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Mapping Boreal Peatland Ecosystem Types from Multi-Temporal Radar and Optical Satellite Imagery

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Abstract

The ability to distinguish peatland types at the landscape scale has implications for inventory, conservation, estimation of carbon storage, fuel loading, and post-fire carbon emissions, among others. This paper presents a multi-sensor, multi-season remote sensing approach to delineate boreal peatland types (wooded bog, open fen, shrubby fen, treed fen) using a combination of multiple dates of L-band (24 cm) Synthetic Aperture Radar (SAR) from ALOS PALSAR, C-band (~5.6 cm) from ERS-1 or 2 and Landsat 5 TM optical remote sensing data. Imagery was first evaluated over a small test area of boreal Alberta Canada to determine the feasibility of using multi-sensor SAR and Optical data to discriminate peatland types. Then object-based and/or machine learning classification algorithms were applied to 3.4 million ha of peatland-rich subregions of Alberta, Canada and the 4.24 million ha region of Michigan's Upper Peninsula where peatlands are less dominant. Accuracy assessments based on field sampled sites show high overall map accuracies (93-94% for Alberta and Michigan), which exceed those of previous mapping efforts.

Keywords: Peatlands, fens, bogs, boreal, synthetic aperture radar, SAR, Landsat, PALSAR, ERS-2, Random Forests, Mapping

Introduction

Peatlands are defined as having saturated soils, anaerobic conditions, and large accumulations of partially decomposed organic plant material (peat) below ground. This accumulation is a result of low rates of decomposition in relation to plant productivity. In Canada, this belowground peat must be greater than 40 cm in depth to be recognized as a “peatland” (e.g. (Halsey et al. 2003; National Wetlands Working Group 1988)) and depths may extend as much as 15 to 20 m belowground (Clymo et al. 1998; Limpens et al. 2008; Turunen et al. 2002). Although peatlands occur in boreal, tropical, and temperate biomes, 80% of global peatlands occur in boreal regions of the northern hemisphere (Wieder et al. 2006). In turn, boreal peatlands represent 25-30% of the global boreal forest region (Gorham 1991; Wieder et al. 2006) with an estimated 270-370 Tg of Carbon stored as peat (Turunen et al. 2002).

Boreal peatland ecosystems not only have important roles in the global carbon and water cycles, but are biologically diverse and provide habitat for a variety of birds, amphibians, mammals, and invertebrates. Climate change predictions estimate that the boreal and arctic regions will be the most strongly affected by projected rising temperatures and changes in precipitation patterns (Chapin et al. 2000; IPCC 2014). These changes have an effect on hydrologic patterns across the landscape, induce permafrost thaw, increase wildfire activity, and could lead to migration of species. The ability to distinguish and monitor various peatland types at the landscape scale, therefore has implications for inventory, conservation, carbon storage estimation, fuel loading, carbon emissions, hydrology, and monitoring ecological shifts in a changing climate.

The distribution of boreal peatlands of Canada has previously been estimated by Tarnocai et al. (2011). That database was built primarily from the Soil Landscapes of Canada (SLC)

database (Ecological Stratification Working Group 1995) which contains information about the proportion of land covered by peatland. The Tarnocai map estimates the total peatland area of Canada as 113.6 million ha with 67% of the area dominated by bogs and 32% by fens with swamps and marshes covering the remaining 1%. However, these maps are not spatially explicit but provide only broad area generalizations of percent peatland area. The distribution of peatlands and soil C must be well characterized for any assessment of C vulnerability (Grosse et al. 2011). Therefore, efforts to map spatially-explicit peatland types, including distinguishing open versus treed characteristics, are needed.

There have been various efforts to create more detailed wetland maps for small regions of boreal Canada using aerial imagery (e.g. (Vitt 2006)), LiDAR data (e.g. (Chasmer et al. 2014)), hyperspectral (Thomas et al. 2003) and polarimetric C-band Synthetic Aperture Radar (SAR) (Touzi et al. 2007). All of these focused on single date imagery. The combination of one or more sensors for detection and mapping of land cover classes has been suggested as a technique to improve map accuracy by allowing for a range of characteristics to be detected (Henderson and Lewis 2008). There was an effort underway to use Landsat and C-band Radarsat data (Fournier et al. 2007; Grenier et al. 2007) for nationwide wetland mapping for the Canadian Wetland Inventory (CWI) with a minimum mapping unit of 1 ha. The CWI classification system requires mapping to 5 main classes (bog, fen, marsh, swamp, and shallow open water), and allows for vegetation type to be mapped in its hierarchical system, but it does not require specific distinction of open (rich) fens from treed (poor) fens or wooded bogs. These are important distinctions for quantifying C content, biodiversity, and fuel loading.

Boreal peatlands develop and persist under a complex set of interacting regional and local factors. The type of peatland that develops at a site is a function of the specific hydrologic

regime, climate, chemistry, landform, substrate, vegetation, and presence or absence of permafrost (Vitt 2006). Some of these variables can be used to identify peatlands in the field and in remotely sensed imagery (e.g. hydrologic regime, vegetation, landform). SAR sensors have been demonstrated to be sensitive to biomass and moisture condition of the canopy and ground layers of vegetated landscapes (Hess et al. 1995). Because of varying moisture/flooding conditions and vegetation structure, different wetland types have been distinguished using two or more dates of L-band SAR imagery (e.g. (Clewley et al. 2015a; Bourgeau-Chavez et al. 2013; Whitcomb et al. 2009)). Recent wetland mapping research has demonstrated the strength of merging L-band SAR and optical data for distinction of forested, shrubby, and herbaceous wetland types (Bourgeau-Chavez et al. 2015b). Others have had success combining C-band SAR and optical data (Dingle Robertson et al. 2015; Kloiber et al. 2015) as well as C-band SAR with LiDAR data (Millard and Richardson 2013)

While several researchers have developed methods for mapping wetlands, peatlands represent a new level of detection since they typically have saturated soils but are usually not inundated and they range in vegetation cover from open to shrubby to forested. Distinguishing bogs from fens can be difficult in the field, as well as with remote sensing; however the landscape context can aid in distinguishing bogs from fens. Further, microwave data are sensitive to changes in moisture patterns if multi-date imagery are used, and thus have potential to detect the differences in hydrologic patterns of bogs, which are rain-fed, versus fens, which are hydrologically connected and more likely to have greater fluctuations in moisture over time.

The overall goal for the research presented was to develop methods to map spatially-varying peatland types (bogs versus fens) and level of biomass (forested bogs, treed fens, shrubby, and open fens) across broad scales in physiographically complex landscapes of northern

Alberta and northern Michigan. This goal was addressed using a combination of medium resolution multi-sensor (C-band and L-band) SAR and optical imagery from multiple dates with a targeted accuracy of more than 80%. The objectives included a comparison of two state of the art classification algorithms (Object Based Image Analysis and Machine Learning Algorithms) to determine the optimal classifier for broad area mapping.

Study Area

The primary study area for development of the peatland mapping approach was located in northeastern Alberta, Canada approximately 175 km north of Edmonton (Figure 1). This region falls within the extensive low-lying valleys and plains of the Boreal Plains Ecozone and contains extensive peatland complexes (>30%) intermixed with uplands. This ecozone extends from Manitoba and Saskatchewan through nearly two-thirds of Alberta (Figure 1 inset). The region is characterized by short, warm summers and long, cold winters with low average annual precipitation, ranging from 300 mm in the west to 625 mm in the east. Permafrost is isolated north of Ft. McMurray and is nonexistent in the remainder of the region (Ecological Stratification Working Group 1995). Four subregions (Utikuma, Wabasca, Fort McMurray, and Kidney Lake) within the Alberta study area were selected for peatland mapping (Figure 1). Each of these represents an area of peatland that contains recent wildfires which were a focus of the broader research study.

The extent of the subregions was partially defined by the intersection of the Landsat TM optical and SAR satellite data used for mapping (Figure 1, Table 1). Each Alberta subregion spans an east-west width of approximately 70 km (based on the footprint of the PALSAR image scene), with the exception of Fort McMurray which is nearly double that, extending across two

adjacent PALSAR swaths. Landsat and PALSAR sensors are described in more detail in the materials and methods section.

<Insert figure 1>

<Insert Table 1>

A second study area was Michigan's Upper Peninsula (UP), which is at the southern limit of the North American Boreal zone, boreal mixedwood (Figure 1). The UP is divided between the flat, lowland Great Lakes Plain areas in the east, and the steeper, more rugged Superior Upland (a part of the Canadian Shield) in the west. The Superior Upland is a region lying to the south of Lake Superior and stretching westward from the UP across northern Wisconsin and Minnesota. The Great Lakes Plain of the eastern UP has a few extensive areas of peatland (e.g. Seney National Wildlife Refuge). Otherwise small peatland areas are intermixed with upland and non-peat-forming wetland. Fens (open, shrubby, and treed) are a dominant peatland type of the UP with few bogs. The UP is permafrost-free and is characterized by short, warm summers and long, cold winters with moderate average annual precipitation (~860 mm in the west to ~785 mm in the east (NRCS 2008)).

