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How wetland type and area differ through scale: A GEOBIA case study in Alberta's Boreal Plains

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ABSTRACT

It is estimated that Canada comprises approximately 28% of the world's wetlands (~1.5 million km^2) providing essential *ecological services* such as purifying water, nutrient cycling, reducing flooding, recharging ground water supplies, and protecting shorelines. In order to better understand how wetland type and area differ over a range of spatial and thematic scales, this paper introduces a multi-scale *geographic object-based image analysis* (GEOBIA) approach that incorporates new object-based texture measures (*geotex*) and a decision-tree classifier (*See5*), to assess wetland differences through five common spatial resolutions (5, 10, 15, 20 and 30 m) and two different thematic classification schemes. Themes are based on *(i)* a Ducks Unlimited (DU: 15 class) regional classification system for wetlands in the Boreal Plain Ecosystem and *(ii)* the Canadian Wetland Inventory (CWI: 5 classes). Results reveal that the highest overall accuracies (67.9% and 82.2%) were achieved at the 10 m spatial resolution for both the DU and CWI classification schemes respectively. It was also found that the DU wetland types experienced greater area differences through scale with the largest differences for both classification schemes occurring in classes with a large treed component. Results further show that the inclusion of geotex channels (generated from dynamically sized and shaped window that measures the spatial variability of the wetland components composing a scene, rather than of individual pixels within a fixed sized window) improved wetland classification.

1. Introduction

It is estimated that Canada comprises approximately 28% of the world's wetlands (~1.5 million km^2), which provide habitat and sustain over 600 different species of animals, and plants, including one-third of species at risk (Reimer, 2009). Wetlands are vital for planetary and human health by providing essential ecological services such as purifying water, nutrient cycling, reducing flooding, recharging ground water supplies, and protecting shorelines. However, in Canada we do not know exactly how many wetlands exist within our borders (in terms of area), what type they are, where they are located, or how they have changed in response to climate change. Furthermore, of those previously identified in developed areas, 70% have been lost through human activities (NRC, 2010). In order to effectively identify, monitor, model, and manage the vast expanse of Canada's wetlands, remote sensing methods using imagery from spaceborne/airborne platforms are necessary (Leahy, 2003).

Recognition of this imperative has recently resulted in the development of the *Canadian Wetland Inventory (CWI) Project* by the Canadian Wildlife Service of Environment Canada (Hélie et al., 2003), whose objectives include developing new Geographic Object Based Image Analysis (GEOBIA) methods using remote sensing imagery to inventory and monitor Canada's wetlands (Fournier et al., 2007). GEOBIA builds on the object-based paradigm, but makes location (i.e., 'geo') a key component of its analysis (Hay & Castilla, 2008). Unlike traditional pixel-based image processing methods, GEOBIA involves partitioning a scene into discrete entities or 'segments' from which meaningful image-objects can be generated based on their spatial and spectral attributes and user experience (often in the form of rule-sets). Image-objects are groups of pixels in an image that represent meaningful objects of different size, shape and spatial distribution within the scene (e.g., individual trees, tree clusters, stands, forests) (Castilla & Hay, 2008). Thus, it is possible to obtain information about image-object *form* and *context*, such as size, shape, texture and topology, etc., over a range of scales—in addition to color (on which pixel-based methods are primarily dependant). Numerous studies report that multiscale information on scene context and form allows for more accurate and useful classifications (Blaschke, 2010; Hay et al., 2005; Johansen et al., 2010). In this study, scale is synonymous with spatial resolution.

Though GEOBIA is recent, several studies have already successfully employed it for wetland classification. Durieux et al. (2007) used GEOBIA to classify bog wetlands in the boreal forest of Western and Eastern Siberia, Russia using a combination of Multi-spectral imagery from the MERIS sensor (300 m spatial resolution) and a GBFM JERS-1 radar mosaic (100 m spatial resolution) with an overall accuracy of

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75%. In Quebec, Canada, Grenier et al. (2007) applied GEOBIA methods to RADARSAT-1 (12.5 and 30 m spatial resolution) and Landsat-7 ETM images (15 and 30 m spatial resolution) to classify five wetland classes (fen, bog, marsh, swamp and shallow water) for two test sites with an overall accuracy of 76% and 67% respectively. Grenier et al. (2008) also used GEOBIA methods to classify five wetland classes and finer peatland classes using SPOT 4 imagery (10 and 20 m spatial resolution) for an overall accuracy of 81% and 75% respectively. Similarly, Frohn et al. (2009) applied GEOBIA to two Landsat-7 ETM images (15 and 30 m spatial resolutions) acquired in January and October to effectively classify isolated wetlands in Florida, USA.

While object-based methods applied to complex scenes often show classification improvement when compared with more traditional pixel based approaches, to the best of our knowledge no studies using GEOBIA have evaluated how scale determines what wetlands can be identified. This is critical in Alberta Canada, where many wetlands in the Boreal Plain Ecosystem are smaller than 1.0 ha. As a consequence, the use of medium resolution imagery (e.g., 30 m) in this ecosystem may not be sufficient to define all wetland types as the smallest wetland 'object' that can be consistently identified using this spatial resolution is approximately 1.0 ha or 3 × 3 pixels. Thus, many small or transitional wetlands could be misclassified or missed. Based on these ideas, it is apparent that (*i*) finer-spatial resolution imagery (<30 m) are required to isolate physically smaller Alberta wetlands, and (*ii*) that unique spatial resolutions need to be selected for each wetland type, as a single scale may not be effective for classifying all wetland types. Furthermore, Castilla et al. (2009) notes that the categorical detail of a thematic map (expressed as the number of different classes) is an inherent component of the scale at which a scene is assessed, and that changing the class number can change the configuration of the patch mosaic (i.e., the classified scene) as much as changing the spatial resolution.

In addition, we have not seen any studies that have fully exploited object-based image-texture for wetland analysis. Image-texture perceptually defines the spatial relationship of scene components ranging from smooth (e.g., a field) to coarse (e.g., a forest). Remote sensing texture methods attempt to quantify these relationships by evaluating a combination of both *structural* (i.e., complexity of shape, edges, number of vertices) and *statistical* characteristics (i.e., average/variance in size, and distance from one another's centroids) (Hay & Niemann, 1994). When evaluated on fine-resolution imagery (≤5 m), image-texture has the potential to yield valuable information about the varying spatial characteristics of the objects within that scene i.e., vegetation density, surface roughness, canopy height/area differences, and neighborhood (or topological) information.

Numerous studies have shown that the judicious use of image-texture improves classification results. However, users are required to select the size and shape of their texture 'window', as well as their algorithms—of which many hundreds exist. Early attempts at object-texture have used Delaunay triangles and Thiessen polygons to represent scene objects (Hay et al., 1996; Hay & Niemann, 1994); however, the world is not comprised of triangles or Thiessen polygons. Never-the-less, it has been shown that considerable improvements to remote sensing landcover classifications can be achieved by incorporating such texture measures (Gong et al., 1992; Hay et al., 1996; Ozesmi & Bauer, 2002). Current GEOBIA software is able to quantify basic image-texture as the spectral variability or the arithmetic mean of pixels composing an image-object; however, they neglect to assess the spatial relationship between image-objects and their respective neighbors at the same or different scale(s). Chen et al. (2011), describes an object-based method capable of quantifying these spatial relationships as *geographic object-based texture analysis* (geotex).

