontario, Canada and determine the success of this technique in mapping at regional scales. Although many have mapped wetlands using an object-based approach, none have tested the transferability of individually derived object-based rule sets in mapping across regions.

Wetlands are inherently difficult to map because they are ecotones whose boundaries exist along a wetland/upland continuum, and are subject to regular changes in inundation (Ozesmi and Bauer 2002) that result in complex assemblages of vegetation and habitat types (Gluck et al. 1996). Remote sensing with satellite imagery is currently the only feasible tool for large-scale, landscape-level mapping and classification of wetland habitats. In the past, coarse spatial resolution (10–30 m) sensors, such as those carried by Landsat (Baker et al. 2006; Grenier et al. 2007; Poulin et al. 2002) and SPOT (Grenier et al. 2008; Jensen et al. 1993; Töyrä et al. 2001) were only capable of discriminating among wetland types (marsh, swamp, fen, and bog). The advent of sensors with high spatial resolution (less than 1 m) carried by satellites such as IKONOS (1-m resolution) (Dechka et al. 2002; Dillabaugh and King 2008; Fuller et al. 2006; Lawrence et al. 2006; Midwood and Chow-Fraser 2010; Wei and Chow-Fraser 2007) and QuickBird (0.60-m resolution) (Ghioca-Robrecht et al. 2008; Wolter et al. 2005) has made mapping within-wetland vegetation possible.

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

Although past studies have applied classification techniques to multiple scenes (Grenier et al. 2007; Wei and Chow-Fraser 2007; Yu et al. 2006), the majority have used pixel-based approaches that require scene-specific training (Lillesand and Kiefer 2004; Navulur 2006). In this study, we empirically examine the transferability of rule sets derived from one scene using an object-based approach, to map vegetation in other scenes that were not used in development of the rule set. Sawaya et al. (2003) have cautioned against applying rule sets to multiple scenes unless they have been acquired during the same satellite pass because time, angle, and atmospheric conditions at acquisition can create considerable inter-scene variation. The feasibility of transferring rule sets derived from a single scene to multiple scenes without the need for additional field data is something worth investigating, especially for mapping habitats at the regional scale such as eastern Georgian Bay.

The rationale behind the focus of this study are that Great Lakes coastal wetlands are highly diverse systems that not only provide critical habitat for a variety of biota but also provide ecological services that benefit humans (Maynard and Wilcox 1997; Mitsch and Gosslink 2000). In our specific context, the historic loss of 80% of southern Ontario’s coastal wetlands post European settlement (Snell 1987) has justified a comprehensive inventory and field verification of remaining coastal wetlands along the shoreline of Lakes Ontario and Erie in Canada (Ingram et al. 2004; Fig. 1). Despite the large number of coastal wetlands in eastern Georgian Bay (Ingram et al. 2004), very little mapping effort and field sampling has been carried out along its shoreline. This is largely attributed to the predominance of Precambrian Shield shoals and the lack of permanent human settlements that make field sampling in this area difficult and costly. Additionally, unlike wetlands of the two lower Great Lakes (Lakes Ontario and Erie), few of the Georgian Bay wetlands have been mapped for their habitat types (i.e. aquatic, emergent, meadow, etc.), and this is an impediment to efforts aimed at conserving critical fish and wildlife habitat in coastal wetlands due to the inability to identify significant habitat.

This study expands on the work of Wei and Chow-Fraser (2007) and was conducted concurrently with Midwood and Chow-Fraser (2010). Wei and Chow-Fraser (2007) successfully classified aquatic coastal wetland vegetation at 11 sites in Lake Huron and Georgian Bay using IKONOS satellite imagery with pixel-based approach. Midwood and Chow-Fraser (2010) expanded upon the work of Wei and Chow-Fraser (2007) for similar habitat classes using an object-based approach. Focusing on the regional identification of fish habitat, they applied an object-based rule set to multiple images. Here, we focus on the terrestrial component of coastal marshes to map high marsh habitat, that which is seasonally inundated from the water's edge or shoreline (boundary with low marsh or permanently inundated habitat) to the upland forest boundary. We investigate the feasibility of using IKONOS imagery and an object-based classification approach to classify coastal high marsh vegetation in three satellite scenes into four classes (meadow/shrub, emergent, senescent vegetation, and rock). Our second objective is to test the scene-to-scene transferability of rule sets developed for images taken during the same satellite pass, to assess the validity and efficacy of developing one ruleset to map a large collection of single-pass scenes for the entire southeastern shoreline of Georgian Bay.