These study areas allow for testing the multi-date, multi-sensor hybrid classification algorithm in two distinct boreal regions that vary in ecology, and vegetation composition and structure. There are large differences between these study areas in the distribution of large versus small peatland complexes, topographic relief, and dominance of bogs in Alberta versus fens in the UP.

Peatland/Wetland Classification Systems

The Canadian Wetland Classification System (CWCS) and the Alberta Wetland Inventory (AWI) Classification define five major wetland classes: bog, fen, marsh, swamp, and shallow open water. The AWI defines two of the five major classes as peatland classes (bog and fen) which are characterized by an accumulation of peat of 40 cm or more; and three as non-peat forming (<40 cm peat) wetlands including marsh and swamp classes which are hydrologically connected and typically associated with open water; and shallow water which often has floating aquatic or submerged vegetation. Our Alberta wetland mapping was focused on the four major wetland classes: bog, swamp, fen and marsh and did not specifically map submerged vegetation. Field data on floating aquatic vegetation was available for Michigan, so that class was mapped for that region. The four main wetland classes as defined by (Warner and Rubec 1997) and (Vitt et al. 1996) are described below. (1) Bog is an ombrotrophic peat landform characterized as being raised or level with the surrounding terrain, with the water table below the surface. Bogs receive their water solely from precipitation and are unaffected by runoff or groundwater from the surrounding landscape. Bogs may be open or wooded with trees limited to *Picea mariana*, and they are usually covered with *Sphagnum spp.*, feather mosses (*Pleurozium schreberi* and *Hylocomium splendens*) and ericaceous shrubs. Bogs are acidic with pH typically below 4.5. (2) Fen is a minerotrophic peatland with a fluctuating water table at, above or just below the surface. Groundwater and surface water flow through the fen is common. The dominant floristic characteristics are grasses, sedges (*Carex*), *Scirpus* or *Eriophorum*, and shrubs (*Betula* and *Salix*) and in the case of poor fens, trees, with larch (*Larix laricina*) and black spruce often dominating. Poor fens are acidic (pH 4.5 to 5.5), rich fens are slightly acid to neutral (5.5 to 7.0 pH). (3) Swamp is defined as a tree or tall shrub-dominated wetland that is influenced by

minerotrophic groundwater. It is not considered a peatland (i.e. peat is less than 40 cm accumulation) and it has strong seasonal fluctuations in water at or above the ground surface. Swamps are diverse and may be composed of *Larix laricina*, *Picea mariana*, *Betula*, *Salix*, etc. in Alberta. In the UP, northern white cedar swamps are common (*Thuja occidentalis*). Marsh (emergent) is an herbaceous-dominated wetland with the typical water table at or below the soil surface, but generally fluctuating dramatically throughout the seasons (or daily in tidal marshes). Dominant species include *Carex*, *Scirpus*, *Typha* and for Michigan native and invasive varieties of *Phragmites australis*. Bryophytes are generally lacking or of low abundance.

For each of these peatland classes, the distinction between the open and wooded modifier was the % tree canopy cover as defined by the AWI (Vitt et al. 1996). With less than 6% tree cover and dominance by sedges, graminoids, herbs and shrubs categorized as “open” and greater than 6 to 70% tree canopy cover resulted in a designation of “treed” or “wooded” (Vitt et al. 1996). In this study, we further distinguished open graminoid-dominated fen from shrub-dominated fens, with the latter having greater than 35% dominance of shrub cover (Figure 2). In Alberta only wooded bog, open fen and treed fens are found. However, the UP of Michigan has all three types of fens: treed, shrubby, and open, and only a few wooded bogs.

<insert Figure 2>

Materials and Methods

The approach used for this peatland classification research was to first assess the feasibility of using a combination of SAR and optical data for distinguishing boreal peatland types over a small preliminary evaluation area (Pelican Lake, Alberta, CA, Figure 1). Next a comparison of

two state-of-the-art classifiers were tested and compared on an expanded study area (Wabasca, Alberta, CA; Figure 1). In addition, comparison of single date optical (summer Landsat) to single date SAR-optical (summer Landsat and summer PALSAR and ERS), and multi-date SAR-optical for Wabasca was tested to quantify any improvement in mapping capability with multi-sensor and multi-date data. Finally, the classifier found most suitable for broad area mapping was used to map four additional areas for testing and evaluation (Table 1).

Feasibility Analysis of Merging SAR-Optical Imagery for Peatland Mapping

Through comparison of known peatland types (based on the Peat Task Force maps created by (Vitt et al. 1995) coupled with field verification) within the various sources of imagery, an assessment was conducted to determine the ability to distinguish different peatland types with SAR and/or optical imagery. The feasibility analysis was conducted using Object Based Image Analysis (OBIA) following the approach by Grenier et al. (2007) in which a top-down hierarchy was used that applied thresholds and nearest neighbor functions to distinguish different peatland types. This approach allowed for exploration of the utility of different optical (Landsat TM5) and SAR (PALSAR L-band and ERS C-band) bands for distinguishing open fen, treed fen, and wooded bog, which are the three main peatland types of northeastern Alberta.

Classifier Comparison

For the classifier comparison, OBIA and a machine learning classifier, Random Forests (Brieman 2001), were tested and compared for the expanded Wabasca subregion (Figure 1, 850,000 ha). The OBIA allowed for further evaluation of the various optical and SAR bands for classification in building the ruleset in the eCognition software. OBIA complements a principle of landscape ecology that it is preferable to work with a meaningful object representing spatial patterns rather than a single pixel (Blaschke and Strobl 2001). The second classifier evaluated,

Random Forests (RF) is a decision tree-based, non-parametric statistical pixel classifier.

Applying both state-of-the-art classification approaches to a single dataset allowed for a direct evaluation of the two classifiers to determine the most efficient and highest accuracy mapping method to meet the broad scale mapping needs, as well as evaluation of the seasonal and multi-sensor bands for detecting and mapping peatlands. Given the remote nature of boreal peatlands, an approach that could be applied with minimal field validation (e.g. OBIA thresholding techniques) was attractive; however, methods that allowed for robust training and validation were also of value. Two other desirable qualities in a classifier were consistency and repeatability, especially between analysts and adjacent image scenes.

In addition, an analysis of the backscatter from treed fens and bogs, which are the most difficult to differentiate, was carried out using a long-time-series (1992-2010) of ERS-1/2 C-band SAR data to evaluate the seasonal trends in C-band backscatter to determine the interannual versus seasonal trends between these two peatland types. Comparable long-term L-band data were not available for a similar evaluation.

The classifier found to be most efficient while still highly accurate was then applied to three other subregions of Alberta (Figure 1) and Michigan's Upper Peninsula (UP). The best approach was based on validation accuracy, lowest omission/commission errors, efficiency, and feasibility for application to broad area peatland mapping. All maps were tested with reserved field validation datasets to conduct accuracy assessments.

Field Data Collection

In order to distinguish peatland types with remote sensing, an understanding of peatland ecology, hydrology, landscape context, and seasonal trends is needed. The spatial and temporal patterns observed (e.g. tone and texture) from remote sensing need to be linked to on-the-ground field

measurements for calibration and validation of the map classifier. Therefore, a large field campaign was implemented that included characterization of field sites to be used as training and validation of the classifiers.

Field data were collected at the minimum mapping unit (mmu) in each of the study areas, which is a function of the spatial resolution of the sensors used. Based on work in the Great Lakes (Bourgeau-Chavez et al. 2015b), the minimum size that could be confidently mapped with a PALSAR-Landsat combination was 0.2 ha. We therefore used 0.2 hectares as the mmu for peatland mapping in this study.

Our protocol for selection of sites to sample consisted of a combination of systematic and random sampling within the regions of interest. In year 1, random sampling within 1.5 km of roads led to many upland sites being sampled relative to wetland/peatland sites. Thus in subsequent years, aerial imagery was used to narrow the field locations to areas that appeared to be potential peatland/wetland. Criteria for site selection included areas greater than 0.2 ha in size with wetland characteristics in the aerial imagery with a maximum distance of 1.5 km from a trail, road or water body. The seven elements (tone, texture, shape, size, shadow, pattern and association) of image interpretation (Olson 1960) were used to identify potential wetland sites. Wet areas generally appear darker in tone in natural color aerial imagery and white in black and white infrared imagery. Texture, association, shape and size were also used to determine potential wetland areas. Using all elements of interpretation in combination can improve the accuracy of identification, but errors and biases can occur depending on the availability of high resolution imagery from different dates and seasons.