Based on these concepts, the main objective of this study is to evaluate how wetland type and area differ over a range of spatial and thematic scales. To achieve this goal, we (*i*) apply a multi-scale GEOBIA approach; (*ii*) incorporated geotex measures; (*iii*) generated and compared classification results from 5 different spatial scales (5, 10, 15, 20, and 30 m), and (*iv*) evaluated differences based on aggregating different thematic classes (i.e., from 15 classes to 5).

2. Study area

The study area (Fig. 1) is located in the Alberta tar sands region near Fort McMurray, Alberta, Canada, which is (~435 km) northeast of Edmonton and west of the Saskatchewan border. The (60 × 60 km) site is situated within the Boreal Plains Ecozone, and its geographic extent is defined by a single SPOT 5 image at N57° 7′56″ to N56° 26′ 32″ and W111° 30′46″ to W111° 53′49″. Most oil extraction activity (e.g., tailing ponds) is located in the northwest; however, seismic lines and oil- and gas-well sites are present throughout. The City of Fort McMurray is situated in the southwest portion of the study area. Topographically, this area is relatively flat at 370 m above sea level, with two rivers, one running south to north (Athabasca River) and the other east to west (Clearwater River). Prominent native tree species include Trembling Aspen [*Populus tremuloides* Michx.], Balsam Poplar [*Populus sect. tacamahaca*], White Spruce [*Picea glauca* (Moench) Voss.], and White Birch [*Betula pubescens* Ehrh.], Black Spruce [*Picea mariana* (Mill.) Britton, Stems & Poggenburg] and Tamarack [Larix laricina (Du Roi) K. Koch], with the later two species located in poorly drained wetland areas.

3. Data

3.1. Optical Imagery

This study used SPOT 5 imagery (60 × 60 km) that was acquired June 29, 2006. It consists of four 10 m multispectral bands (i.e., visible green, visible red, near infrared, and short—wave infrared) and one 2.5 m panchromatic band. This cloud-free image has an 8-bit radiometric resolution and was obtained at a low angle of incidence (6.8°). The imagery was geometrically corrected using a first order affine polynomial and a nearest-neighbor resampling method for a RMSE of 0.5. The Gram–Schmidt Spectral Sharpening image fusion technique (Laben et al., 2000) was then applied to the multispectral and panchromatic bands to produce a 2.5 m *pan-sharpened* image. This technique was selected because it (i) preserves the original spectral information in the sharpened image and (ii) is not restricted in the number of spectral bands that can be processed at a single time

Fig. 1. Study area.

(Laben et al., 2000). The pan-sharpened image was then resampled to 5 different spatial resolutions using an averaging method that aggregated pixels to 5, 10, 15, 20, and 30 m; which are consistent with the spatial resolutions of commonly available satellite imagery.

3.2. Reference data

Ducks Unlimited (DU) Canada Western Boreal office provided the reference data used for classification training and testing. All reference samples (i.e., polygons) were collected in accordance with their field guide classification scheme and methodology (Smith et al., 2007). While their regional classification system was developed for wetlands in the Boreal Plain ecosystem, it is compatible with existing classification systems such as the national CWI and the Alberta Wetland Inventory. The regional classification system was developed using a multi-scale sampling approach, where ecological processes observed at fine scales (i.e., ground and stand level) are linked to the spatial and spectral characteristics of a corresponding Landsat TM scene (30 m spatial resolution), that in-turn is associated with ecological determinates (e.g., vegetation, soil and hydrology) of wetland types (Smith et al., 2007). For our study, the location of the reference field sites was determined using a stratified random sampling strategy from the 2002 regional classification of a Landsat TM scene. These locations were visited and verified in the field 20 days prior to the acquisition date of the SPOT 5 image (June 9, 2006) via helicopter (Bell Jet Ranger) by a five-person crew consisting of a pilot, biologist, recorder, navigator and alternate. Ground and stand level characteristics of each field site were verified by the biologist who *(i)* described the site and its wetland type at 300 m above ground level, *(ii)* estimated the percentage of species, slope and drainage for the site at 100 m above ground, and *(iii)* identified a complete list of observed vegetation species at a height of 5–10 m above the vegetation. In addition, each site was documented with an overhead (stand level) and oblique (ground level) photograph. Once the field collection was complete and its consistency and accuracy verified, the field sites were then digitized (235 polygons in total). Two thirds (157) of these polygons were used to train the classification and the remaining (78) were used to assess classification accuracy. The average polygon size was 2.3 ha, with a minimum and maximum size of 0.05 and 9.8 ha respectively.

4. Methods

The method illustrated in Fig. 2 was applied to all five resampled images. In simple terms, the images were first segmented, then image-objects were defined based on spectral and spatial characteristics; and their spectral and geotex information were extracted. Following this, a decision-tree classification was performed using the Ducks Unlimited thematic classification scheme (15 classes), and classified maps were generated for each scale (5–30 m). These classified maps were then generalized into 5 CWI wetland classes based on functional types, and change detection was applied between the 10 classified maps (5 DU and 5 CWI).

4.1. Multi-scale Segmentation

Segmentation was conducted using *Sized-Constrained Region Merging* (SCRM) (Castilla, et al., 2008), a segmentation software, developed with Interactive Data Language (IDL) [ITT Visual Information Solutions, Boulder, CO, version 7.0]. SCRM is able to partition an image to derive meaningful image-objects where each image-object is internally distinct and coherent with respect to its neighboring image-objects. It was selected over other segmentation methods because (*a*) it is based on conceptually sound object-based principles, (*b*) the results produced are similar to those of a human interpreter without *a priori* knowledge, (*c*) it does not require extensive user input, (*d*) user defined segmentation parameters are not unitless and (*e*) errors can easily be corrected (Castilla et al., 2008). SCRM requires three user defined parameters (in hectares) to control the size of the generated image-objects: (*i*) mean object size, (*ii*) minimum object size, or minimum mapping unit size, and (*iii*) maximum object size. This segmentation method was applied to each of the five resampled images where the minimum object size was set to 3×3 pixels (e.g., 0.0225 ha for the 5 m image, and ~1.0 ha for the 30 m image). Mean and maximum object sizes were adjusted until the resultant image-objects visually represented features of interest (i.e., wetland classes).