Study area

Georgian bay

All of the coastal wetlands mapped are situated along the eastern shoreline of Georgian Bay, Ontario, Canada (Fig. 1) within the UNESCO Georgian Bay Bioshpere Reserve. Georgian Bay is the large eastern bay of Lake Huron, separated by the Bruce Peninsula

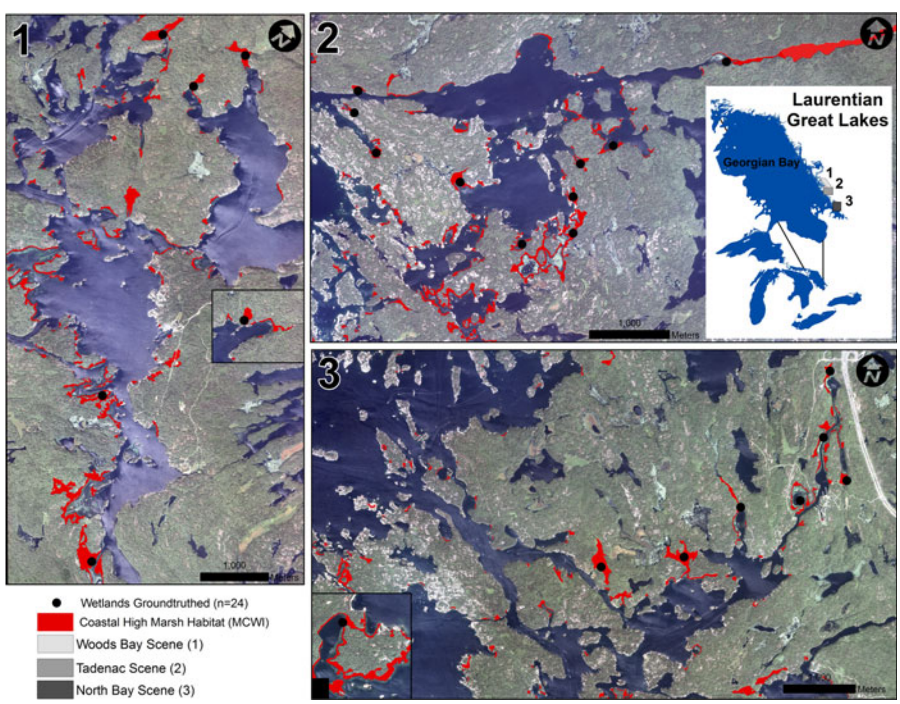

Fig. 1 Subsets of IKONOS scenes highlighting wetlands sampled in eastern Georgian Bay, Lake Huron. The three regions mapped are: Woods Bay (*inset 1*), Tadenac Bay (*inset 2*), and North Bay (*inset 3*). Accompanying regional high marsh habitat information can be found in Table 2 for the entire scenes. Red areas in the imagery insets represent high marsh habitat identified by the McMaster Coastal Wetland Inventory (MCWI; Chow-Fraser unpub data)

and Manitoulin island. It is the worlds largest freshwater archipelago with 30,000+ islands on its eastern shore. It has a maximum width of 95 km and a maximum length of 215 km along the NW–SE axis with a surface area of 15,111 km^2 (Sly and Munawar 1988). Eastern Georgian Bay is an insular dominant landscape where exposed Precambrian Shield is common and vegetation exists on thin soils. Tremendous coastal wetland development has occurred along the lee of islands and in protected embayments along a highly complex and convoluted shoreline (Maynard and Wilcox 1997). Coastal wetlands in this region are heavily influenced by fluctuating water levels of the Lake Michigan-Huron system that act as a natural disturbance on wetland vegetation (Keddy and Reznicek 1986) maintaining high diversity of macrophytes relative to the Great Lakes (Chow-Fraser 2006; Croft and Chow-Fraster 2007).

Description of regional differences

The 24 wetlands that were classified in this study are located in three regions named for the major bay focused on: Woods Bay, Tadenac Bay, and North Bay (Fig. 1). The Woods Bay scene is the most northerly, smallest in area, and ranks second in terms of high marsh habitat among the three scenes. Within the scene, six wetlands were classified covering 38 ha of a possible 147 ha. The Woods Bay region also includes Port Rawson Bay to the north, Blackstone Bay to the northwest, and Moon River Bay to the south (Fig. 1). The Tadenac Bay scene is located south of Woods Bay, ranks second in area, and has the least high marsh habitat. Within this scene, 10 wetlands were classified covering 38 ha of a possible 77. The Tadenac Bay region also includes Twelve-Mile Bay to the north and Tadenac Lake to the east (no surface hydrological connection to Georgian Bay) (Fig. 1). The coastal marshes of Tadenac Bay have some the least impacted water quality in the Great Lakes and have been used as reference sites in past studies (Chow-Fraser 2006; Croft and Chow-Fraster 2007; Croft and Chow-Fraser 2009; Decatanzaro et al. 2009). The North Bay scene covers the largest area and has a total high marsh habitat of 242 ha, and of this, 37 ha belonging to eight wetlands were classified (Fig. 1, Table 1). The North Bay region also includes the major recreational port of Honey Harbour, South Bay to the South, Beausoleil Bay to the west, and Musquash Channel to the north.

Methods

Coastal marshes are operationally defined in this study as wetlands that are hydrologically connected to Georgian Bay via surface water within 2 km of the shoreline (Ontario Wetland Evaluation System [OWES]; OMNR 1993). All coastal marshes in this study occur at the lake/land interface and none are considered inland. IKONOS imagery (Geoeye, Dulles, VA, USA) was acquired during the same satellite pass on July 1st, 2002 for all three scenes used in this study. All images are cloud-free, multispectral (Red, Green, Blue, and Near Infrared bands), and were pan-sharpened and radiometrically corrected by the image provider with a resolution of 1 m. All imagery was acquired just prior to maximal vegetative growth in midsummer to capture the full extent of the wetlands.