Then random sampling within these areas was conducted. Ideally, locations of somewhat homogeneous cover are needed for sampling. For example, Figure 3 shows an aerial image with

polygons delineating a treed fen and an open fen surrounded by upland forest. The black dots show the targeted central GPS location for field sampling. Once in the field, the homogeneous area represented by the red boxes (40 x 50 m) of Figure 3 were characterized. Next, the larger areal extent of the wetland types sampled in the field (red boxes) were extended via air photo interpretation to the polygons shown in black in Figure 3.

<insert Figure 3>

To aid field researchers in determining wetland ecosystem type in the field, a field classification key was created (Figure 4). The field key assumes the site being assessed is a wetland site and starts with the depth of peat. From this variable the field team would work through the hierarchy represented in Figure 4 to key out the peatland/wetland type. Soil pH was measured to aid in distinguishing bogs from fens since bogs tend to be more acidic and fens slightly acidic to neutral.

In the field, site characteristics were recorded for each location including ecosystem type, dominant species, water depth, peat depth, soil moisture and pH, biophysical measurements for tree species, and vegetation diversity, distribution, and density all with a date/time stamp. GPS-tagged field photos in 4 cardinal directions and nadir were also collected to aid in development of the training polygons. Sketches of the 40 m x 50 m plot in the context of the overall site were completed while in the field, and the larger extent of the particular cover type was hand delineated on a laminated aerial image of the area. Figure 3 shows the training polygons that were then created from the field collection and aerial image interpretation. Care was taken not to approach the edges of each ecosystem type in defining the polygons in the aerial image (1 m) because of the difference in resolution of the Landsat (30 m) and PALSAR (20m) to the higher resolution aerial images (Figure 3).

<Insert figure 4>

Imagery and Data Processing

Image Datasets

For each of the study areas, multi-date data were obtained from ALOS PALSAR L-band HH and HV polarized 20 m resolution imagery, Landsat-5 TM 30 m resolution imagery, and C-band 30 m resolution imagery from ERS-1 or 2 (C-VV). Data collected from 2-3 dates in the growing season were desired from each sensor. Since data from multiple satellites were used, simultaneous data collection over the study area was not possible. Also, since it was archival data, available imagery from the seasons desired were often not collected in the same year by each sensor and sometimes suitable data were unavailable (e.g. Kidney Lake and UP C-band). In the absence of fire, vegetation changes were expected to be minimal, and a threshold of 5-6 years was used for image acquisitions. Most changes occurring in the region are due to wildfire, oil and gas exploration, or logging, and such changes in these disturbance variables would be obvious and with spatial data on wildfire available from the Canadian Large Fire Database (Stocks et al. 2002). Vegetation growth is slow in the boreal zone and transition from one ecosystem type to another is also slow compared to this timeline.

<insert Table 2>

Optical Imagery

Cloud-free Landsat-5 TM data sets from multiple dates were downloaded from the United States Geological Survey (USGS) Earth Explorer database. Although three seasonal dates (spring, summer, and fall) were desired for analysis, sometimes only two seasons of cloud-free data were available (Table 2). Three seasons were available for the Kidney Lake study area and Michigan's UP, and two seasons for each of the other subregions of Alberta. The Landsat-5 TM

data were converted from radiance through a top-of-atmospheric reflectance (TOA) conversion algorithm after Chander et al. (2009). The TOA reflectance algorithm reduces variance in the seasonal Landsat-5 TM data sets by removing the cosine effect that occurs at different data acquisition times due to the changing solar zenith angles. The algorithm also compensates for data variation caused by earth-sun distances in data acquisition dates and corrects for the different values of the exoatmospheric solar irradiance rising from spectral band variances (Chander et al. 2009).

Synthetic Aperture Radar (SAR)

ALOS PALSAR images in fine beam dual (FBD) mode were acquired in level 1.5, four-look, linear amplitude format from the Alaska Satellite Facility (ASF) for each study area from two to three dates during the growing season. The PALSAR L-band sensor has a wavelength of 23.62 cm and HH and HV polarizations are sampled in FBD mode with an incidence angle of 37.5°. The radiometric accuracy is ± 0.64 dB (Shimada et al. 2007; Shimada et al. 2005). C-band data were used from ERS-1 or 2 for each Alberta study region (Table 2). A complete coverage of C-band data was unavailable for Michigan's UP, thus only L-band data were used there. The ERS-2 has a wavelength of 5.6 cm with VV polarization, a central incidence angle of 23° and calibration accuracy of 0.16 dB (Meadows et al. 2005). Although ERS-1 was stable over its lifetime, there was a decrease in the SAR transmitter pulse power of ERS-2 over its lifetime (0.66 dB to 0.82 dB per year). This loss in gain in the ERS-2 SAR imagery may be accounted for in the processing by use of the replica pulse power, as was done for the data used in this research.

All SAR data sets were acquired from ASF. SAR calibration to sigma nought (σ^0 , backscatter coefficient), terrain correction, and geolocation were applied using ASF's MapReady

software program with bilinear interpolation and output to 32-bit floating point linear intensity data. A 15 m ASTER DEM was used for radiometric terrain correction in MapReady which uses the Ulander approach to mitigate the effect of local terrain variability (Ulander 1996). The files were then exported from MapReady into geoTIFF format for import into ERDAS Imagine for further geolocation correction to the reference Landsat data using the raster geocorrection tools with bilinear interpolation. Approximately 50-90 ground-control-points (GCP) were manually selected in each image. A second-order polynomial model was used to geocorrect all SAR data to within 1 pixel of the reference Landsat data. A mean speckle filter with a 3 x 3 window was then applied to the SAR data. For SAR, spatial averaging and/or speckle filtering needs to be applied to correct for the inherent speckle noise. This is due to the coherent nature of the SAR systems and results in bright and dark adjacent pixels, which produces a “salt and pepper” effect. Therefore, a single pixel of SAR data cannot be used to directly relate to field variables, instead a group of pixels must be averaged or otherwise filtered to reduce speckle. The original multi-looked SAR imagery has 20–30 m resolution in the ground plane. This allows for a 3x3 speckle filtering window for the 12.5 m spaced pixels (note that SAR imagery is typically oversampled in relation to the resolution, and therefore pixel spacing is smaller than the resolution). All data (Landsat, ERS-1, ERS-2, and PALSAR) were resampled to 12.5 m pixel spacing and stacked into a single file containing each band from each image date.

Object-Based Image Analysis

Object-based approaches incorporate two steps: segmentation and classification. In the segmentation phase, homogeneous image objects are derived from both spectral and spatial information (Benz and Pottier 2001). In the classification phase, image objects (rather than

pixels) are classified using established classification algorithms, knowledge-based approaches, or a combination of classification methods (Civco et al. 2002).

In our research, a top-down OBIA hierarchical approach was employed by first delineating water from land, then burned from non-burned areas within the land category, then upland from lowland within the non-burned land category, etc. (Figure 5). Through development of rule sets, OBIA tools in eCognition allowed for further exploration in increasing an understanding of those remote sensing layers that were helpful in distinguishing different characteristics of the landscape to best identify different peatland types. Advantages of the OBIA approach are that rulesets may be developed without field training data sets. This is the case for part of our decision tree (Figure 5), but for the final wetland classes in the last part of the tree, field data and aerial imagery were used to assign classes to a set of image objects for nearest neighbor classification.

<Insert figure 5>

Machine Learning Image Processing - Random Forests Classification

For a pixel-based, supervised approach to image processing, the Random Forests algorithm was used. The Random Forests algorithm creates trees which successively conduct binary splits of the data in order to produce separations making the outcome as homogenous as possible. Several successful wetland mapping projects have relied on RF (Bourgeau-Chavez et al. 2015b; Clewley et al. 2015a,b; Corcoran et al. 2012; Whitcomb et al. 2009). For this research, the algorithm was set to generate 500 decision trees for each classification run. The number of variables used to split each node was approximately equal to the square root of the total number of variables in that scene. The approach included delineation of training polygons from field data and air photo

interpretation (as described in detail below), then running the RF classification algorithm, and checking the output maps and associated accuracies. RF favors the classes that are most prevalent in the training data. Therefore, the number of training polygons needs to be representative of the prevalence of each class on the ground, something that is not always known apriori. Using an iterative process allows for adjustments to remedy this problem. In the event of erroneous classifications, additional training data were added or adjusted and the RF algorithm was rerun as necessary to reduce over-classification of one or more classes.

Training Data and Air Photo Interpretation

Training and validation polygons were interpreted by an image analyst through the use of field data and air photos (Figure 3). The amount of training data per class was proportional to the area of that class for each region. Efforts were made to evenly distribute training polygons throughout each of the study areas. Validation polygons, which were reliant on field data, were skewed towards locations accessible via roads to enable field crews to collect as much data as possible. Black-and-white infrared aerial photography was acquired in GeoTIFF format from the Alberta Environment and Sustainable Resource Development Ministry. The black-and-white aerial photography allow for better distinction of tone and texture for wetland delineation (Halsey et al. 2003). For Michigan the National Agriculture Imagery Program (NAIP) imagery from 2010 and 2012 were used. Google Earth imagery was also used for all sites when sub-meter resolution imagery was available to augment the other high resolution imagery sources.