4.2. Generating geotex (geographic object-based image-texture)

Two sets of variables were used for the multi-scale classifications that were derived from: (*i*) the spectral and NDVI bands, and (*ii*) the

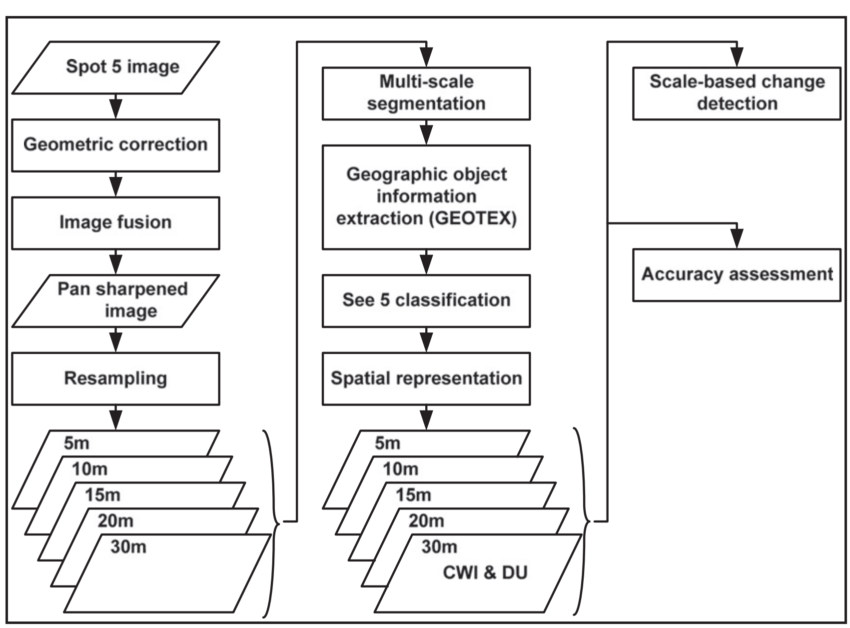

Fig. 2. Methods flow chart.

Table 1
Spectral, NDVI and 0, 1st and 2nd order geotex bands.

	Band type	Description	#	Band type	Description
1	Spectral (green)	Mean_000_band1	14	1st order geotex	STDV_1st_band1
2	Spectral (red)	Mean_000_band2	15	1st order geotex	STDV_1st_band2
3	Spectral (NIR)	Mean_000_band3	16	1st order geotex	STDV_1st_band3
4	Spectral (SWIR)	Mean_000_band4	17	1st order geotex	STDV_1st_band4
5	NDVI band ratio	NDVI_000	18	1st order geotex	NDVI_1st
6	0 order texture	STDV_000_band1	19	2nd order geotex	Mean_2nd_band1
7	0 order texture	STDV_000_band2	20	2nd order geotex	Mean_2nd_band2
8	0 order texture	STDV_000_band3	21	2nd order geotex	Mean_2nd_band3
9	0 order texture	STDV_000_band4	22	2nd order geotex	Mean_2nd_band4
10	1st order geotex	Mean_1st_band1	23	2nd order geotex	STDV_2nd_band1
11	1st order geotex	Mean_1st_band2	24	2nd order geotex	STDV_2nd_band2
12	1st order geotex	Mean_1st_band3	25	2nd order geotex	STDV_2nd_band3
13	1st order geotex	Mean_1st_band4	26	2nd order geotex	STDV_2nd_band4
			27	2nd order geotex	NDVI_2nd

geotex bands. Here, spectral bands (#1–4, Table 1) refer to the original SPOT 5 multispectral bands. A Normalized Difference Vegetation Index (NDVI) band (#5, Table 1) was made to assess photosynthetic activity of vegetation. NDVI was calculated as the difference between the near-infrared and red wavelengths divided by the sum of the near-infrared and red wavelengths (Curran, 1983 and Sellers, 1985).

Geotex channels (Table 1, #6-26) were generated with a recently developed algorithm (Chen et al., 2011), that measures the spatial variability of the entities composing a scene, not of individual pixels within a fixed sized window. These texture channels provide additional spatial information for classifying the different wetland image–objects (e.g., Bog, Fen, Treed Bog etc.). Geotex can be adapted to a variety of images and spatial scales, and it addresses current object-based texture limitations by dynamically adapting and evaluating the spatial variability within objects, as well between neighboring image-objects. Adapted from early work by Hay and Niemann (1994), this texture method was modified to work with image-objects to define 0, 1st and 2nd order geotex measures (Fig. 3). 0 order geotex is calculated as the variability (i.e., standard deviation) of the digital numbers (DNs) composing each image-object. 1st order geotex is the variability of the neighboring image-objects surrounding each image-object; while 2nd order geotex measures the variability of their neighbors. In total, 22 geotex information bands were created in addition to the four multispectral and one NDVI band. We note that 2nd order geotex measures were newly developed for this project.

4.3. Multiscale classification

Wetlands were initially classified into 15 different thematic wetland classes [i.e., Marsh (Emergent and Meadow), Bog (Shrubby and Treed), Fen (Graminoid Poor, Graminoid Rich, Shrubby Poor, Shrubby Rich, Treed Poor, and Treed Rich), Swamp (Conifer, Hardwood, Mixedwood, and Shrub) and Open Water (aquatic bed)] at 5 different spatial resolutions, based on the Ducks Unlimited (DU) Canadian Western Boreal office classification scheme. These classes were then aggregated (based on functional types) to fit within 5 more generalized thematic classes based on the CWI classification scheme

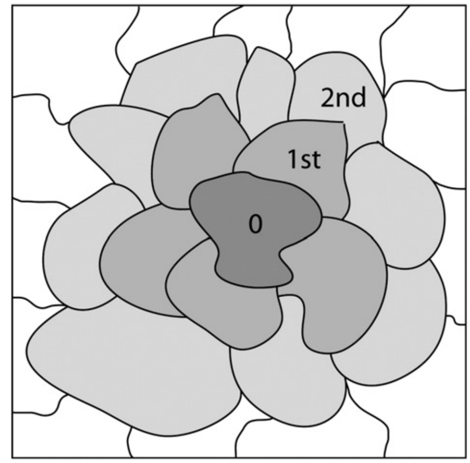

Fig. 3. Image-objects measured using 0, 1st, and 2nd-order texture.

[i.e., Bog, Fen, Marsh, Swamp and Open Water (aquatic bed)]. Details of this classification are presented in the following sections.

4.3.1. Decision-tree classification

The See5 or C 5.0 (Quinlan, 1996) decision-tree software was used to classify each image-object into one of the 15 DU wetland classes. Decision-tree classifiers (Fig. 4) are a non-parametric classification technique, meaning it does not assume the population fits any particular distribution. Rather, it uses a series of sequential steps or tests to assign labels instead of a single complicated decision, such as those made using traditional classifiers (e.g., maximum likelihood). At each step, a decision or rule is applied (a node) that leads to two outcomes (branches). Terminal nodes (leaves) represent the class labels and have their own uniquely defined rule-set. The rules are formulated using values from variables/attributes within the provided modeling data set (i.e., training samples) where they recursively split the data set into subsets until the decision-tree algorithm determines that (*i*) no gain can be achieved by additional splitting in terms of an error measure or (*ii*) if a user defined condition set is met.

The advantages to using decision-trees over traditional classifiers are that they can (*i*) incorporate a variety of data sources (e.g., GIS layers, digital elevation models, multispectral imagery etc.), (*ii*) handle both continuous and categorical information, (*iii*) automatically select the most important variables among those provided for the classification and (*iv*) studies by Lawrence and Labus (2003) and Pal and Mather (2003) have shown that decision-tree classifies can outperform other land cover classification methods (Lawrence et al., 2004).

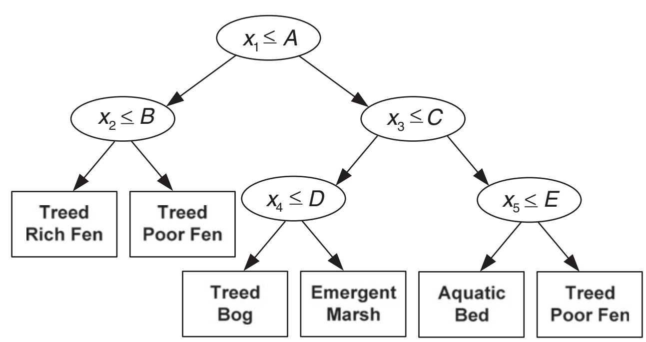

Fig. 4. Decision-tree with 5 resultant classes, where x_i represents attributes and A, B, C, D, and E are thresholds.