The IKONOS imagery was imported into a GIS and all coastal wetlands within each scene were manually delineated as part of the McMaster Coastal Wetland Inventory (MCWI; Chow-Fraser unpub data) using ArcGIS 9.2 (ESRI™, Redlands, CA, USA). Binary masks were created in ENVI™ (ITT Visual Informations Solutions, White Plains, New York, United States; v4.1) to isolate the wet meadow habitat for classification from the entire image. Masks excluded upland islands within wetlands but did include solitary rocks.

Wetland vegetation classes

Classes that were mapped correspond to major vegetation habitat types found in Georgian Bay coastal wetlands: meadow/shrub (high marsh), senescent vegetation (low or high marsh), emergent (low marsh) and rock (no equivalent OWES class) (Table 2, Fig. 2). We have indicated in parentheses the corresponding wetland types (marsh [high and low]) to be consistent with the classification procedures of the Ontario Wetland Evaluation System (OWES; OMNR 1993), which evaluates wetlands on biological, social, hydrological, and unique habitat features at the provincial level. Unfortunately, it was not possible to accurately separate meadow from shrub classes, and therefore meadow and shrub

Table 1 Summary of the five classes sampled and mapped in this study including dominant vegetation and class descriptions

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

Table 2 Summary of regional high marsh habitat and scene information including high marsh habitat area, scene size, and number and area of study sites

Scene	Number of sites visited	Total area of high marsh habitat (ha)	Total area of sites visited (ha)	Coastal 2 km buffer area (ha)
Woods Bay	6	147	43	7564
Tadenac Bay	10	77	38	8897
North Bay	8	242	37	9448

Study site locations and high marsh distribution within each scene can be found in Fig. 1. Area is reported in hectares (ha)

classes were merged into meadow/shrub (Fig. 2). We have included the emergent vegetation class to reflect the transition from aquatic (low) to terrestrial (high) marsh habitat (Wei and Chow-Fraser 2007), and the latter class, rock, was included due to the predominance of exposed Precambrian Shield that defines this landscape.

Classification procedure

The classification approach includes creating a decision tree (Lillesand and Kiefer 2004) composed of rules at each decision or node (Fig. 3a; Midwood and Chow-Fraser 2010). The process tree is a decision tree created in Definiens Developer 7™ (Definiens Imaging GmbH, München, Germany) with image objects. It is non-stepwise but hierarchical in that rules lower on the tree can still affect the classification of classes above. This is the concept of optimization, where subsequent rules are used to optimize or correct misclassification from an initial rule. For example, shrub and floating vegetation have similar spectral values, and to minimize misclassification of shrub pixels, we can apply a rule that forces all vegetation objects occupying an area <15 pixels that are surrounded by shrub pixels to be classified as "shrubs", even if spectral properties are more consistent with "floating". The logic is that floating vegetation is not naturally found in small discrete clumps within shrubs which has been verified from field observations.

In this study, criteria used to create the ruleset were spectral, spatial, relational, and contextual in nature (Table 3; Definiens 2007). We used a multiresolution segmentation algorithm to create the objects from the initial image of pixels. We found that segmenting for a small object size (scale factor of 7) was most beneficial for identifying the desired classes and that spectral properties rather than shape were the most important for grouping the pixels. The layout of the ruleset was dictated by how each class could be separated and the best order was selected from numerous trials. The classification strategy was to first use spectral thresholds to separate a class mainly using a band, band ratio (i.e. NIR/R), or a vegetation index (i.e. Normalized Difference Vegetation Index—NDVI; Lillesand and Kiefer 2004). This would produce the base classification with some

