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ABSTRACT
Circumboreal Canadian bogs and fens distinguished by differences in soils, hydrology, vegetation and morphological features were classified using combinations of Radarsat-2 synthetic aperture radar (SAR) quad-polarization data and Landsat-8 Operational Land Imager (OLI) spectral response patterns. Separate classifications were conducted using a traditional pixel-based maximum likelihood classifier and a machine learning algorithm following an object-based image analysis (OBIA). This study focused on two wetland classes with extensive coverage in the area (bog and fen). In the pixel-based maximum likelihood classification, accuracy increased from approximately 69% user’s accuracy and 79% producer’s accuracy using Radarsat-2 SAR data alone to approximately 80% user’s accuracy and 87% producer’s accuracy using Landsat-8 OLI data alone. Use of the Radarsat-2 SAR and Landsat-8 OLI data following principal components analysis (PCA) data fusion did not result in higher pixel-based maximum likelihood classification accuracy. In the object-based machine learning classification, higher bog and fen class accuracies were obtained when using Radarsat-2 and Landsat OLI data individually compared to the equivalent pixel-based classification. Subsequently, a PCA-data fusion product outperformed the individual bands of the Radarsat-2 and Landsat-8 imagery in object-based classification. Greater than 90% producer’s accuracy was obtained. The margin of error (MOE) was less than 5% in all classifications reported here. Further research will examine alternative data fusion techniques and the addition of Radarsat-2 SAR interferometric digital elevation model (DEM)-based geomorphometrics in object-based classification of different morphological types of bogs and fens.

1. Introduction
Bogs and fens are important wetland types in circumboreal Canada that are recognized primarily by differences in soil type and constituents (e.g. fibrisols versus humisols), dominant vegetation cover (e.g. sphagnum versus sedge), nutrient status...
(e.g. ombrotrophic versus eutrophic), and slope/basin morphology (Stewart and Kantrud 1971; NWWG 1997; Keddy 2010). Satellite sensor classifications of such wetlands have improved in recent years with several methodological innovations, such as the use of multiple sensor datasets and data fusion techniques (Grenier et al. 2007; Idol, Haack, and Mahabir 2015), implementation of object-based image analysis (OBIA) (Dingle Robertson, King, and Davies 2015), extraction of geomorphometric variables from digital elevation models (DEMs) (Difebo, Richardson, and Price 2015), and application of more complex classifiers, such as evidential reasoning and machine learning algorithms, rather than traditional statistical classification techniques (Millard and Richardson 2013). Further tests of these and related methodological improvements for remote sensing wetland classification and mapping have been recommended (Tiner, Lang, and Klemas 2015). In particular, additional examples of the methods and benefits of object-based machine learning classification approaches are needed (Dronova 2015).

Typically, workflows for satellite sensor wetland object-based classification are complex and few guidelines exist to help users navigate the many options available depending on the desired mapping scale and extent and the level of accuracy required. To cite only one potentially important decision, an image analyst must select the source imagery to use in the classification; for example, satellite multispectral or synthetic aperture radar (SAR) imagery – or, increasingly – both. If a multispectral/SAR multiple sensor dataset is employed, the analyst could decide to ‘fuse’ the images to create new variables (Jiang et al. 2011; Pohl 2016) or simply rely on the power of the classification algorithm to extract complementary information from individual bands of multiple sensors (Peddle et al. 1994). In addition, since wetland form and process are often related to morphometric and basin characteristics (Minar, Evans, and Krcho 2013), interferometric SAR images (or other data sources, such as lidar) may be acquired to enable DEM-based geomorphometric analysis (Short et al. 2011). The differences in resulting wetland classification accuracy based on the selection of variables alone may or may not justify the differences in investment in software costs, training the classifier (and the personnel involved) and ease of interpretation of the results. Of course, wetland conditions at the time of image acquisition (e.g. standing water, type, phenology, moisture content and amount of vegetation) will strongly influence classification results (Henderson and Lewis 2008; Corcoran et al. 2012).

This article introduces a wetland mapping case study in the Hudson Bay Lowlands Ecoregion of northern Ontario in which Radarsat-2 SAR quad-polarization data and Landsat-8 Operational Land Imager (OLI) spectral response patterns were classified in pixel-based and object-based classification approaches in separate analyses. First, the spectral response patterns observed by the Landsat-8 OLI sensor and quad-polarization C-band SAR data acquired by Radarsat-2 sensors were analysed in a traditional pixel-based maximum likelihood supervised classification. Second, those results were compared to the accuracy obtained using an object-based image analysis (OBIA) classification based on a machine learning algorithm with access to a similar set of classificatory variables. Results are presented for the two major wetland classes of interest – bogs and fens, which in this lowland region differ principally in their characteristic vegetation and eco-hydrological conditions (Wells and Zoltai 1985). The overall objective of this article is to interpret the classification maps and compare the classification accuracy when using
Radarsat-2 SAR and Landsat-8 satellite sensor in pixel-based maximum likelihood and object-based machine learning classification methods.