For this study, a univariate decision-tree algorithm within See5.0 software was used to perform the multi-scale classifications. This algorithm differs from those used for creating multivariate decision-trees, such the Quest algorithm (Loh & Shih, 1997), in that it applies tests to single attributes instead of a linear combination of attributes. As such, each node contains a single attribute (e.g., red band, blue band, NDVI band etc.) that is used to recursively split the dataset. Splitting continues until a terminal node (leaf) is reached. The attributes used to split the dataset are determined using a method known as the *information gain ratio* (Quinlan, 1993), where attributes that exhibit the highest normalized information gain are selected. A more detailed description of this algorithm can be found in Quinlan (1993).

Using See5.0 for the image classification involved (*i*) preparing the training dataset into a compatible format, (*ii*) constructing the tree classifier and (*iii*) evaluating the classification. Preparing the training dataset for See5.0 required creating two files: a *name* file and a *data* file. The name file was used to describe the attributes and classes, which in this case included (*i*) 15 wetland classes, (*ii*) a forest class, (*iii*) a null class, and (*iv*) 27 bands (e.g., multispectral, NDVI and geotex bands) as attributes. The data file contained the information on the training cases (e.g., samples from bogs, fens and marsh etc.) needed to extract patterns for classification. For each scale, area weighted training samples were extracted from image-objects based on their proportion within 157 DU reference polygons. Our objective was to create the 'best' classified map possible for each scale, based on training data selected at the same scale, rather than biased by a single scale.

Global pruning, the process of reducing the size of the decision-tree by excluding less important branches, was set to 25% with a minimum of at least 2 cases. This prevented "overfitting" the decision-tree (i.e., over calibration). Furthermore, the decision-trees were converted to rule-sets, a series of simple and unordered *if-then* statements. This simplified the classifier and made it more adaptable for creating a classified image in IDL. IDL was used as it is the language that SCRM and ENVI [ITT Visual Information Solutions, Boulder, CO, version 4.5] – our image processing software are developed with, thus providing seamless integration for segmentation, programming and visualization. After each classification, See5.0 outputs a table showing the influence of each attribute (e.g., band) within the classification; similar to Factor Scores in Principle Component Analysis. This information was then used to evaluate the usefulness of the spectral and geotex bands.

4.3.2. Spatial representation of the classified maps

The predictions or 'rule-sets' constructed by See5.0 cannot be used to produce a classified map in itself; thus, additional programming was necessary. The programming language MATLAB [MathWorks Inc., Natick, MA] was first used to reconfigure the See5.0 generated rule-set into a format compatible with IDL. Next, a program was written in IDL that used the rule-sets to evaluate the 27 bands and assign wetland and upland class labels (e.g., 3 = emergent marsh). It is important to be aware that when the 27 bands are evaluated, areas (e.g., pixel locations) can meet the conditions of several rules. That is, since the evaluated pixels have 27 attribute values, or a single value for each band (i.e., 27 dimensions), it is likely that several of the rules are applicable where the combined conditions of their unique if-then statements are satisfied. To avoid assigning multiple "class labels" to the same location (i.e., overlapping classes), precedence was given to the class with the highest aggregated *confidence value*.

In See5.0, each rule is assigned a confidence value from 0 to 1 that summarizes its performance. This is estimated using the Laplace ratio as shown in Eq. (1):

$$ConfidenceValue = (n - m + 1) / (n + 2) \tag{1}$$

where n is the number of training samples that are covered by the rule and m is the number of samples that do not belong to the same class the rule is trying to predict. Once these confidence values were aggregated for each class, they were used to create a classified map. In this way, each pixel in the classified map was given a single class value. This was then applied for each scale of imagery. The DU classified image for each scale was then produced, and thematically aggregated (reclassified) into the broader CWI wetland types using ArcGIS software [Environmental Systems Research Institute (ESRI), Redlands, CA, version 9.3]. In total, 10 classified maps were generated from both classification schemes. The area of each DU and CWI wetland type was then calculated for each of the 5 scales.

4.4. Accuracy assessment

A classification accuracy assessment was performed for each of the 10 classified maps. There were a total of 320 reference points used for each map with a minimum of 20 points defined for each of the 15 DU wetland types. 224 of these points were randomly selected from within 78 DU reference polygons (field verified June 9, 2006). A expert interpretation of the remaining 96 stratified random sample points, was verified using the same SPOT 5 2.5 m pan-sharpened image (acquired June 29, 2006) used in this study to derive our coarser resolution scenes.

Since we use a multi-scale classification approach, using image-object samples at a single scale to evaluate accuracy for all scales would bias all other scales. Therefore, we used the same set of 320 sample points to evaluate the classified image-objects at each scale (5, 10, 15, 20 and 30 m). This way, the sample point location and type remains constant, even though image-object size, shape and cover-type may differ through scale. Once classified, each of the resulting (10) confusion matrices was converted into *a population matrix* (Pontius & Millones, 2011) and calculated for the overall, user's and producer's accuracy (Congalton & Green, 1999). An estimated population matrix better represents the entire study area than a typical confusion matrix, and the summary statistics derived from it are less biased, particularly if a sampling strategy is implemented to obtain reference data (Pontius & Millones, 2011).

4.5. Scale-based change detection

Change detection is a family of methods used to detect differences between two or more images (Chen et al., in press), that typically represent instances of the same location at different times, or spatial resolutions. Here, image-differencing of the classified images was applied to evaluate the class-to-class difference over scale (5 – 30 m). To accomplish this, the change detection statistics tool, available in the ENVI remote sensing software, was used. This tool produces a matrix that identifies those areas that change classes between scales, and was able to report these differences as pixel counts, areas and percentages. To apply the change detection tool, it was first necessary to resample all scales to a common spatial resolution (5 m). Change detection was performed for both the CWI and DU classified maps between each scale.

5. Results

5.1. Accuracy assessment comparisons

The overall accuracy (Table 2) for the DU wetland classifications varied from 55.6% to 67.9% over the 5 scales, with user and producers accuracies ranging from 20% to 100% for the 15 wetland types. The 10 m classification produced the highest overall accuracy, with many classes having high user (U) and producers (P) accuracies [e.g., Meadow Marsh (U:93%, P:56%) Shrubby Rich Fen (U:65%, P:89%), and Conifer Swamp (U:74%, P:84%)].

Table 2
DU and CWI overall accuracy.

Scale	DU	CWI
	Overall accuracy	Overall accuracy
5 m	59.81	77.22
10 m	67.92	82.23
15 m	55.64	72.40
20 m	60.15	77.44
30 m	56.14	75.80

In contrast, the overall accuracies for the CWI wetland classifications were higher than those for the DU classifications and ranged from 72.4% to 82.2% between scales (Table 2). This was not unexpected since there were fewer distinct classes (5 vs. 15) and no within-class differences. User and producer accuracies ranged between 56% and 94% for the 5 CWI wetland types. Again, the highest classification accuracy occurred for the 10 m classification with the Fen wetland type, each showing a user and producer accuracy of 85% and 87% respectively.