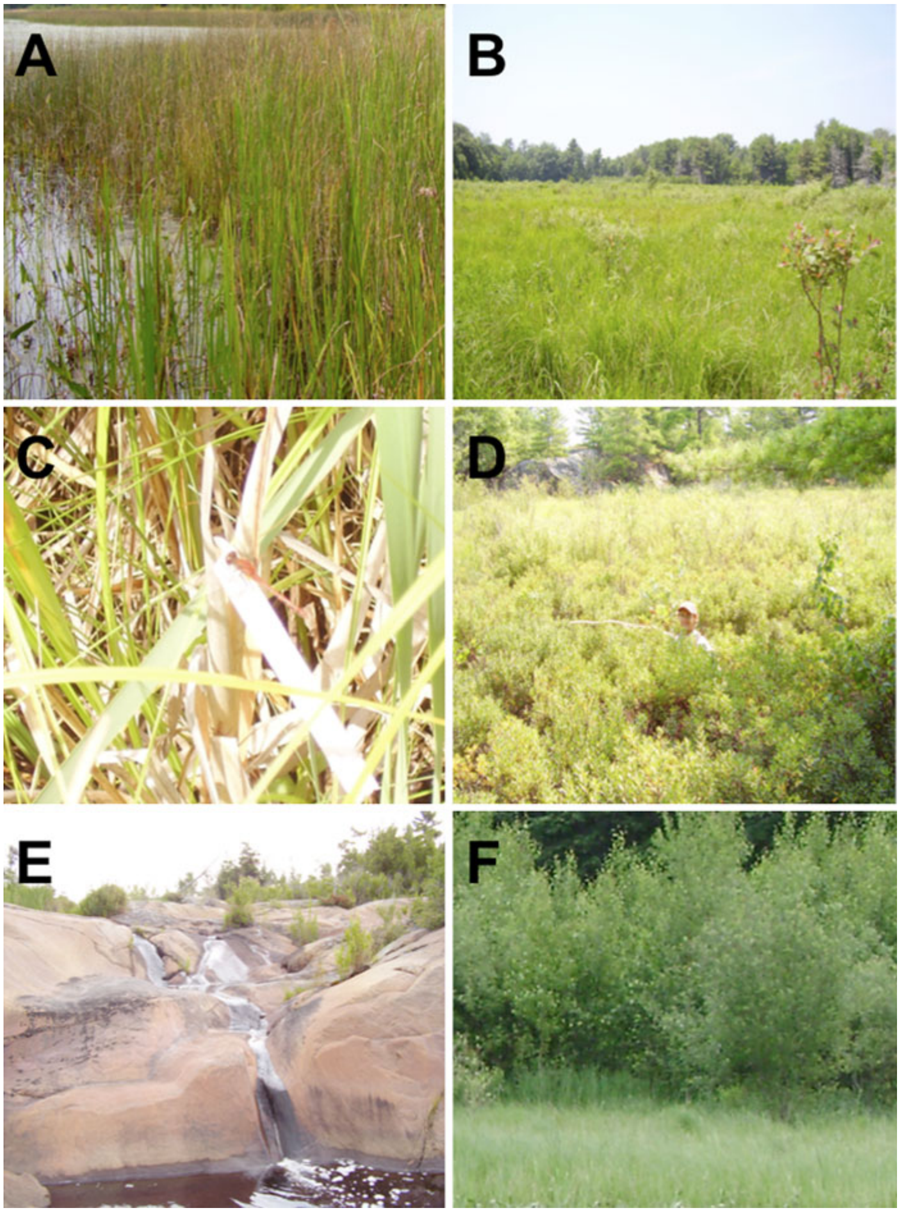

Fig. 2 Examples of the coastal high marsh vegetation and non-vegetation classes including: **a** Emergent, **b** Meadow, **c** Senescent vegetation, **d** Shrub, **e** Rock and the eventual merged class of **f** Meadow/Shrub. See Table 1 for class descriptions

misclassification. Optimization would then be used to correct for the misclassifications.

A mass exploratory pixel-data-mining exercise was used to extract spectral values for over 10,000 pixels from all sites and scenes. Some of these pixels were selected based on expert knowledge of the sites (from field observations) and were different from pixels used for classification validation; the majority, however, were not based on field observations but used this field data as a guide for their selection. These pixels were then used to find base thresholds and to determine significant differences between spectral properties of different classes. A portion of the field data were used in conjunction with base thresholds from data mining to create each scene's rule set. To determine within-scene rule sets, we chose sites in each scene that were sufficiently large to generate data for both training and validation.

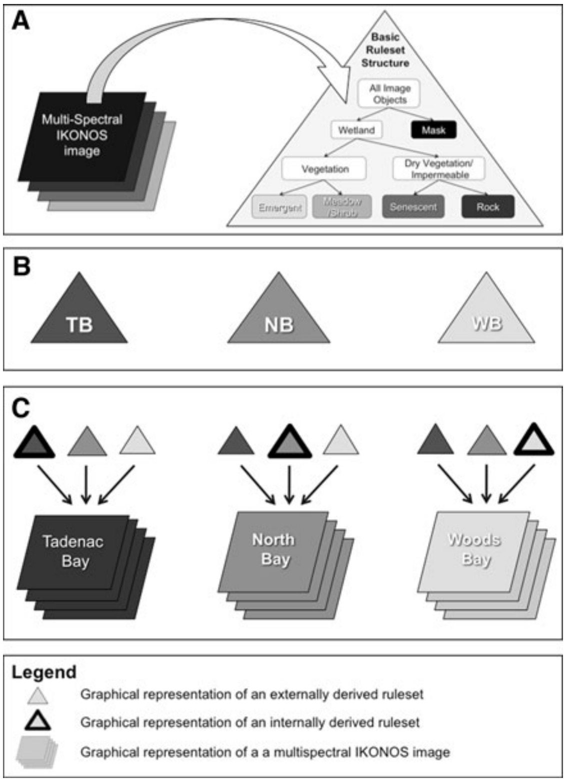

Fig. 3 Graphical representations of the study layout. A method to classify wet meadow habitat using objects from multispectral IKONOS imagery was developed in the form of a rule set (**a**). Rule sets were independently created for each of three regions, with each region's rule set represented as differently shaded triangle (**b**). Each rule set was separately applied to each IKONOS image (**c**). A rule set applied to its region of origin we term internally derived and are represented with *dark lines* and match the IKONOS image's shade. A rule set applied to a region that was not involved in its creation we term externally derived

These were Black Rock West for Tadenac Bay, North Bay 4 East for North Bay, and Grapps Marsh for Woods Bay (Table 4).