Accuracy Assessment

To create a robust validation dataset for the peatland type maps, training polygons which were equivalent to approximately twenty percent of the total polygon area of each class were withheld

from the classifications and reserved for validation. Whole polygons and not partial polygons were reserved. Polygons created from field data were automatically withheld, and the remaining polygons were randomly selected. This approach was used because the out-of-box validation of Random Forests does not represent an independent dataset for validation (Bourgeau-Chavez et al. 2015b; Millard and Richardson 2015). The 20% reserved validation data were used to assess the accuracy of both the OBIA and Random Forests classified maps. The assessments included producer's accuracy, which is a measure of how accurately the analyst classified the image data (errors of omission = $100 - \text{producer's accuracy}$) and user's accuracy, which is a measure of how accurately a classification performed in the field (errors of commission = $100 - \text{user's accuracy}$) (Congalton and Green 1999; Congalton and Green 2008).

Results and Discussion

Feasibility Analysis

Initial evaluation of the SAR and optical datasets was conducted for the 25 km x 15 km area near Pelican Lake (Figure 6) within the Wabasca, Alberta study region (Figure 1). Initially, two dates of PALSAR imagery (displayed in false color composite in Figure 6A and C); two dates of Landsat (Figure 6D); and two dates of ERS-2 (Figure 6B) were evaluated. The Pelican Lake imagery showed open fens as bright in TM bands 3 and 4 of Landsat-5 (cyan in Figure 6D) and very dark in PALSAR L-HV (Figure 6A). These open fens appear to be detectable from Landsat alone, but PALSAR L-HV provides a cross validation. Conversely, the PALSAR cannot be used alone because open fens may be confused with recent burns that are also dark (Annotated in Figure 6D). Thus, PALSAR alone would result in confusion, but the cross validation of the two sensor types should aid in distinguishing the burned and open fen classes. The two-date PALSAR L-HH shows distinction between forested bog and fen peatlands (Figure 6C). Since

forested bogs are isolated and rainfed they are not expected to change as much hydrologically over a short timeframe as would treed fens that are hydrologically connected through surface or groundwater. This is apparent in the July & August 2007 L-HH imagery (Figure 6C), where the bogs are a pinkish gray color and the wooded fens that are brighter on the second date (due to higher moisture) result in a cyan color in Figure 6C. Approximately 33 mm of rain fell in the two weeks prior to the acquisition of the July 2007 image, while approximately 65 mm fell in the two weeks prior to the August image (ACIS 2016). The cross polarized signal (L-HV) is known to be sensitive to the biomass of different ecosystem types. The upland forest has the greatest biomass and appears bright in both dates (bright white in the imagery of Figure 6A). The swamps in the L-HH imagery are red indicating that they have a stronger return on the first date likely due to greater inundation on the first date (July 2007 Figure 6C). Inundation is known to cause a double bounce from the tree trunks to water surface and back to the sensor (Hess et al. 1995). The C-band ERS-2 imagery is most sensitive to moisture in areas without trees. The open fens and the old fire scar areas appear bright white (wet on both dates) or cyan (wetter in June 2004) in Figure 6B. In contrast, the forested areas with denser canopies (uplands and some wooded bogs) are red in the ERS-2 imagery (Figure 6B) with strong signatures when biomass has reached its peak in the growing season. The denser forest areas are not penetrable by the C-band energy and thus, information about ground moisture is not retrievable. This preliminary study area demonstrates the suitability of PALSAR data to detect hydrologic and biomass characteristics of the bogs versus fens. Landsat was able to capture the different spectral signatures of open fens and burns and deciduous versus coniferous canopy cover. The shorter wavelength, C-band data show moisture patterns in the lowest biomass ecosystems (open fen and recently burned areas e.g.) but also in some of the wooded bogs and fens (Figure 6B). An analysis of mean backscatter from 3

bog complexes and 3 fen complexes near Utikuma, Alberta (Figure 1) was conducted for the growing seasons (May to August) of 1992 to 2010 (Figure 7). Generally, a greater seasonal change in backscatter was found for the fen (~ 3 dB) than in the bog complexes (~ 1 dB). The plots of Figure 7 show not only high variability in backscatter from the fens across dates for a single complex, but also between fen complexes on a given date, while the bogs have more consistent backscatter values between complexes (Figure 7). This analysis indicates that when the timing of the images is optimal (i.e. collected in wet vs. dry conditions), 2 or 3 image dates showing change could be used in distinguishing bogs from fens. Appropriate timing of the SAR data collections is critical to detecting changes in hydrology that allow for distinction of ecosystem types.

<Insert figures 6 & 7>

The analysis of multi-date C- and L-band SAR backscatter and spectral signatures of Landsat from bogs vs. fens at the small Pelican Lake, Wabasca, and Utikuma study areas (Figures 6 and 7) indicated that a combination of the PALSAR, ERS-2, and Landsat would be suitable for mapping broadscale boreal peatland types. The OBIA was then applied to the 850,000 ha Wabasca study area in eCognition (Figure 5), as well as the RF classifier.

Wabasca OBIA and RF Map Results

A side-by-side comparison of the OBIA and random forests maps for the Wabasca region is shown in Figure 8 and an accuracy comparison is presented in Table 3 (A&B). The OBIA and RF maps both had overall accuracy greater than 90%, however the OBIA classification map has much more treed fen across the scene than the RF map (Figure 8), which shows more of these areas as bog. From field observations and the (Tarnocai et al. 2011) map, bog is much more abundant than fen in this region. This exemplifies the importance of field data collection, as well

as reconnaissance and research of the region of study, to determine if the output map appears accurate, because the difference in OBIA and RF classification results was not apparent from the statistical accuracy assessment (Table 3). For the OBIA classification, the largest confusion error based on the statistical accuracy assessment was between open water and open fen, with 71% commission error (Table 3 CE). For the RF classification, open water was never mapped as open fen, however, the distinction between open fen and tree fen was more often confused, with 23% commission error for treed fens and 21% for open fens. Open fens may have just a few trees in an open sedge cover and the transition between the open ($< 6\%$ tree cover) and treed fen (>6 to 70% tree canopy cover) is where the commission and omission errors of open fen/poor (treed) fens are primarily occurring. This is where adjustments of the training data that distinguishes treed from open fens would need to be applied by the image analyst. For general detection of peatlands, the RF classifier was comparable to the OBIA classifier for the Wabasca study area. However, using the OBIA ruleset of Figure 5 appears to result in misclassification of wooded bog as treed fen (Figure 8) that was not apparent from the statistical accuracy assessment, as well as a misclassification of open water as open fen (Table 3). A fine tuning of the OBIA algorithm could likely fix these issues by adjusting thresholds and adding or removing training data. However, developing the OBIA rulesets is also time consuming and less flexible than RF. Previous research has found RF to be more consistent and repeatable between image analysts (Bourgeau-Chavez et al. 2015b). Therefore, RF was selected as the classifier for subsequent mapping.

<insert figure 8 and Table 3>

Landsat thermal bands had not been initially included in the mapping. However, other research has demonstrated the thermal channels to be of high importance in wetland detection

(e.g.(Bourgeau-Chavez et al. 2015b)). The thermal channel is often removed from the dataset when conducting land cover mapping due to the low spatial resolution. To determine the value of reintroducing thermal back into the layer stack, an evaluation of RF with and without thermal data layers was conducted (third panel of Table 3C). Results show a slight improvement in the RF classification that included the thermal bands for bog and open fen and a greater improvement for treed fen (commission error reduced from 23 to 12% and omission error reduced from 26 to 23%, table 3). Since all classes improved with the inclusion of the thermal channels, all subsequent mapping included the thermal channels.

To test the improvement in using multiple seasons of data and multiple sensors, the RF classifier was run on (A) summer Landsat only, and (B) summer Landsat and SAR for the Wabasca study area to compare accuracies to (C) the multi-season multi-sensor approach (Table 4). The summer (single season) only Landsat had 71% overall accuracy, while summer Landsat and SAR (single season – multi-sensor) had an improvement to 78% overall accuracy and the multi-season, multi-sensor approach had 89% overall accuracy (Table 4). These results show improvement in the peatland classes as multiple sensors are used and multiple seasons of imagery for distinction of the different peatland classes. The wooded bog class shows the strongest improvement, with commission/omission errors reducing from 32%/27% for summer optical-only to 26%/25% for summer SAR optical to 1%/2% for Multi-date SAR optical. Treed fen also shows a large reduction in commission error when multi-seasonal datasets are used (38% & 43% to 12%) and a smaller reduction in omission error from 36% & 32% to 23%.