5.2. Geotex evaluation

See5.0 summarizes the degree to which each attribute (band) was used for the construction of the classifier. Specifically, it details what percentage of training samples used which attributes (i.e., bands) for the construction of the classifier. Fig. 5 summarizes the attribute usage across all five scales for the top 10 variables/bands that most influenced the DU classification.

In general, all of the 0, 1st and 2nd order geotex bands and five non-geotex (spectral) bands were used to some degree for each classification scale. In this sense, the relatively large usage of the geotex bands, particularly 0 and 1st order, implied that the additional spatial information they supplied were useful for class separation. Overall, the non-geotex bands were the most widely used, followed by the 1st order mean and NDVI bands, 0 order standard deviation bands, and the 2nd order mean, NDVI and standard deviation bands (Fig. 5).

However, at certain scales, some geotex bands were used more than non-geotex bands. For instance, at the 20 m scale the 1st order geotex band (STDV_1st_band3) was used 88%, 6% higher than the next most used non-geotex band. Similarly, at the 5 m scale the 1st order mean geotex band was used at 100% or 37% more than the next most used non-geotex band. At the 30 m scale, another 1st order geotex band was used 24% more than the next most used non-geotex band. It is also important to note that there was a large band usage difference observed between the 1st and 2nd order geotex bands, where the 2nd order geotex bands were not as useful, especially as scale increased. Specifically, as spatial resolution increased, differences between the larger image-objects decreased, thus information about their structural relationships were less practical for distinguishing between geographical entities.

5.3. Differences in wetland type and area through scale

5.3.1. Visual evaluation

Fig. 6 provides an example that illustrates how the classified DU wetland types differ through scale. To emphasize these differences, two areas were selected as examples. Fig. 6(A) illustrates differences for the scales 1–5 that cover the same geographic extent.In this example, there were considerable differences in class distribution and area observed through scale, with wetland classes becoming more generalized (fewer) and objects sizes becoming larger with increasing scale. There were eight classes identified at 5 m and 10 m spatial resolutions, and four at 15, 20 and 30 m spatial resolutions. For instance, Mixedwood Swamp, which was present at all scales, increased in area between 5 m and 20 m, and decreased between 20 m and 30 m, where much of its area was replaced with Hardwood Swamp. The Treed Poor Fen wetland class was also shown to decrease between 5 and 10 m, and was absent from the remaining coarser spatial resolutions. The areas it used to occupy were replaced largely with Treed Rich Fen and/or Treed Bog.

Fig. 6(B) shows the wetland type and distribution differences for a second sample area. In general, there were fewer larger wetland types identified at coarser spatial resolutions. In this case, the Hardwood Swamp, Shrubby Rich Fen and Treed Bog wetland types completely disappear after 10 m and were replaced primarily with Shrub Swamp, Treed Rich Fen and Conifer Swamp. Through scale there was also confusion between the Treed Rich Fen, Conifer Swamp and Treed Rich Fen. Small pockets of Emergent Marsh were distributed throughout the sample area at 5 m and 10 m, but were largely absent between

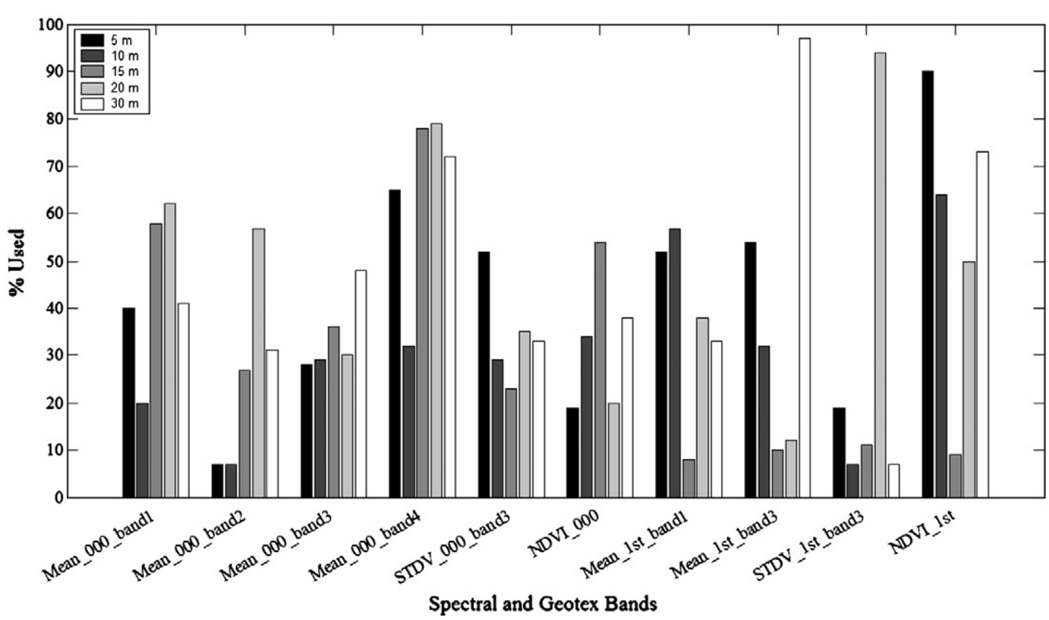

Fig. 5. Top 10 used spectral and geotex bands.

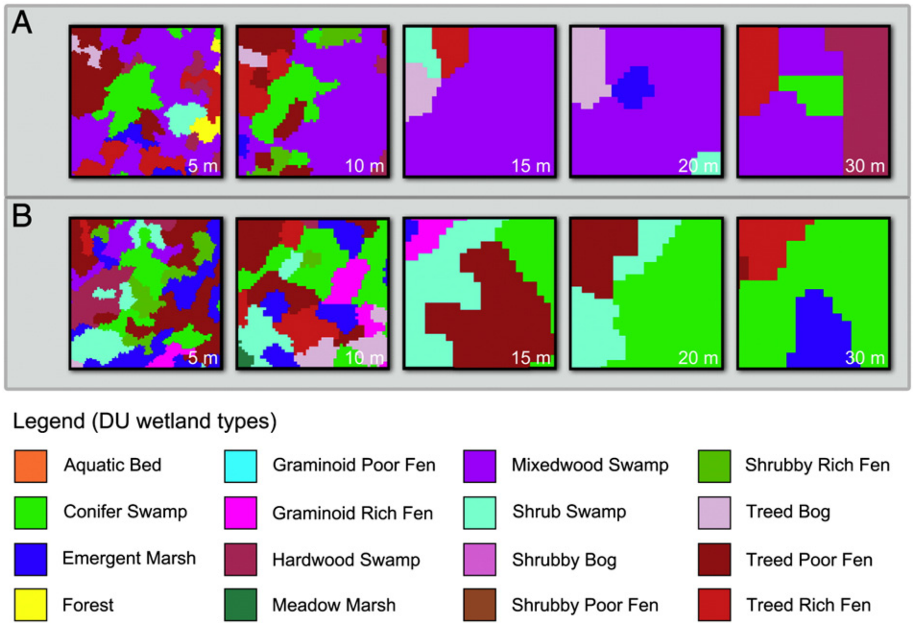

Fig. 6. A visual evaluation of DU wetland area and distribution change through scale for example areas (A) and (B).