Initially, masks were used to isolate all wetlands and then a multi-resolutional segmentation was used to create objects within each wetland. Masks were created by manual delineation of the high marsh habitat boundary from the IKONOS imagery created for the McMaster Coastal Wetland Inventory ([MCWI]; Chow-Fraser unpublished data). Rules were then created with the "feature-space optimization view" in Definiens, where value intervals can be selected for a band or a feature, and the analyst is given the opportunity to preview which objects would be classified by the given rules. The final rule-set is then applied to the entire scene or scene subset, and accuracy is assessed on a site-by-site basis. Each class was then exported as a shapefile to be analyzed in a GIS. Area analyses were conducted using ArcGIS 9.2 (ESRI^{TM}, Redlands, CA, USA).

Field data

Twenty-four wetlands were visited in the summers of 2007 and 2008 and the locations of at least 4 m × 4 m quadrats of homogenous vegetation corresponding to our four classes were recorded with a GPS. Although 5 years is considered the limit in the time difference between image acquisition and in-field data collection (Belluco et al. 2006), we do not attribute large errors to the data collected in 2008. In addition, Lake Michigan-Huron water levels when the imagery were acquired and field

Table 3 Object-based classification features and algorithms used in the creation of high marsh rule sets (Definiens 2007)

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

Table 4 Summary of the accuracies by wetland and by each of the three regional rule sets

Scene/region	Wetland	Accuracy of regional rule sets		
		TB	NB	WB
Tadenac Bay	Black Rock North	88.4	80.9	64.7
	Black Rock West†	80.0	80.4	77.3
	Blasted Channel	80.0	78.3	68.6
	Coffin Rock	83.6	78.7	71.9
	East of Thunder	83.4	77.1	77.8
	Miners Creek	84.7	89.8	90.4
	Pamplemousse	83.2	80.9	69.3
	Petite Pamplemousse	76.1	72.6	67.5
	Thunder Bay	78.9	75.8	74.8
	West of Black Rock	76.0	68.8	62.9
	Mean	81.4[a]	78.3[a]	72.5[b]
North Bay	North Bay 1	68.1	72.6	72.1
	North Bay 2	71.5	73.1	72.4
	North Bay 4 East†	75.7	90.5	90.1
	North Bay 4 West	81.4	62.3	54.4
	North Bay River North	60.7	72.4	71.9
	North Bay River South	70.5	93.3	91.3
	North Bay River	61.7	74.4	72.8
	Treasure Bay North	80.1	81.4	77.0
	Mean	71.2[a]	77.5[b]	75.3[ab]
Woods Bay	Blackstone 1	71.2	78.2	78.3
	Blackstone 2	64.1	71.9	74.7
	Grapps Marsh†	58.9	73.8	78.6
	Moon River 1	78.3	82.4	88.4
	Port Rawson	67.6	74.8	75.1
	Woods Bay 1	79.1	84.4	89.8
	Mean	69.9[a]	77.6[b]	80.8[b]

Each wetland is grouped by scene (region) and has three values corresponding to the accuracy of each rule set. The Mean row refers to the mean accuracy of all wetland in a given scene and the Overall Mean row refers to the accuracy for each rule set for all wetlands. Different letters following values in the mean row (i.e. a and b) indicate they are significantly different (ANOVA, Tukey–Kramer; $P < 0.05$). Shared letters in (i.e. a and ab) following values indicate they are not significantly different (ANOVA, Tukey–Kramer; $P \geq 0.05$)

† Indicates that portion of the wetland data was used in rule set creation

data were collected (both July) do not vary considerably from 2002 to 2008 although natural, seasonal and annual variation was observed (DFO 2010). At each location, the dominant species were recorded and any pertinent features were noted. Since the error of the GPS ranged from 2 to 6 m, we only used validation pixels that occurred in a very large homogeneous area indicated by the GPS coordinates. The number of validation pixels per class were proportionate to the class in question within the wetland. In some instances, the error of the GPS was too great to be used and the boundary of the class was manually delineated on a printed copy of the IKONOS image while the analyst was in the field. We decided to use pixels for the validation data rather than objects as to not assume that object boundaries are completely accurate representations of the class boundaries.

Study layout

Initially, we determined whether an object-based approach using IKONOS imagery can accurately classify wet meadow vegetation. To do so we developed a ruleset-based method for mapping (Fig. 3a). To test transferability across regions we independently created a single rule set for each of three regions or scenes (WB, TB, NB; Fig. 3a and b). We then applied each rule set to each region's IKONOS image to produce a separate classification with an accompanying accuracy for each rule set. This allowed us to determine if the accuracy significantly differs depending on the rule set applied and the region classified. We applied rule sets created from its scene of origin (internally derived rule sets) and rule sets created from other scenes (externally derived rule sets) to determine if transferability among regions is possible (Fig. 3c).