Results of RF Classifier for Four Sub-Regions of Alberta, Canada

The four subregions of Alberta that were mapped represent 3,384,890 ha (Figure 9, (Bourgeau-Chavez et al. 2015a)). The error matrix for the RF Peatland Classified maps for all 4 Canada

subregions shows 93% overall accuracy (Table 5) with all classes having 84% or better producer's and user's accuracies; with the lowest user's accuracy of 84% for the logged and barren class, thus meeting our research goal of greater than 80% accuracy. In fact, the peatland classes all had greater than 88% accuracy. The commission errors (between 6 and 11%) and omission errors (between 3 and 12%) were very low for the peatland classes, with most of the confusion within these classes, and to some degree with the swamp class.

<insert Figure 9 and Table 5>

Application of RF Classifier with combination of multi-date PALSAR and Landsat to Southern Limit of Boreal Zone

Peatlands of the southern boreal limit in Michigan's UP were mapped with the RF classifier in a merging of 3 dates of PALSAR and 3 dates of Landsat (spring, summer, and fall) to create a map of the 4.24 million ha peninsula. The landscape of the UP is significantly different than that of Alberta, with a majority of the peatlands being fens and including a shrubby fen class that did not exist in Alberta. Bogs on the other hand were sparse on the UP landscape and therefore difficult to classify or validate. Therefore, the treed fen classes include some wooded bog, because there were too few bogs to train or validate in the map. The map is presented in Figure 9, and the accuracy results (Table 6) show this map to have 94% overall accuracy, with user's accuracy for peatland classes ranging from 63 to 84% and producer's accuracy from 67 to 84%. The highest error was for treed fens (33% commission and 37% omission), however it was confused primarily with shrubby fens.

<insert figure 10>

<insert Table 6>

The mapping goal of 80% accuracy for each class was not met for Michigan's UP, and this is to a large degree due to the overlap in presence of trees in open, shrubby and treed peatlands. The shrubby fens often have some trees in them (Figure 2), so the distinction of shrubby (>50% shrubs) and treed (> 6% to 70% trees) from a remote sensing perspective is a difficult distinction. Some of the open fens also contain some trees (< 6%). When shrubby and treed fens are combined into a woody fen class, the accuracy increases to 91% producer's accuracy and 86% user's accuracy and the accuracy for all peatlands combined into a single class is 92% user's accuracy and 96% producer's accuracy. It has been shown that the ~24 cm wavelength of L-band SAR is insensitive to variation in low biomass differences in peatlands of Alaska (Kasischke et al. 2007). For improved separation of shrubby from treed fens, C-band (~5.6 cm) data (as was used in Alberta) may have improved the distinction due to its greater sensitivity to low biomass differences.

Comparison of Peatland and Wetland Mapped Areas of the UP to Alberta

The map accuracies reported for Alberta and the UP are comparable or exceed previous wetland and peatland mapping studies (Table 7) using high and medium resolution sensors in boreal regions (Dingle Robertson et al. 2015; Grenier et al. 2007; Li and Chen 2005; Millard and Richardson 2013; Whitcomb et al. 2009). In addition, for the Alberta study area the percent of the landscape mapped as peatland is comparable (although slightly higher) to that previously reported by Tarnocai et al. (2011) (Table 8; 39% vs 31%), with the SAR-optical map showing a greater proportion of fen (13% vs. 9%) and comparable amount of bog (26% vs. 22%) on the landscape.

<insert Table 7>

<insert Table 8>

Much of the study areas of the UP and Alberta are known to be wetlands. However, due to differences in climate, bedrock, permafrost status and other variables there are many more widespread expanses of peatland in Alberta than the UP and our mapping approach is able to capture peatlands in both regions. When considering only the wetland classes, our Alberta map classifications (Figure 9) show 45% total wetland (marsh, swamp, open fen, bog, etc.) mapped on the landscape (Table 8), with 86% of that wetland being designated as peatland (58% bog and 29% fen) and lesser amounts of swamp (10%) and marsh (4%). The eastern Great Lakes Plains (eastern UP, Figure 10), also had 45% of the land mapped as wetland but only 12% of that was peatland, with an even lesser amount (29%) of wetland mapped in the western UP and merely 5% of that designated as peatland (Table 9).

<insert Table 9>

This demonstrates the robust nature of the peatland mapping capability using medium resolution, multi-temporal, SAR-optical approach in RF to be applicable to a wide range of landscapes; from the peatland-dominant Boreal Plains Ecozone to the swamp-dominant Great Lakes Plains and the more varied upland physiography of the western UP.

Summary and Conclusions

A combination of multi-date Landsat and SAR datasets have been demonstrated as suitable for distinguishing the saturated soils of peatlands versus the seasonally inundated non-peat swamps and marshes in a variety of landscapes. Further, the research presented here has shown that the temporal differences in hydrology of fens vs. bogs allows for discrimination through the use of multi-date L-band SAR imagery and the potential of C-band SAR (Figure 7). The timing of the SAR collections is critical to capture these environmental changes.

In addition, the cross polarized channel (L-HV) of L-band SAR was found sensitive to the biomass of different peatland landscapes allowing for distinction of open, shrubby, and treed peatlands with moderately high accuracy, particularly when merged with optical imagery (>65% for Michigan's UP). Inclusion of C-band may aid in distinguishing more of the subtle differences in biomass between shrubby and sparsely forested sites as defined here, particularly if polarimetric imagery were available.

Although having to collect large amounts of field data in such remote regions is time consuming and often logistically difficult, this was deemed a necessity to improve the accuracy of the peatland type mapping, for not only the training of the classifier and calculating statistical accuracy assessments, but also to understand the landscape that was being mapped such that we were able to visually assess the final maps.

In this study, RF worked well in the mapping of peatlands in regions of large (Alberta Canada) and small (Michigan's UP) distributions of peatlands among other wetland types in distinctly different landscapes. Some of the strong advantages to using Random Forests are its ability to work with high dimensional data, missing values and correlation. The Random Forests machine learning methods are therefore becoming increasingly popular for wetland mapping (e.g. (Bourgeau-Chavez et al. 2015b, 2016; Clewley et al. 2015a,b; Whitcomb et al. 2009)).

Peatlands represent a diversity of ecosystem types that vary considerably in hydrology, vegetation structure, peat depth, and composition. The development of a mapping capability for distinction of bog and fen types provides the spatially-explicit information needed to allow for monitoring and assessment of these important C-rich ecosystems.

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List of Figures

Figure 1. Map of the study area including Alberta Canada and Michigan's Upper Peninsula at the southern limit of the boreal zone. Inset shows the location of four subregions (Wabasca, Utikuma Lake, Kidney Lake and Fort McMurray) of the northeastern Alberta study area used for mapping peatland types. The study areas lie within the Boreal Plains Ecozone as shown as the hatched area on the inset map. The blue box shows the Pelican Lake region of preliminary study which is the focus area in Figure 6. The base Ecoregions map for Canada is from the Ecological Stratification Working Group (1995). For boreal mixedwood it is from EPA's Ecoregions of North America level III (US Environmental Protection Agency 2010).

Figure 2. Field photos of Open and Treed Fens and Wooded Bog in Alberta Canada, and Shrubby Fen in Michigan's UP

Figure 3. Field validation sampling plot in relation to the 1 m resolution aerial imagery, 30 m resolution Landsat, and 20 m resolution PALSAR. The red box shows field measured plot of 40 m x 50 m, black dot is the center of this plot. Black outline polygons are examples of air photo interpreted areas used for training data in the classifier.

Figure 4. Field guide developed for use in distinguishing peatland/non-peatland wetland types based on species presence/absence, depth of peat, etc.

Figure 5. Ecognition OBIA flow chart showing the rulesets used in the top-down hierarchical classification.

Figure 6. Imagery from Pelican Lake area within the Wabasca subregion. See Figure 1, blue box for location. A) PALSAR L-HV July and August 2007 false color composite; B) Radarsat-1 CHH two date false color composite; C) L-HH July and August False Color composite and D: Landsat-5 TM bands 7,4,3 from August 2008.

Figure 7. Plots of Seasonal (May through August) ERS backscatter through time (1992-2010) for 3 Wooded Bogs (left) and 3 Treed Fens (right) of the Utikuma, Alberta study area. To obtain the backscatter coefficients in dB for plotting the equation: $\sigma_{dB}^0 = 10 * \log_{10}(\sigma^0)$ was used.

Figure 8. Comparison of OBIA peatland classified map (left) and RF classified map (right) for Wabasca, Alberta study region.