15 m and 20. At 30 m, Emergent Marsh is identified as a large single region.

5.3.2. Evaluating DU wetland types (15 classes) through scale

Table 3 and Fig. 7 further illustrate how the DU wetland classification scheme and their associated areas differ through scale. In general, through scale there were many observed changes in class area, with only a third of the 15 wetland types remaining constant: Shrubby Rich Fen, Shrubby Poor Fen, Shrub Swamp, Meadow Marsh and Shrubby Bog. The largest difference among the DU wetland types occurred within the Treed Poor Fen [Fig. 7(A)], which began at 70,836 ha at 5 m, then rapidly decreased by 26,251 ha or 37% until it leveled off at 20 m. Most of this areal decrease was attributed to this class changing into Conifer Swamp (8837 ha), Treed Bog (5053 ha), Treed Rich Fen (5007 ha), Mixedwood Swamp (2303 ha) and Emergent Marsh (2287 ha). It is important to note that most of these differences occurred in wetland types with a large treed component.

Other notable examples of area difference are present in the Mixedwood and Hardwood Swamp, Treed Bog and Emergent Marsh wetland types. Specifically, from 20 m to 30 m the Hardwood Swamp increased by 18,707 ha (112%) and the Mixedwood Swamp deceased by 16,903 ha (61%) [Fig. 7(B)]. Here, most of the area increase for Hardwood Swamp came from a change in Forest (3457 ha), Conifer Swamp (1828 ha), Mixedwood Swamp (4301 ha), Shrub Swamp (2837 ha), Emergent Marsh (2313 ha), Treed Bog (2115 ha), Treed Poor Fen (877 ha) and Graminoid Rich Fen (728 ha). For the Mixwood Swamp, its decrease in area was attributed to these areas being partially classified as Hardwood Swamp (4031 ha), Treed Poor Fen (2401 ha), Conifer Swamp (1404 ha), Emergent Marsh (1218 ha), Forest (1723 ha), Graminoid Rich Fen (1369 ha), Shrub Swamp (603 ha) and Treed Rich Fen (819 ha).

Both Emergent Marsh [Fig. 7(C)] and Treed Bog [Fig. 7(D)] increase in area with a change in scale from 5 m to 15 m and from 15 m to 20 m respectively. From 5 to 15 m, Emergent Marsh increased by 10,604 ha or 33% due to changes in Conifer Swamp (2289 ha), Forest (1501),

Table 3
Area through scale for DU wetland types (ha).

Scale	Fen						Marsh	
	Poor Fen			Rich Fen			Emergent	Meadow
	Graminoid	Shrubby	Treed	Graminoid	Shrubby	Treed		
5 m	2360	2552	70,836	11,890	24,876	14,034	32,053	32,053
10 m	3991	3650	62,149	6579	18,649	23,742	34,786	34,786
15 m	8342	3871	51,591	8657	18,974	16,362	42,657	42,657
20 m	2611	4377	44,585	16,892	16,766	25,271	36,701	36,701
30 m	2494	5458	45,553	20,179	15,051	31,074	33,758	33,758
Ave.	3960	3982	54,943	12,839	18,863	22,097	35,991	35,991
STD.	2536	1060	11,304	5654	3713	6915	4089	4089

Scale	Swamp				Bog	
	Conifer	Hardwood	Mixedwood	Shrub	Shrubby	Treed
5 m	41,912	24,161	20,523	10,634	1523	28,977
10 m	41,035	10,915	24,967	9589	1232	31,514
15 m	54,692	18,989	29,653	16,984	3619	25,116
20 m	51,220	16,679	27,761	17,599	212	36,524
30 m	41,021	35,386	10,858	17,209	2528	30,292
Ave.	45,976	21,226	22,752	14,403	1823	30,485
STD.	6499	9234	7484	3941	1299	4143

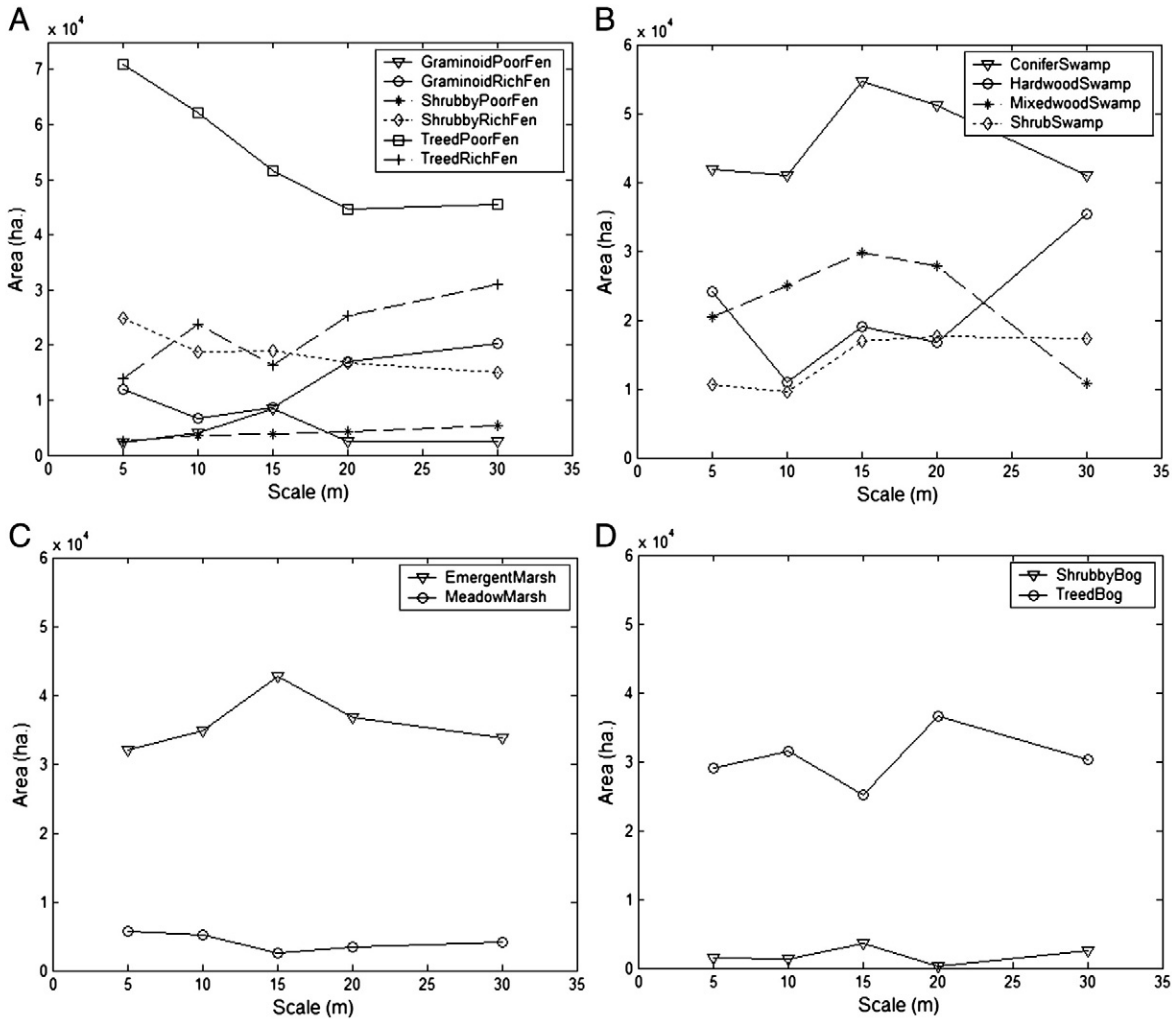

Fig. 7. DU wetland areas through scale for (A) Fen; (B) Swamp; (C) Marsh and (D) Bog.