2. Study area and data used

The study area encompasses an active open pit diamond mine in the Hudson Bay Lowlands in northern Ontario (Figure 1). Structural anomalies and kimberlite diamond-bearing intrusions of Archaean age occur in younger and sub-horizontally bedded

![Figure 1. Location of the study area in northern Ontario, Canada.](image)
Silurian limestone in this region (Morris and Kaszycki 1997). Further expansion of the mine site and other resource extraction developments are planned in the near future as part of the Ontario ‘Ring of Fire’ Mineral Development Strategy (Ontario Ministry of Northern Development and Mines 2015).

The area is dominated by poorly-drained organic and mineral soils, discontinuous permafrost, shallow basal Quaternary glacial tills, and glaciolacustrine clays (CEAA 2005). The mean annual precipitation ranges between 528 and 833 mm, and the mean daily July temperature ranges between 12°C and 16°C (Crins et al. 2009). The growing season is short, and the presence of saturated peatlands in low (but continuing positive isostatic) topographic relief creates diverse eco-hydrological wetland features, which cover approximately 90% of the area (Crins et al. 2009). Relatively small amounts of stunted, upland forest are located on higher slopes and close to the shorelines of small creeks, riverine systems, and lentic systems (CEAA 2005). Wetlands in this region are typically recognized as different types of fens and bogs according to the Canadian Wetland Classification System (NWWG 1997). Many contain significant standing or pooled water (Keddy 2010). Fens occur in gradations of low-lying open-, patterned- and graminoid vegetation communities on saturated organic soils and peat up to 2 m in depth. Some fens have modest levels of shrub or coniferous tree cover and may be ribbed or sloped (Wells and Zoltai 1985). Bogs are typically drier, with substantial build-up of peat, and are expressed as lichen-, graminoid-, shrub- and treed vegetation communities. Bogs occur in ombrotrophic domes, mounded or flat conditions (Peckham, Ahl, and Gower 2009; Anderson et al. 2010).

The classification variables in this study are listed in Table 1. Landsat-8 imagery was acquired on 21 August 2014 from the United States Geological Survey (USGS) as an orthorectified and top-of-atmosphere corrected product. Radarsat-2 SAR quad-polarization imagery was acquired the following day, on 22 August 2014, in fine resolution mode with a spatial resolution of 5 m. These images were georeferenced to the pansharpened Landsat-8 imagery with sub-pixel root mean square error using 175 ground control points per scene. Two Radarsat-2 scenes were required to cover the entire study area, which were georeferenced independently and mosaicked. The SAR imagery was calibrated using a sigma-nought calibration in order to reduce both backscatter and issues stemming from altitude-calibration, and was then converted from raw units to power units (decibels) (Ulaby et al. 2014).

Additional reference data used to interpret wetland classes and develop training and validation areas included: (i) a Worldview-2 image acquired on 7 July 2013, (ii) a SPOT-5 imagery acquired on 11 September 2006, and (iii) wetland and land cover classification map products for this area primarily based on earlier Landsat imagery and aerial photography interpretations (AMEC 2004; Hogg et al. 2009; OMNRF 2014).

<table>
<thead>
<tr>
<th>Data type</th>
<th>Classification inputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Radarsat-2 SAR</td>
<td>Quad-polarization VH, HH, HV, VV, GLCM textures (variance, correlation), PCA-fusion</td>
</tr>
<tr>
<td>Landsat-8 Optical</td>
<td>Blue, green, red, near-infrared, shortwave infrared (2), PCA-fusion</td>
</tr>
<tr>
<td>Object shape metrics</td>
<td>Area, perimeter, compactness ratio, elongation direction, linearity index, circumscribing circle, shape complexity index</td>
</tr>
</tbody>
</table>
Classification accuracies in those mapping efforts, however, were estimated to be quite low (e.g. 64% overall by Hogg et al. 2009).