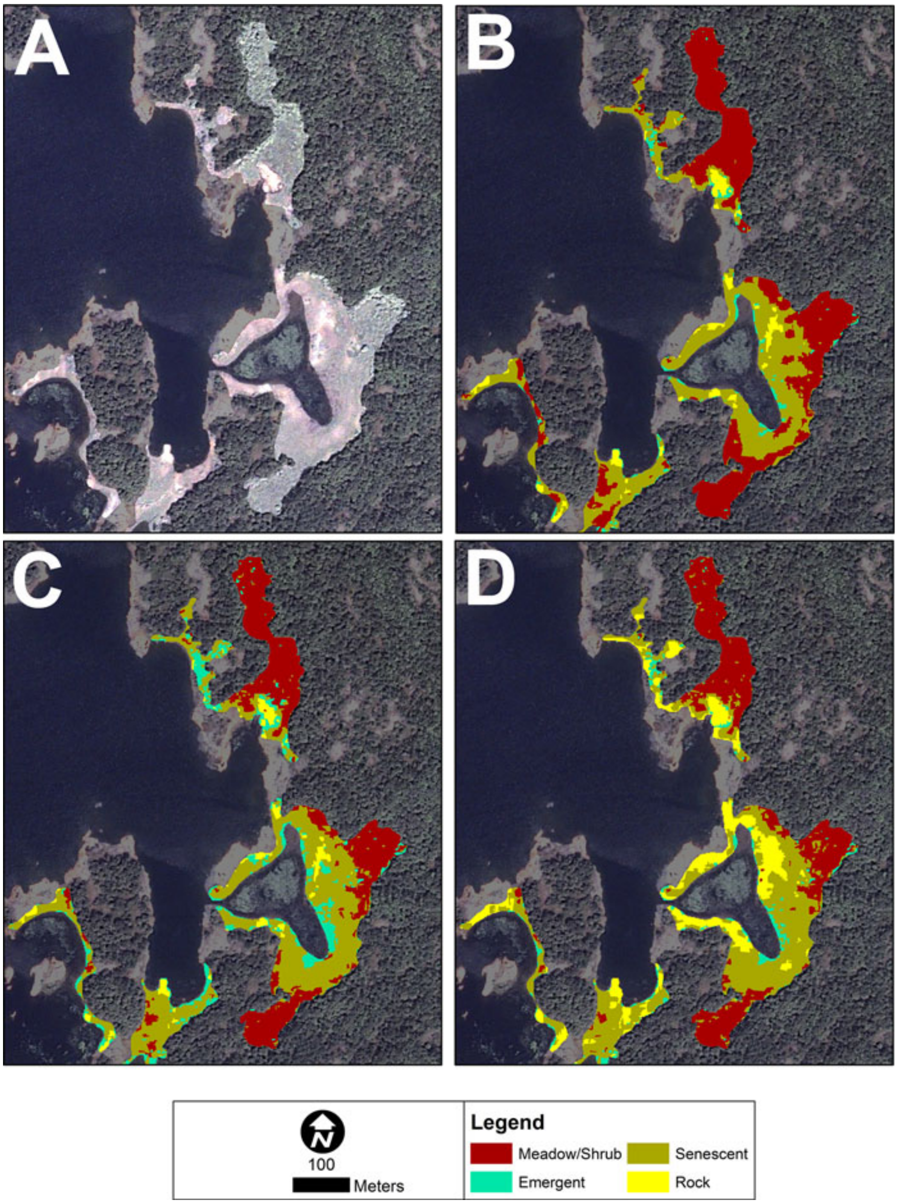

Fig. 4 Classification of Black Rock Bay North in the Tadenac Bay scene. Unclassified image with non-wet meadow habitat masked out in translucent black (**a**). Classified image of Black Rock Bay using the TB rule set (**b**, 88.4% accuracy), NB rule set (**c**, 80.9% accuracy), and WB rule set (**d**, 64.7% accuracy)

Accuracy assessment

We used error matrices produced by Definiens Developer 7™ to assess the transferability of the rule sets to each site (Congalton 1991; Lillesand and Kiefer 2004). More specifically, the end result was three separate error matrices (each matrix representative of the regional rule set applied) for each wetland visited. The error matrices summarized errors of omission (producer's accuracy) and commission (user's accuracy), and overall accuracy, per class and for the wetland. Producer accuracy is the proportion of correctly classified samples of a class. In other words, it is the frequency of omitting the correct class for a given habitat feature. User accuracy is the proportion of correctly classified samples of all samples in that class, or how often a sample in a particular class actually belongs to that class. Overall accuracy is computed as the proportion of all correctly classified validation samples and provides a means of presenting data in a manner understandable by an end user (Congalton 1991; Story and Congalton 1986). To maintain consistency and provide valid comparisons, the same validation data was used for each rule set at each site.