Figure 9. RF peatland type maps for the four subregions of Alberta, Canada

Figure 10. RF peatland type map for the Upper Peninsula of Michigan

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Literature Cited

- ACIS. 2016. Interpolated Weather Data Since 1961 for Alberta Townships [online]. Available from <http://agriculture.alberta.ca/acis/township-data-viewer.jsp> [accessed 29 August 2016].
- Benz, U., and Pottier, E. 2001. Object based analysis of polarimetric SAR data in alpha-entropy-anisotropy decomposition using fuzzy classification by eCognition. *In* Geoscience and Remote Sensing Symposium, 2001. IGARSS'01. IEEE 2001 International, Sydney, Australia. pp. 1427-1429.
- Blaschke, T., and Strobl, J. 2001. What's wrong with pixels? Some recent developments interfacing remote sensing and GIS. *GeoBIT/GIS* 6(1): 12-17.
- Bourgeau-Chavez, L., Lee, Y.M., Battaglia, M., Endres, S.L, Laubach, Z.M., and Scarbrough, K. 2016. Identification of Woodland Vernal Pools with Seasonal Change PALSAR Data for Habitat Conservation. *Remote Sensing* 8(6):490. doi:10.3390/rs8060490
- Bourgeau-Chavez, L., Endres, S., Banda, E., Powell, R.B., Turetsky, M., Benscoter, B.W., and Kasischke, E. 2015a. NACP Peatland Landcover Type and Wildfire Burn Severity Maps, Alberta, Canada. ORNL DAAC, Oak Ridge, Tennessee.
- Bourgeau-Chavez, L., Endres, S., Battaglia, M., Miller, M., Banda, E., Laubach, Z., Higman, P., Chow-Fraser, P., and Marcaccio, J. 2015b. Development of a Bi-National Great Lakes Coastal Wetland and Land Use Map Using Three-Season PALSAR and Landsat Imagery. *Remote Sensing* 7(7): 8655. doi: 10.3390/rs70708655.
- Bourgeau-Chavez, L., Kowalski, K.P., Mazur, M.L.C., Scarbrough, K.A., Powell, R.B., Brooks, C.N., Huberty, B., Jenkins, L.K., Banda, E.C., and Galbraith, D.M. 2013. Mapping invasive *Phragmites australis* in the coastal Great Lakes with ALOS PALSAR satellite imagery for decision support. *Journal of Great Lakes Research* 39: 65-77. doi: 10.3390/rs70708655.
- Brieman, L. 2001. Random Forests. *Machine Learning*, 45: 5. doi:10.1023/A:1010933404324.
- Chander, G., Markham, B.L., and Helder, D.L. 2009. Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors. *Remote Sensing of Environment* 113: 893-903. doi: 10.1016/j.rse.2009.01.007.
- Chapin, F., McGuire, A., Randerson, J., Pielke, R., Baldocchi, D., Hobbie, S., Roulet, N., Eugster, W., Kasischke, E., and Rastetter, E. 2000. Arctic and boreal ecosystems of western North America as components of the climate system. *Global Change Biology* 6(S1): 211-223. doi: 10.1046/j.1365-2486.2000.06022.x.
- Chasmer, L., Hopkinson, C., Veness, T., Quinton, W., and Baltzer, J. 2014. A decision-tree classification for low-lying complex land cover types within the zone of discontinuous permafrost. *Remote sensing of environment* 143: 73-84. doi: 10.1016/j.rse.2013.12.016.
- Civco, D.L., Hurd, J.D., Wilson, E.H., Song, M., and Zhang, Z. 2002. A comparison of land use and land cover change detection methods. *In* Proceedings of ASPRS-ACSM Annual Conference, Washington, DC.

- Clewley, D., Whitcomb, J., Moghaddam, M., McDonald, K. 2015a. Mapping the state and dynamics of boreal wetlands using synthetic aperture radar. Chapter 17 in *Remote Sensing of Wetlands: Applications and Advances*. ed by R. Tiner, M. Lang, & V. Klemas, CRC Press, 369-398.
- Clewley, D., Whitcomb, J., Moghaddam, M., McDonald, K., Chapman, B., and Bunting, P. 2015b. Evaluation of ALOS PALSAR Data for High-Resolution Mapping of Vegetated Wetlands in Alaska. *Remote Sensing* 7(6): 7272. doi: 10.3390/rs70607272.
- Clymo, R., Turunen, J., and Tolonen, K. 1998. Carbon accumulation in peatland. *Oikos* 81(2): 368-388. doi: 10.2307/3547057.
- Congalton, R., and Green, K. 1999. *Assessing the accuracy of remotely sensed data: principles and applications*. Lewis Publishers, Boca Raton, Fla.
- Congalton, R.G., and Green, K. 2008. *Assessing the accuracy of remotely sensed data: principles and practices*. CRC press, Boca Raton, FL.
- Corcoran, J., Knight, J., Brisco, B., Kaya, S., Cull, A., and Murnaghan, K. 2012. The integration of optical, topographic, and radar data for wetland mapping in northern Minnesota. *Canadian Journal of Remote Sensing* 37(5): 564-582. doi: 10.5589/m11-067.
- Dingle Robertson, L., King, D.J., and Davies, C. 2015. Object-based image analysis of optical and radar variables for wetland evaluation. *International Journal of Remote Sensing* 36(23): 5811-5841. doi: 10.1080/01431161.2015.1109727.
- Ecological Stratification Working Group. 1995. *A National ecological framework for Canada*. Agriculture and Agri-Food Canada and Environment Canada.
- Fournier, R.A., Grenier, M., Lavoie, A., and Hélie, R. 2007. Towards a strategy to implement the Canadian Wetland Inventory using satellite remote sensing. *Canadian Journal of Remote Sensing* 33(sup1): S1-S16. doi: 10.5589/m07-051.
- Gorham, E. 1991. Northern peatlands: role in the carbon cycle and probable responses to climatic warming. *Ecological applications* 1(2): 182-195. doi: 10.2307/1941811.
- Grenier, M., Demers, A.-M., Labrecque, S., Benoit, M., Fournier, R. a, & Drolet, B. 2007. An object-based method to map wetland using RADARSAT-1 and Landsat ETM images: test case on two sites in Quebec, Canada *Canadian Journal of Remote Sensing* 33(S1): S28-S45. doi: 10.5589/m07-048.
- Grosse, G., Harden, J., Turetsky, M., McGuire, A.D., Camill, P., Tarnocai, C., Froking, S., Schuur, E.A.G., Jorgenson, T., Marchenko, S., Romanovsky, V., Wickland, K.P., French, N., Waldrop, M., Bourgeau-Chavez, L., and Striegl, R.G. 2011. Vulnerability of high-latitude soil organic carbon in North America to disturbance. *Journal of Geophysical Research: Biogeosciences* 116(G4): n/a-n/a. doi: 10.1029/2010jg001507.
- Halsey, L., Vitt, D., Beilman, D., Crow, S., Mehelcic, S., and Wells, R. 2003. *Alberta Wetlands Inventory Standards, Version 2.0*.

Henderson, F.M., and Lewis, A.J. 2008. Radar detection of wetland ecosystems: a review. *International Journal of Remote Sensing* 29(20): 5809-5835. doi: 10.1080/01431160801958405.

Hess, L.L., Melack, J.M., Filoso, S., and Wang, Y. 1995. Delineation of inundated area and vegetation along the Amazon floodplain with the SIR-C synthetic aperture radar. *IEEE Transactions on Geoscience and Remote Sensing* 33(4): 896-904. doi: 10.1109/36.406675.

IPCC. 2014. *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment*

Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Kasischke, E.S., Bourgeau-Chavez, L.L., and Johnstone, J.F. 2007. Assessing spatial and temporal variations in surface soil moisture in fire-disturbed black spruce forests in Interior Alaska using spaceborne synthetic aperture radar imagery—Implications for post-fire tree recruitment. *Remote sensing of environment* 108(1): 42-58. doi: 10.1016/j.rse.2006.10.020.

Kloiber, S.M., Macleod, R.D., Smith, A.J., Knight, J.F., and Huberty, B.J. 2015. A semi-automated, multi-source data fusion update of a wetland inventory for east-central Minnesota, USA. *Wetlands* 35(2): 335-348. doi: 10.1007/s13157-014-0621-3.

Li, J., and Chen, W. 2005. A rule-based method for mapping Canada's wetlands using optical, radar and DEM data. *International Journal of Remote Sensing* 26(22): 5051-5069. doi: 10.1080/01431160500166516.

Limpens, J., Berendse, F., Blodau, C., Canadell, J., Freeman, C., Holden, J., Roulet, N., Rydin, H., and Schaepman-Strub, G. 2008. Peatlands and the carbon cycle: from local processes to global implications—a synthesis. *Biogeosciences* 5(5): 1475-1491. doi: 10.5194/bg-5-1475-2008.

Meadows, P., Rosich-Tell, B., and Santella, C. 2005. The ERS-2 SAR performance: the first 9 years. *In* *Proceedings of the 2004 Envisat & ERS Symposium. Edited by H. Lacoste, L. Ouwehand* Salzburg, Austria. p. 3.

Millard, K., and Richardson, M. 2013. Wetland mapping with LiDAR derivatives, SAR polarimetric decompositions, and LiDAR–SAR fusion using a random forest classifier. *Canadian Journal of Remote Sensing* 39(4): 290-307. doi: 10.5589/m13-038.