3. Methods

3.1. Texture and data fusion

Directional invariant grey level co-occurrence matrix (GLCM) texture measures of variance and correlation were derived over multiple window sizes for the Radarsat-2 and Landsat-8 image data (Haralick, Shanmugam, and Dinstein 1973). Two relatively small window sizes were retained for analysis (3 × 3 and 5 × 5 windows). These textures appeared to correspond visually with the high degree of local variability in the two classes of interest. A number of initial data fusion tests on the original dataset using wavelet, Brovey transformations, and other data fusion routines (Wang et al. 2005; Dong et al. 2009; Jiang et al. 2011; Kumar, Sinha, and Taylor 2014; Joshi et al. 2016; Sukawattanavijit and Chen 2015; Vivone et al. 2015; Khorram et al. 2016) resulted in the selection of the principal components analysis fusion output based on a visual inspection of the quality of the imagery. Bhattacharyya-distance statistics were calculated in a sample of well-known wetland areas to support the visual interpretation; in those areas, the PCA-data fusion showed good B-distance separability between the bog and fen wetlands. PCA-data fusion was accomplished using ENVI 5.4 (Exelis Visual Solutions 2017). Five eigenvectors explaining more than 98% of the Radarsat and Landsat image variance were retained for classification purposes.

3.2. Pixel-based maximum likelihood classification

A pixel-based supervised classification method was implemented using the original Landsat spectral response patterns and Radarsat-2 SAR quad-polarization data in non-fusion and PCA-data fusion runs. First, individual Landsat and Radarsat image and texture variables were classified alone and then the same training areas were used to drive a combined or PCA-data fusion classification. A total of 78 individual pixel training areas in the bog and fen class were sampled based on the available reference data. The analyst selected training areas fully contained within the wetland classes of interest (i.e. not isolated single-pixel locations). Validation of the pixel-based classification of the bog and fen classes was based on an independent sample of 81 wetlands not used in the training data collection following minor post-classification filtering. An illustrative example of a fen training site for the pixel-based classification is shown in Figure 2.

3.3. Object-based machine learning classification

Multiresolution image segmentation was performed using Trimble eCognition Developer (Trimble 2015) with user-defined parameters of scale, shape, and compactness. These parameters were finalized after a number of object primitives were compared to the wetlands interpreted as training areas in the reference data. Different objects were generated by segmentation of the original imagery and data fusion products, which were then independently classified. As is typical in object-based
image analysis (e.g. Hay and Castilla 2008; He et al. 2011), the relatively subjective trial-and-error approach was based on visual interpretation of the available high resolution imagery, existing map products, and analyst expertise in recognizing bog and fen wetland features. Overall, this approach was considered effective in determining the appropriate image segmentation parameter values to yield visually acceptable wetland objects for subsequent classification (see also Costa et al. 2008; Drăguț, Tiede, and Levick 2010; Dingle Robertson, King, and Davies 2015). A class-specific multicollinearity test was conducted to eliminate highly correlated input variables prior to executing the classification ($R^2 > 70$).

The Random Forest machine learning classification algorithm (Breiman 2001) was implemented based on the $R$ package formulation (Lantz 2013). Random Forest is a non-parametric algorithm that creates multiple decision trees for each image object and the mode of the classification decision parameter values to yield visually acceptable wetland objects for subsequent classification (see also Costa et al. 2008; Drăguț, Tiede, and Levick 2010; Dingle Robertson, King, and Davies 2015). A class-specific multicollinearity test was conducted to eliminate highly correlated input variables prior to executing the classification ($R^2 > 70$).

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3.4. Classification accuracy and variable importance

Confusion matrices showing overall accuracy, user’s accuracy, producer’s accuracy and margin of error (MOE) were produced and interpreted for each classification run. Summaries of those tables for the bog and fen classes of interest are reproduced in

Figure 2. Example of a fen training area sample: (a) Landsat-8 OLI bands 5, 4, 3 displayed as false colour composite; (b) Worldview-2 bands 5, 3, 2 displayed as false colour composite; (c) Radarsat-2 SAR HV polarization image displayed as a continuous grayscale. Image area shown approximately 2.5 km².
while the sample sizes varied depending on the classification methods, the margin of error (MOE) was less than 5% in all classifier tests reported here. As others have noted, the sample sizes in classification accuracy validation tests are often relatively small, especially in object-based classifications, which rely on homogeneous objects rather than multiple pixel identifiers within a single feature (Dingle Robertson, King, and Davies 2015). However, the validation samples in this study were considered appropriate as each classification run was assessed following standard procedures that were consistent within that classification test, i.e. in a way that was internally consistent with known levels of confidence (Stehman and Czaplewski 1998; Pond 2016).

### 4. Results

Table 2 contains the pixel-based classification accuracies obtained in this study for the bog and fen wetland classes using Radarsat-2 SAR quad-polarization data alone, Landsat-8 OLI spectral response patterns alone, and a PCA-fusion dataset of combined Radarsat-2/Landsat-8 variables. Table 3 contains the equivalent classification results obtained following the object-based image analysis and machine learning classification methods.