Statistics

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

Results

Mass data mining and exploration

Vegetation classes across all three satellite scenes were found to be broadly homogeneous with respect to spectral properties from data mining and exploration. Across all three scenes, we detected no significant differences in mean spectral properties with respect to a single vegetation class, including mean band spectral values, mean band ratio spectral values, and mean Normalized Difference Vegetation Index (NDVI) values (ANOVA, $P > 0.05$) based on about 10,000 pixels. The meadow and shrub classes; however, had overlapping ranges in spectral signatures and would have been frequently misclassified if we had not combined these into one class in this study (Fig. 4). This is the main reason for combining the two into one class of meadow/shrub, even though they each support distinctive bird and wildlife habitats (Maynard and Wilcox 1997). This class is still useful for identifying habitat because wet meadow is already considered a broader habitat type. We are therefore identifying very narrow habitat ranges that can be merged without major consequence.

Rule set accuracies across scenes

When data across all scenes were considered, there were no significant differences among mean rule set accuracies, with an overall mean accuracy of 76.1%, with <4% difference between the highest (77.8%; NB rule set) and lowest (74.2%; TB rule set) overall accuracy (Table 4). The range of individual wetland accuracies was from 54 to 93% (Table 4). As expected, the accuracy associated with each scene was generally dependent on the origin of the training set (Table 4). There are two ways to examine this trend, how accurate each rule set is with regard to one scene/region and how accurate one rule set is with regard to all scenes/regions. For example, with regard to the Tadenac Bay scene, the mean accuracy of all wetlands was 81.4% when the TB rule set was applied compared with 78.3 and 72.5% for the NB rule set and WB rule set, respectively. With regard to the TB rule set's performance across all three regions, it is highest when applied to the Tadenac Bay scene at 81.4%; however, when applied to wetlands in North Bay and Woods Bay, the mean accuracies dropped accordingly to 71.2 and 69.8%, respectively (Table 5). Although significant differences among rule sets existed at the scene level, no single rule set emerged as being superior when applied to the other two scenes.

Producer and user accuracies

Both producer- and user-accuracies show that emergent and meadow/shrub classes were classified with the greatest accuracies, and the dry and impervious classes of senescent and rock were classified with lowest accuracies (Table 5). These latter classes

Table 5 Summary of individual class producer and user accuracies with respect to each rule set across all scenes

Class	Rule set		
	TB	NB	WB
Overall mean class producer accuracy			
Emergent	75.8^{a}	88.9^{b}	81.7^{ab}
Meadow/shrub	93.6^{a}	85.3^{ab}	82.2^{b}
Senescent	52.0^{a}	59.1^{a}	48.8^{a}
Rock	44.1^{a}	42.8^{a}	63.8^{b}
Overall mean class user accuracy			
Emergent	95.8^{a}	82.6^{b}	93.4^{a}
Meadow/shrub	72.1^{a}	83.7^{b}	83.8^{b}
Senescent	69.1^{a}	70.2^{a}	69.3^{a}
Rock	54.5^{a}	57.0^{a}	47.6^{a}

Producer accuracy is the proportion of correctly classified samples of a class. User accuracy is the proportion of correctly classified samples of all samples in that class. Different letters in superscript following values (i.e. a and b) indicate they are significantly different (ANOVA, Tukey–Kramer; $P < 0.05$). Shared letters in superscript (i.e. a and ab) following values indicate they are not significantly different (ANOVA, Tukey–Kramer; $P \geq 0.05$)

were, however, consistently misclassified across rule sets and scenes (Table 5). When all three scenes were taken into consideration, the NB rule set had significantly greater producer accuracy, but had the lowest user accuracy with respect to emergent vegetation (ANOVA, Table 5). By comparison, the TB rule set had significantly greater producer accuracy and lower user accuracy with respect to meadow/shrub vegetation (ANOVA, Table 5).

Rule set origin

There is a significant effect of rule set origin on mean accuracy. Mean accuracy for internally derived rule sets (i.e. rule set applied to the scene from which it was created) have significantly greater accuracy than externally derived rule sets (80.0 vs. 74.3% respectively; ArcSine transformed proportion wetland accuracy, *t*-test, $P < 0.05$). This amounts to a 5.7% difference in mean accuracy depending on rule set origin.

Discussion

In this study, we used IKONOS imagery to classify high marsh habitat in coastal wetlands of eastern Georgian Bay into four classes (meadow/shrub, emergent, senescent, and rock) with an overall accuracy of 76.1%. The mapping accuracies overall for each of the scenes were 74.2, 77.8, and 76.2% for Tadenac Bay, North Bay, and Woods Bay respectively. These values indicate that we attained mapping accuracy that we consider very successful in all cases, because the focus of this study is on vegetation within a very narrow zone, high marsh. We therefore conclude that IKONOS imagery should be used to map high marsh habitat in eastern Georgian Bay. It is unlikely that we would ever achieve "excellent" mapping accuracy using only satellite imagery (>85%), since the composition of this zone in marshes along the coast of eastern Georgian Bay consist of similar vegetation types whose boundaries are not clearly defined spectrally.