Millard, K., and Richardson, M. 2015. On the Importance of Training Data Sample Selection in Random Forest Image Classification: A Case Study in Peatland Ecosystem Mapping. *Remote Sensing* 7(7): 8489. doi: 10.3390/rs70708489.

National Wetlands Working Group. 1988. *Wetlands of Canada: Ecological land classification series*. Environmanet Canada, Montreal, Quebec.

NRCS. 2008. *Monthly Precipitation by County for Michigan. Edited by NRCS*. U.S. Department of Agriculture, Washington, D.C.

- Olson, C.E., 1960. Elements of photographic interpretation common to several sensors. *Photogrammetric Engineering*, 26(4), pp.651-656.
- Shimada, M., Isoguchi, O., Tadono, T., Higuchi, R., and Isono, K. 2007. PALSAR CALVAL Summary (JAXA-PI193). In First Joint PI Symposium of ALOS Data Nodes for ALOS Science Program, Kyoto, Japan.
- Shimada, M., Rosenqvist, A., Watanabe, M., and Tadono, T. 2005. The polarimetric and interferometric potential of ALOS PALSAR. In Proceedings of the 2nd International Workshop POLINSAR 2005. Edited by H. Lacoste, Frascati, Italy. p. 41.
- Stocks, B., Mason, J., Todd, J., Bosch, E., Wotton, B., Amiro, B., Flannigan, M., Hirsch, K., Logan, K., and Martell, D. 2002. Large forest fires in Canada, 1959–1997. *Journal of Geophysical Research: Atmospheres* 107(D1). doi: 10.1029/2001jd000484.
- Tarnocai, C. 2006. The effect of climate change on carbon in Canadian peatlands. *Global and Planetary Change* 53(4): 222-232. doi: 10.1016/j.gloplacha.2006.03.012.
- Tarnocai, C., Kettles, I.M., and B, L. 2011. Peatlands of Canada. Geological Survey of Canada.
- Tarnocai, C., Kettles, I.M., and Lacelle, B. 2002. Peatlands of Canada Database. Geological Survey of Canada.
- Thomas, V., Treitz, P., Jelinski, D., Miller, J., Lafleur, P., and McCaughey, J.H. 2003. Image classification of a northern peatland complex using spectral and plant community data. *Remote sensing of environment* 84(1): 83-99. doi: 10.1016/s0034-4257(02)00099-8.
- Touzi, R., Deschamps, A., and Rother, G. 2007. Wetland characterization using polarimetric RADARSAT-2 capability. *Canadian Journal of Remote Sensing* 33(1): S56-S67. doi: 10.1109/igarss.2006.423.
- Turunen, J., Tomppo, E., Tolonen, K., and Reinikainen, A. 2002. Estimating carbon accumulation rates of undrained mires in Finland—application to boreal and subarctic regions. *The Holocene* 12(1): 69-80. doi: 10.1191/0959683602hl522rp.
- Ulander, L.M. 1996. Radiometric slope correction of synthetic-aperture radar images. *IEEE Transactions on Geoscience and Remote Sensing* 34(5): 1115-1122. doi: 10.1109/36.536527.
- US Environmental Protection Agency. 2010. Ecoregions of North America. Corvallis, OR.
- Vitt, D.H. 2006. Functional characteristics and indicators of boreal peatlands. In *Boreal peatland ecosystems*. Springer. pp. 9-24.
- Vitt, D.H., Halsey, L., Thormann, M., and Martin, T. 1996. Peatland inventory of Alberta Phase 1: Overview of peatland resources in the Natural Regions and Subregions of the province. National Centres of Excellence in Sustainable Forest Management. Publication No. 96-1.
- Vitt, D.H., Li, Y., and Belland, R.J. 1995. Patterns of bryophyte diversity in peatlands of continental western Canada. *Bryologist* 98(2): 218-227. doi: 10.2307/3243306.

Warner, B.G., and Rubec, C. 1997. The Canadian wetland classification system. Wetlands Research Branch, University of Waterloo, Waterloo, Ontario.

Whitcomb, J.B., Moghaddam, M., McDonald, K., KelIndorfer, J., and Podest, E. 2009. Mapping vegetated wetlands of Alaska using L-band radar satellite imagery. *Canadian Journal of Remote Sensing* 35(1): 54 – 72. doi: 10.5589/m08-080.

Wieder, R.K., Vitt, D.H., and Benscoter, B.W. 2006. Peatlands and the boreal forest. *In* *Boreal peatland ecosystems*. Springer. pp. 1-8.

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Table 1. List of the four study areas of east central Alberta and Michigan's Upper Peninsula including the area mapped, years of recent wildfires within each subregion and number of field validation locations sampled within each subregion.

Subregion	Extent of Map Area (Mha)	Recent burned areas (post 2008)	# Field validation locations
Utikuma	106.4	2011 Wildfire	96
Wabasca	85	None	215
Fort McMurray	114.7	2009 Wildfires	24
Kidney Lake	37.8	2009 Wildfire	15
Michigan's Upper Peninsula	424	2013 Prescribed Burn	439

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Table 2. List of image datasets (YY-MM-DD) used for each of the Alberta subregion study areas. Data availability limited selection dates, particularly C-band data from ERS-1 and 2.

<i>Imagery</i>	<i># bands</i>	<i>Utikuma</i>	<i>Wabasca</i>	<i>Fort McMurray</i>	<i>Kidney Lake</i>
<i>PALSAR Date-1 L-HH and HV</i>	2	07-07-07	07-07-02	07-06-10, 07-06-27	07-06-20
<i>PALSAR Date-2 L-HH and HV</i>	2	07-08-22	07-08-17	07-07-26, 07-08-12	07-08-05
<i>Landsat-5 TM Spring – bands 1- 5 & 7</i>	6		05-04-03	04-05-30	06-05-15, 09-05-29
<i>Landsat-5 TM Summer - bands 1-5 & 7</i>	6	08-08-08	05-08-25	05-06-28	02-08-24
<i>Landsat-5 TM Fall bands 1-5 & 7</i>	6	09-09-12			02-09-09
<i>ERS-1 Date 1 C-VV</i>	1		04-06-06		
<i>ERS-1 Date 2 C-VV</i>	1		04-08-15		
<i>ERS-2 Date 1 C-VV</i>	1	09-05-19		09-07-02	
<i>ERS-2 Date 2 C-VV</i>	1	08-08-12			

Table 3. Comparison of Accuracy Statistics for A) OBIA vs. B) Random Forests SAR-optical based maps of Wabasca without the Landsat thermal channel and C) Random Forests with the Thermal channel included. Terms are User's accuracy (UA), Commission Error (CE), Producer's Accuracy (PA) and Omission Error (OE).

	A) OBIA SAR Optical, no thermal				B) Random Forests SAR Optical, no thermal				C) Random Forests SAR Optical, with Thermal			
<i>Class</i>	UA	CE	PA	OE	UA	CE	PA	OE	UA	CE	PA	OE
Water	100	0	99	1	99	1	100	0	100	0	100	0
Wooded Bog	93	7	92	8	98	2	96	4	99	1	98	2
Treed Fen	94	6	96	4	78	23	74	26	88	12	77	23
Open Fen	29	71	63	37	79	21	90	10	80	20	93	7

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Table 4. Comparison of Random Forests classifier Accuracy Statistics for Wabasca study area for: A) Summer Optical-only vs. B) Summer SAR-optical ; and C) Multi-date SAR-optical . All RF runs included the thermal channel. Terms are User’s accuracy (UA), Commission Error (CE), Producer’s Accuracy (PA) and Omission Error (OE).

	A) Summer Optical-only				B) Summer SAR Optical				C) Multi-date SAR Optical			
<i>Class</i>	UA	CE	PA	OE	UA	CE	PA	OE	UA	CE	PA	OE
Water	100	0	100	0	100	0	100	0	100	0	100	0
Wooded Bog	68	32	73	27	74	26	75	25	99	1	98	2
Treed Fen	62	38	64	36	57	43	76	32	88	12	77	23
Open Fen	83	17	88	12	84	16	85	15	80	20	93	7

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Table 5. Classification accuracy for all 4 subregions of Canada (Figure 10), Total Accuracy = 93%. Numbers represent pixels.