Treed Poor Fen (2452 ha), Shrubby Rich Fen (1460 ha) and Treed Bog (1489 ha). At 15–20 m, a large amount the Treed Bog's area gain came from changes in Treed Poor Fen (1946 ha), Conifer Swamp (2487 ha), Mixedwood Swamp (1309), Forest (1021 ha), Hardwood Swamp (858 ha), Shrub Swamp (1431 ha) and Shrubby Bog (1274 ha), nearly all of which had a large treed component.

5.3.3. Evaluating CWI wetland types (5 classes) through scale

As indicated in Table 4 and Fig. 8, the areas classified as Marsh, Bog and Aquatic Bed remained fairly constant through scale. However, it is important to note that the standard deviation of area for the Aquatic Bed was considerably large compared to its average area through scale. It experienced a 28% change in standard deviation compared to the 7.4% and 9.3% shown in the Marsh and Bog wetland types respectively. This indicates that Aquatic Bed is proportionally more confused with other CWI wetland types. The greatest difference in area for Aquatic Bed occurred between 20 m and 30 m, where it went from 12,065 ha to 5593 ha, a decrease of 46%. The majority of this 6472 ha decrease was attributed to it changing into Fen (3278 ha), Swamp (529 ha), Bog (669 ha) and Marsh (1132 ha). The greatest areal difference for the Swamp wetland type occurred between 10 m and 15 m, where it increased from 86,508 ha to 120,319 ha, a

Table 4
Area through scale for CWI wetland types (ha).

	Marsh	Fen	Swamp	Bog	Aquatic Bed
Scale 5 m	37,805	126,551	97,232	30,500	13,160
Scale 10 m	39,924	118,763	86,508	32,747	11,344
Scale 15 m	45,179	107,799	120,319	28,735	9825
Scale 20 m	40,201	110,505	113,261	36,737	12,065
Scale 30 m	37,930	119,812	104,475	32,820	5593
Average	40,208	116,686	104,359	32,308	10,398
Standard Deviation	2989	7559	13,261	3004	2945

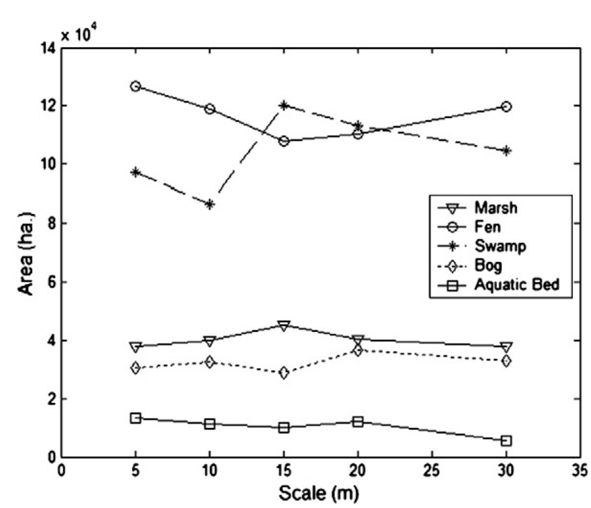

Fig. 8. CWI wetland areas through scale.

difference of 33,811 ha or 39% of its total class size. Most of this gain came from a change in the Forest class (18,679 ha) and the Fen (10,060 ha) and Bog (2661 ha) wetland classes. From 20 m to 30 m, the Fen wetland class increased by approximately 9307 ha or 8.4% of its total class area, most of which came from the Swamp wetland type being classified as Fen (8418 ha). Thus, the majority of area increases and decreases observed in the Fen and Swamp classes at 20 m to 30 m were inversely proportional to each other.

6. Discussion

Both the qualitative (i.e., visual) and quantitative results indicate that there were many differences in class distribution and area between different scales, contrary to what was implied by the accuracy assessment (confusion matrix). Similar findings were also noted in studies done by Pontius and Cheuk (2006), Kuzera and Pontius (2008), and Pontius and Connors (2009), which investigate how information in categorical maps is altered as resolution coarsens. Here we suggest that much of the observed differences through scale were attributed to (*i*) classification accuracies, (*ii*) discrepancies between image-object size and shape, and (*iii*) the use of DU and CWI classification schemes. These reasons as they relate to the overall patterns observed through scale are described in the following sections.

6.1. Classification accuracy considerations

In general, the CWI overall accuracy was comparable to other wetland classifications that had roughly the same number of classes and similar wetland types (Grenier et al., 2007 and Grenier et al., 2008). Since the overall accuracies for the DU wetland types were around 56%–68%, more of the observed area differences in wetland type could have been a result of class error. As such, differences observed between two (or more) classified images (at different scales) could have been attributed to error in either image. For example, there were instances at different scales where even very similarly sized and shaped image-objects of the same class [Fig. 9(A) and (B)] were not classified the same. In this example of the DU classification scheme, it appears that the inclusion of a small section of forested area (i.e., Treed Poor Fen) caused the decision-tree algorithm to misclassify the image-object at 20 m as Treed Bog [Fig. 9(D)] when it should have been classified as Shrubby Bog [Fig. 9(C)]. Examples such as these imply that at 20 m, the decision-tree algorithm had difficulty separating Shrubby Bog from other spectrally and/or texturally similar wetland types, particularly Treed Bog, Treed Poor Fen, and Shrubby Rich Fen. However, it is important to keep in mind that it might not be entirely the fault of the classifier. If we consider that the DU training samples are accurate, then for a classifier to

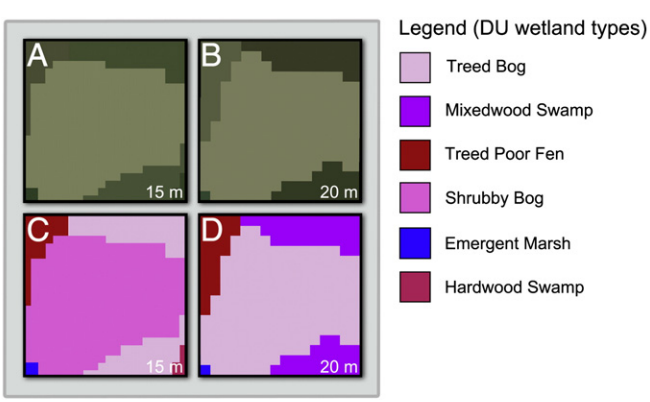

Fig. 9. A comparison of two similarly shaped and sized image-objects for 15 m (A) and 20 m (B) and their respective DU classifications (C) and (D) for the same area.

function properly there first needs to be some observable difference between the spectral and geotex profiles (i.e., classes need to be distinct). If there are very few, or no spectral and geotex differences between wetland types, it is unlikely that any another similar classifier could improve the situation.