The use of Radarsat-2 SAR quad-polarization data alone resulted in a pixel-based maximum likelihood user’s/producer’s classification accuracy for bogs and fens of approximately 69%/79% (Table 2). This is a good result that exceeds accuracies reported in Canada with Radarsat-1 datasets (e.g. Grenier et al. 2007). Landsat-8 OLI spectral response patterns alone yielded approximately 80%/87% user’s/producer’s classification accuracy, a significant improvement of approximately 9% over the Radarsat-2 SAR results. This result is consistent with, or slightly better than, earlier levels of Landsat sensor wetland classification accuracy in Canada (e.g. Li and Chen 2005). The PCA-fusion dataset did not result in higher accuracies in the pixel-based maximum likelihood classification of the wetland classes of interest. The object-based machine learning
The algorithm provided approximately 80%/84% user’s/producer’s classification accuracy for bogs and fens using Radarsat-2 SAR quad-polarization data alone (Table 3). This was a significant improvement, more than 10% classification accuracy increase, over the Radarsat-2 SAR pixel-based maximum likelihood classification results.

The object-based machine learning classification accuracy improved when using Landsat-8 OLI data, to approximately 87%/84% user’s/producer’s accuracy. Again, this represents a significant increase over the pixel-based classification results (within an MOE of less than 5%). An additional increase of approximately 7% was observed when the object-based machine learning algorithm was implemented with the PCA-data fusion of Radarsat-Landsat variables (to approximately 91%/93% for user’s and producer’s accuracies). These object-based classification results are similar to those obtained recently in other Canadian wetland mapping projects using higher spatial resolution multispectral data (e.g. Dingle Robertson, King, and Davies 2015).

Visual interpretation of the resulting maps (Figure 3) suggested the following general guidelines for image analysts working on wetland remote sensing projects similar to this case study:

![Figures](image-url)
(1) The use of multiple sensor data, in this case the combined Radarsat-2/Landsat-8 PCA-data fusion products, was preferred over the individual Radarsat and Landsat image data when interpreting wetland extent and type.

(2) Multispectral Landsat images were frequently more readily interpreted and appeared to display wetlands in ways that were consistent, ‘realistic’ and familiar to the analysts; for example, after delineating training features in the Landsat imagery, it was less difficult to identify the same feature in the Radarsat imagery.

(3) The Radarsat-2 SAR quad-polarization classifications, while less accurate in a statistical sense, did appear to show distinctive wetland features and spatial context well that may be related to local wetland form (e.g. morphological identifiers).

(4) A reduction in wetland feature fragmentation was noticed when object-based image analysis methods were employed; note that this comment is consistent with the recent literature comparing higher spatial resolution multispectral pixel-based and object-based wetland classifications (e.g. Dingle Robertson, King, and Davies 2015); and, finally.

(5) Object-based classifications were more accurate based on statistical tests, and also appeared to have fewer isolated ‘salt-and-pepper’ wetland pixels and greater overall coherence and wetland integrity compared to the pixel-based classification maps.

Overall, the pixel-based and object-based classification results in the Hudson Bay Lowland Region were consistent with those reported in the literature in other wetland mapping studies that have compared pixel-based maximum likelihood classification and object-based classification approaches with multispectral and SAR images. The increases in object-based classification accuracy observed in the present study based on PCA-data fusion of Radarsat and Landsat data sets also confirm the value of multiple sensors for wetland mapping as has been noted elsewhere (e.g. Rodrigues and Souza-Filho 2011). In addition, accuracies greater than 90% (such as obtained in this study for bogs and fens) are comparable to those reported using fusion of Radarsat-2 SAR quad-polarization data and higher spatial resolution optical data sets, and to those which employed detailed DEM analysis to reveal wetland geomorphological and topographic characteristics (e.g. Mui, He, and Weng 2015). Additional research is now warranted to examine more powerful data fusion techniques and to incorporate wetland geomorphological conditions captured in DEMs (Lecours et al. 2017). Such wetland geomorphometric analysis may be feasible through interferometric processing of the Radarsat-2 SAR data (Short et al. 2011).

5. Conclusion

Extensive circumboreal bogs and fens in the Hudson Bay Lowlands Ecoregion of northern Ontario differ in eco-hydrological characteristics and dynamics and were classified using Radarsat-2 SAR quad-polarization data and Landsat-8 OLI images. Pixel-based maximum likelihood classification and object-based machine learning classification methods generated good results and map output. The best accuracies were approximately 85% and 93% for pixel- and object-based classifiers, respectively, with a MOE of
less than 5%. Significant increases were not observed when using a Radarsat-Landsat PCA data fusion product with the pixel-based maximum likelihood algorithm. Object-based machine learning classification accuracies did benefit following PCA-data fusion of the two datasets. Additional research in data fusion and interferometric SAR analysis of wetlands is warranted to explore the performance of Radarsat-2 and Landsat-8 datasets in wetland classification.

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