<i>RF Classification</i>	<i>Ground Truthed Values</i>										Sum	Commission Error	User's Accuracy
	Water	Marsh	Swamp	Open Fen	Treed Fen	Bog	Deciduous	Coniferous	Logged/Barren	Developed			
Water	1005	0	0	0	0	0	0	0	0	0	1005	0%	100%
Marsh	0	928	29	1	5	0	0	0	0	37	1000	7%	93%
Swamp	0	29	929	0	1	0	3	2	28	2	994	7%	93%
Open Fen	0	2	3	994	53	6	1	0	0	0	1059	6%	94%
Treed Fen	0	7	24	15	901	64	0	0	1	3	1015	11%	89%
Bog	0	0	17	10	61	962	2	19	0	3	1074	10%	90%
Deciduous	0	0	0	0	0	0	997	51	10	0	1058	6%	94%
Coniferous	0	1	0	0	0	1	12	954	17	5	990	4%	96%
Logged/Barren	0	35	3	1	0	0	1	0	966	146	1152	16%	84%
Developed	0	5	0	0	1	0	0	0	1	821	828	1%	99%
Sum	1005	1007	1005	1021	1022	1033	1016	1026	1023	1017			
Omission Error	0%	8%	8%	3%	12%	7%	2%	7%	6%	19%		Overall Accuracy	
Producer's Accuracy	100%	92%	92%	97%	88%	93%	98%	93%	94%	81%			93%

Table 6. Classification accuracy for Michigan’s Upper Peninsula Peatland map. Numbers represent pixels.

	Ground Truthed Values													Commission Error	User's Accuracy
	Urban	Agriculture	Forest	Barren	Water	Marsh	Open Fen	Shrubby Fen	Treed Fen	Shrub Swamp	Forested Swamp	Sum			
Remotely Classified															
Urban	7889	556	923	1535	0	47	0	3	0	38	0	10991	28%	72%	
Agriculture	206	93603	1991	144	0	141	16	1	0	0	0	96102	3%	97%	
Forest	104	1182	220368	266	54	271	132	52	550	1297	4258	228534	4%	96%	
Barren	336	745	17	13433	38	51	0	0	0	0	0	14620	8%	92%	
Water	454	0	54	82	540237	50	0	0	0	0	0	540877	0%	100%	
Marsh	108	683	2065	55	6067	13514	328	189	49	1375	108	24541	45%	55%	
Open Fen	0	62	187	20	0	316	14639	1920	83	134	0	17361	16%	84%	
Shrubby Fen	5	28	99	0	1	269	1900	18787	4102	412	2	25605	27%	73%	
Treed Fen	20	5	1132	7	7	48	261	2821	10285	213	1515	16314	37%	63%	
Shrub Swamp	60	261	8344	31	181	408	70	430	331	11948	789	22853	48%	52%	
Forested Swamp	21	15	6813	42	11	24	3	3	42	386	47963	55323	13%	87%	
Sum	9203	97140	241993	15615	546596	15139	17349	24206	15442	15803	54635				
Omission Error	14%	2%	9%	14%	1%	11%	16%	22%	33%	24%	12%		Overall Accuracy		
Producer's Accuracy	86%	96%	91%	86%	99%	89%	84%	78%	67%	76%	88%				
														94%	

Table 7. List of reported accuracies for wetland and peatland mapping publications from the recent literature using SAR data and either OBIA or RF classifiers.

Publication	Reported Accuracy	Input Imagery	Classifier
Whitcomb <i>et al.</i> 2009	89.5% Overall – peatlands not distinguished	Summer and Winter JERS L-band SAR	RF
Grenier <i>et al.</i> 2007	67-76% Peatland Classes	Radarsat-1 C-HH and Landsat	OBIA
Li and Chen 2005	71-92% Peatland classes	Radarsat-1 C-HH and Landsat, DEM data	OBIA
Dingle Robertson <i>et al.</i> 2015	70% Overall – peatlands distinguished	WorldView-2 and Radarsat-2 polarimetric	OBIA
Millard and Richardson 2013	72.8% Overall – peatlands distinguished	Radarsat-2 polarimetric and LiDAR derivatives	RF

Table 8. Comparison of area mapped in Alberta for each of the wetland map classes using the SAR-optical approach with RF versus the Tarnocai map results (Tarnocai et al. 2011). The total row includes all land area mapped (upland and lowland) and % total area is based on all land cover types.

SAR-optical Map					Tarnocai Map		
Class	Area (ha)	% of Total area	% of Wetland	% of Peatland	Area (ha)	% of Total area	% of Peatland
Water	189,497	6%					
Marsh	59,276	2%	4%		0	0	
Swamp	153,586	5%	10%		0	0	
Bog	881,464	26%	58%	67%	721,141	22%	72%
Open Fen	64,641	2%	4%	5%			
Treed Fen	375,299	11%	25%	28%			
TOTAL FEN	439,941	13%	29%	33%	279,272	9%	28%
TOTAL PEATLAND	1,321,404	39%	86%		1,000,413	31%	
TOTAL WETLAND	1,534,266	45%					
Total Land Area	3,384,878	100%			3,243,662		

Table 9. Summary of area mapped using the SAR-optical approach in RF by class for the Western, Eastern and Complete UP

Western UP			Eastern UP		Complete UP	
Class	Area (ha)	% Area	Area (ha)	% Area	Area (ha)	% area
<i>Urban/Suburban</i>	35310.0	1.6%	38337.6	1.8%	73638.6	1.7%
<i>Agriculture</i>	22838.8	1.0%	67078.2	3.1%	89902.5	2.1%
<i>Fallow Field</i>	23680.7	1.1%	49050.5	2.3%	72716.2	1.7%
<i>Orchard</i>	0.7	0.0%	1542.6	0.1%	1543.4	0.0%
<i>Forest</i>	987752.5	44.9%	454059.8	21.1%	1441730.3	33.1%
<i>Pine Plantation</i>	117669.7	5.3%	240589.5	11.2%	358214.4	8.2%
<i>Shrub</i>	322520.6	14.6%	250794.9	11.6%	573245.7	13.2%
<i>Barren</i>	10903.5	0.5%	7266.0	0.3%	18167.6	0.3%
<i>Water</i>	43035.9	2.0%	83622.9	3.9%	126647.3	2.9%
<i>Aquatic Bed</i>	16614.1	0.8%	15679.8	0.7%	32291.4	0.7%
<i>Marsh</i>	46171.1	2.1%	47966.8	2.2%	94126.9	2.2%
<i>Schoenoplectus</i>	1541.3	0.1%	3254.0	0.2%	4794.9	0.1%
<i>Typha</i>	1723.9	0.1%	2831.7	0.1%	4555.7	0.1%
<i>Phragmites</i>	15.8	0.0%	472.3	0.0%	488.1	0.0%
<i>Open Fen</i>	4112.3	0.2%	27693.6	1.3%	31802.4	0.7%
<i>Shrubby Fen</i>	8863.9	0.4%	42947.8	2.0%	51807.2	1.2%
<i>Treed Fen</i>	20784.0	0.9%	48921.4	2.3%	69694.6	1.6%
<i>Wetland Shrub</i>	190309.1	8.6%	234952.6	10.9%	425224.9	9.8%
<i>Forested Swamp</i>	347816.1	15.8%	536903.0	24.9%	884613.4	20.3%
Total	2201664.1	100.0%	2153965.0	100.0%	4355205.6	100.0%
Total Wetland	637951.6	29.0%	961623.0	44.6%	1599399.5	36.7%
Total Peatland	33760.2	1.5%	119562.8	5.6%	153304.1	3.5%
% of Wetland that is Peatland		5.3%		12.4%		9.6%

Figure 1. Map of the study area including Alberta Canada and Michigan’s Upper Peninsula at the southern limit of the boreal zone. Inset shows the location of four subregions (Wabasca, Utikuma Lake, Kidney Lake and Fort McMurray) of the northeastern Alberta study area used for mapping peatland types. The study areas lie within the Boreal Plains Ecozone as shown as the hatched area on the inset map. The blue box shows the Pelican Lake region of preliminary study which is the focus area in Figure 6. The base Ecoregions map for Canada is from the Ecological Stratification Working Group (1995). For boreal mixedwood it is from EPA’s Ecoregions of North America level III (US Environmental Protection Agency 2010).

279x215mm (300 x 300 DPI)

Open Fen

Poor Fen

2010 Utikuma Wooded Bog

2011 Utikuma Burned Bog

Figure 3. Field validation sampling plot in relation to the 1 m resolution aerial imagery, 30 m resolution Landsat, and 20 m resolution PALSAR. The red box shows field measured plot of 40 m x 50 m, black dot is the center of this plot. Black outline polygons are examples of air photo interpreted areas used for training data in the classifier.

279x215mm (300 x 300 DPI)

Peatland Classification Guide

Figure 4. Field guide developed for use in distinguishing peatland/non-peatland wetland types based on species presence/absence, depth of peat, etc.

486x308mm (300 x 300 DPI)

Figure 5. Ecognition OBIA flow chart showing the rulesets used in the top-down hierarchical classification.

190x242mm (150 x 150 DPI)

Figure 8. Comparison of OBIA peatland classified map (left) and RF classified map (right) for Wabasca, Alberta study region.

279x215mm (300 x 300 DPI)

Figure 9. RF peatland type maps for the four subregions of Alberta, Canada
279x215mm (300 x 300 DPI)

Figure 10. RF peatland type map for the Upper Peninsula of Michigan

279x215mm (300 x 300 DPI)