A second goal of this study was to evaluate the use of an object-based approach to map wetlands at a regional scale. In this study, we created rule sets that employed both spectral and contextual information. Class accuracies varied greatly depending on the scene and rule set used. We see that the meadow/shrub class was the most accurately classified, followed by the emergent class. It was important for these two classes to be classified accurately because the separation of these classes is the boundary between land and water and represent the majority of the habitat of interest. The senescent and rock classes were not classified as accurately because they are spectrally similar and in many cases formed somewhat mixed objects. These two classes often occurred adjacent to each other, and were difficult to separate even with expert visual image interpretation. Since geographic coverage of the senescent class is related to soil moisture, it is worthwhile to investigate further how best to accurately detect this habitat feature so that annual changes in this class could be monitored effectively.

Dillabaugh and King (2008) also found it difficult to separate meadow from shrub classes in similar riparian systems using IKONOS imagery. Shrubs exist at the periphery of wetland/upland boundaries and are also scattered among the wet meadow and emergent vegetation. We were partially successful identifying peripheral shrubs, but had great difficulty identifying the scattered shrubs. One contributing factor to the difficulty in identifying peripheral shrubs is that shadows were often confused with inundated vegetation, and Sawaya et al. (2003) have already warned of potential problems with shadows being artifacts of high-resolution imagery. Our inability to separate meadow vegetation from shrubs limited the usefulness of this approach to predict habitat quantity for specific bird and wildlife assemblages. Since shrub thickets and meadow vegetation provide habitat for different species, a combined estimate of meadow/shrub limits our ability to make specific predictions at the species level. This we feel is not a large impediment for the application of this approach to habitat mapping, as we have been able to separate tall shrubs from other vegetation types much more successfully in upstream wetland habitats (Rokitnicki-Wojcik unpub data). The homogeneity of these habitat classes and the inability to separate them are a technological limitation at this point. We expect that this limitation would be easily adverted with the incorporation of ancillary data (i.e. elevation, slope or, soil type layers; Yu et al. 2006) especially LiDAR (Light Detection and Ranging) data, which can identify canopy and vegetation height. LiDAR has been shown to augment wetland mapping accuracy using IKONOS imagery (Maxa and Bolstad 2009). A potential future direction could be to use a hybrid approach where pixel-based classification is used for highly confused features and object-based classification for others.

This is one of the first studies in the Great Lakes basin to use an object-based approach to map wetlands (see also Midwood and Chow-Fraser 2010) and has great implications for future mapping projects focused on wetland habitat. Midwood and Chow-Fraser (2010) applied an object-based rule set to a large collection of similar images without testing regional-specific rule set performance. Here we provide evidence to support the transferability of their rule set to images not included in rule set development. Mapping projects using rule set transferability such as Midwood and Chow-Fraser (2010), illustrate that quality large-scale habitat data can be produced while minimizing expensive field surveying which is highly sought after by wetland managers.

In this study, we were able to use IKONOS and the object-based classification to map highly complex and specific habitat types at very fine spatial scales in small wetlands. To the authors knowledge this is the first study to evaluate rule set transferability and will lay the groundwork for large-scale mapping initiatives without the need for expensive field surveys. This has very positive implications for wetland and habitat mapping of large natural shorelines like eastern Georgian Bay. Within 2-km of the Georgian Bay shoreline, majority of the wetlands that are upstream of high marsh habitat include many swamps and fens (Rokitnicki-Wojcik unpub data). By incorporating high resolution LIDAR data, to the current approach used here, we will be able to develop classification rule sets that can separate vegetation based on height, and thereby distinguish large shrubs/trees in swamps from the herbaceous meadow/mosses of fens and bogs.

We assessed the transferability of three rule sets derived independently to other scenes acquired during the same satellite pass. We know that the application of a model to a different scene usually results in lower accuracy because of the potential effect of spatial autocorrelation (Wei and Chow-Fraser 2008). Mapping accuracy was significantly higher for scenes based on internally derived rule sets compared with externally derived rule sets, but these differences were relatively small (Table 4), and from a practical perspective, these differences should not dissuade a manager from using externally derived rule set to identify habitat, given the high cost of field surveys. Since we found no significant differences in spectral and index values among classes in the initial data mining and exploration, we conclude that the scenes are sufficiently similar in spectral properties that transferability should be expected. In addition, there were very similar accuracies associated with externally derived rule sets presented in Table 3. Although we expected higher accuracies for internally derived rule sets, there was slight variation at the scale of the wetland depending on the rule set used (Table 4) and not all wetlands showed higher accuracy for internally derived rule sets. Mean wetland accuracy values for each rule set do show the general trend and are in agreement of the assumption that accuracy is higher for internally derived rule sets than externally derived rule sets. We present this as a tool to be used in future transferability studies. Classification producers should first select a broad range of exploratory pixels for each mapping class and test for differences among scenes, sites, or the unit of transferability. Practical and ecologically meaningful differences should also be determined prior to classification development to aid in concluding whether transferability is sufficient for specific applications.

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