Classification error is but one explanation for the differences in area and wetland type observed through scale. For instance, the DU Conifer Swamp wetland type exhibited a consistently high user and producer accuracy (76% on average). However, its difference(s) in area through scale [Fig. 7(B)] are quite high, despite its reputable classification accuracies. This implies that something other than classification error is responsible for the observed area differences.

6.2. Why were there observed area differences for DU and CWI wetland types through scale?

It is clear from Figs. 7 and 8 that the wetland types with a large treed component undergo the largest area differences through scale. Specifically, the areas of CWI wetland types remain fairly constant through scale with the exception of the Swamp wetland class (comprised of up to 80% treed), which dramatically increases between 15 m and 20 m resolutions. Similarly, DU Swamp and Treed Fen wetland types also experience large area differences through scale.

6.2.1. Differences in image-object size and shape

In Remote Sensing, spatial resolution plays an important role in how the landscape is perceived or observed. This is because—at least in part—at different (spatial) scales, different patterns emerge or 'appear' as the aggregation of smaller units (i.e., leaves, tree crowns, tree clusters, stands, forests, etc.)—though at a specific scale we seldom see the smaller constituent units, only the new larger whole they 'create' through aggregation. The effect or sensitivity of data aggregation on landscape analysis results was first described in the geographical literature as the Modifiable Areal Unit Problem (MAUP) (Openshaw, 1984; Openshaw & Taylor, 1979) where it consists of two interrelated problems: (*i*) the *scale problem* and (*ii*) the *zoning problem*. The zoning problem relates to the variation in results caused by differences in the areal units that are recombined as areas of the same size, but with a different configuration (i.e., variation in results caused by boundary differences between similarly sized areal units). In contrast, the scale problem refers to variations in results caused when areal data are aggregated into successively larger areal units. In both cases, these variations in results can lead to different inferences simply because the scene has physically and thus perceptually changed. Marceau et al., first recognized that remote sensing imagery represented a specific case of the MAUP (Marceau & Hay, 1999).

In this study, differences between image-object size and their non-nested boundaries (through scale) contributed to variations in image-object DNs for the 'same' landscape feature through scale. These variations were often enough to result in wetlands being missed through spatial aggregation (i.e., small wetlands were not identified at coarser spatial resolutions) and/or classified differently (e.g., Treed Rich Fen vs. Treed Poor Fen). Furthermore, since many of the wetland types were spectrally and texturally similar, their classifications were sensitive to slight differences in these spatially aggregated values. This exacerbated the discrepancies observed between the wetland types through scale, which can be attributed to MAUP.

In addition, the smooth or gradual transitions between wetland types (e.g., Treed Rich Fen to Treed Poor Fen) make placing a discrete boundary between them problematic—especially at coarser scales. This increased the likelihood of introducing error by including discrete parts of different (spatially adjacent) geographic entities (i.e., treed wetland types) within a single class. As Bian (2007) notes, not all environmental phenomena are amiable to object-based representations. We suggest that at fine spatial resolutions, transition zones should be classified as separate mixed classes. However, defining what this range of scales should be is not trivial, and will change with different scene conditions—though a clear example can be found in Fig. 7(A), where a critical difference occurs for the DU Fen wetlands types between the 15 and 20 m resolutions.

6.2.2. DU and CWI classification scheme

The classification scheme developed by DU was created through a process where the spatial and spectral characteristics in Landsat TM imagery (30 m spatial resolution) associated with ecological determinates of wetland types were linked to ecological processes observed at fine scales (Smith et al., 2007). However, it is possible that the relationship(s) between the radiometric and semantic (classification scheme) similarities established by DU for this sensor may not hold true at other spatial and spectral resolutions using a different sensor (e.g., SPOT 5). For example, SPOT 5 wavelengths are centered at different locations than TM data, and, the SPOT sensor has no blue channel, whereas TM does. As such, there could be instances where, at certain scales, some of the DU wetland classes are less distinguishable from each other. If this were the case, it could have lead to some image-objects being misclassified through scale, thus introducing error.

As Castilla et al. (2009) notes, changes to the thematic scheme, can dramatically change the classified results. Pontius and Malizia (2004) have also noted that the influence of the categorical aggregation on class categories can greatly affect confusion matrixes used to report map accuracy—this is illustrated in our results, where the reduction of 15 DU wetland types to 5 CWI wetland types improved the accuracy of our classified maps. Consequently, another concern is whether the DU classification scheme is appropriate. Specifically, to what degree are these wetland types functionally and spectrally different (e.g., treed bog vs. treed poor fen vs. conifer swamp etc.)? If wetland type groups (e.g., Treed Poor Fen or Treed Rich Fen) are functionally similar, does it make sense to have them as distinct classes? Here the severity of the confusion/error occurring between these classes is quite slight. Instead, it seems more prudent to consider wetlands in a broader context where wetland groups (Bog, Fen, Swamp etc.), such as those found in the CWI classification scheme, represent more distinct landscape features. In this case, any confusion/error made between these classes would be more severe and visually apparent.

7. Conclusion

Current GEOBIA approaches used for Canadian wetland inventorying and monitoring typically use medium spatial resolution imagery (30 m) and employ image-processing texture methods that do not take full advantage of the spatial interaction of scene objects. As such, if the area being inventoried contains many small wetlands (as is the case in the Boreal Plan Ecosystem) or wetlands that are spectrally similar, there is a potential for them to be misclassified or completely missed.

In this study we have evaluated how wetland type and area differ through scale using two wetland classification schemes and the incorporation of geotex information. Geotex quantifies the spatial interaction of image-objects and their neighbors using their shape characteristics as a dynamically sized moving window. A quantitative assessment of our results shows that the overall classification accuracy based on the Canadian Wetland Inventory (CWI) scheme through a range of scales was comparable to other similar wetland classifications (ranging from 72.4 to 82.2%); whereas the overall accuracy based on the Ducks Unlimited (DU) classification scheme (55.64–67.92) had confusion between the additional (finer detailed) 10 thematic classes. We found that the highest overall accuracy for both classification schemes was achieved at the 10 m scale. We also observed that there was a greater area difference for the DU wetland types through scale than CWI wetland types, particularly within functional class types. Furthermore, the largest area differences in both classification schemes occurred for those wetland types with a large treed component, suggesting that spectrally and/or texturally similar classes are more sensitive to changes in scale. Results further show that the inclusion of geotex information was useful for wetland classifications; and that at specific scales, geotex bands were used more than spectral bands for the construction of the See5 classifier. For example, at 5 m resolution, 100% of the 1st order mean geotex band was used (this is 37% more than the next most used spectral band). However, spectral bands were the most used overall and should be included in any wetland classification. It was also observed that 2nd order geotex bands were not as useful as 0 and 1st order geotex bands, particularly as scale increased.

In summary, we have demonstrated the importance of scale and how it affects wetland classification in terms of (*i*) what wetlands types are identified and (*ii*) their change in associated areas by applying a multi-scale GEOBIA approach to 5 resampled images. Users will find this research useful for increasing their understanding of spatial resolution and how it plays a role in wetland classifications that employ GEOBIA approaches. Potential extensions to this study will examine how the selection of segmentation parameters (i.e., mean object size) affects multi-scale classification results and if such object parameterization can reduce the influence of MAUP.

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