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Mapping wetlands in Nova Scotia with multi-beam RADARSAT-2 Polarimetric SAR, optical satellite imagery, and Lidar data

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ABSTRACT

Wetland maps currently in use by the Province of Nova Scotia, namely the Department of Natural Resources (DNR) wetland inventory map and the swamp wetland classes of the DNR forest map, need to be updated. In this study, wetlands were mapped in an area southwest of Halifax, Nova Scotia by classifying a combination of multi-date and multi-beam RADARSAT-2 C-band polarimetric SAR (polSAR) images with spring Lidar, and fall QuickBird optical data using the Random Forests (RF) classifier. The resulting map has five wetland classes (open-water/marsh complex, open bog, open fen, shrub/treed fen/bog, swamp), plus lakes and various upland classes. Its accuracy was assessed using data from 156 GPS wetland sites collected in 2012 and compared to the one obtained with the current wetland map of Nova Scotia. The best overall classification was obtained using a combination of Lidar, RADARSAT-2 HH, HV, VH, VV intensity with polarimetric variables, and QuickBird multispectral (89.2%). The classified image was compared to GPS validation sites to assess the mapping accuracy of the wetlands. It was first done considering a group consisting of all wetland classes including lakes. This showed that only 69.9% of the wetland sites were correctly identified when only the QuickBird classified image was used in the classification. With the addition of variables derived from lidar, the number of correctly identified wetlands increased to 88.5%. The accuracy remained the same with the addition of RADARSAT-2 (88.5%). When we tested the accuracy for identifying wetland classes (e.g. marsh complex vs. open bog) instead of grouped wetlands, the resulting wetland map performed best with either QuickBird and Lidar, or QuickBird, Lidar, and RADARSAT-2 (66%). The Province of Nova Scotia's current wetland inventory and its associated wetland classes (aerial-photo interpreted) were also assessed against the GPS wetland sites. This provincial inventory correctly identified 62.2% of the grouped wetlands and only 18.6% of the wetland classes. The current inventory's poor performance demonstrates the value of incorporating a combination of new data sources into the provincial wetland mapping.

1. Introduction

Wetlands are complex ecological systems that are only form when processes of hydrology, geomorphology and biology work collectively to create the necessary conditions (Lynch-Stewart et al., 1996). Accurate mapping of wetlands is important to many applications, including long-term monitoring and natural resource management. In 2011, Nova Scotia released a wetland conservation policy implemented in part to ensure no net loss of wetlands (i.e. equal offsetting of loss using reclamation or restoration). It is a critical policy that aims to protect an essential feature of the landscape. The application of such policy requires an accurate and up-to-date wetland map. The classifications are quite distinct, but in practice wetlands often comprise a mixture of various classes (Canada Committee on Ecological (Biophysical) Land Classification, 1988). Wetland classification is further complicated by environmental characteristics that vary temporally (e.g. emerging vegetation in the spring) and spatially. Considering which factors affect wetland formation and recognizing these factors can aid in the proper identification of wetland class.

The current wetland map in Nova Scotia was produced by the Department of Natural Resources (NSDNR) in 2004 by photo-interpretation of digitized aerial photographs that were acquired in the 1980s and 1990s (Nova Scotia Environment, 2009). The wetland map was subsequently integrated with the forest map, a geospatial dataset primarily designed to guide timber harvesting and land management activities. However, a number of authors have suggested that photo-

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interpretation of digitized aerial photography is unreliable for the identification, delineation, and classification of wetlands (Jacobson et al., 1987; Sader et al., 1995; Hogg and Todd, 2007). This is particularly true in forested regions because of errors due to dense tree cover (Hogg and Todd, 2007). Such limitations also exist for satellite optical imagery that are acquired with short wavelength radiation, but not for synthetic aperture radar (SAR) imagery that is acquired with longer wavelengths that have a deeper penetration. In addition, by contrast to optical imagery, SAR images can be acquired whatever the sky conditions because the sensor transmits its own energy and does not depend on sunlight.

Wetlands form in a variety of landscapes; however, in all settings, terrain morphology will influence where surplus water will move and collect, and so plays a key role in determining where wetlands will form (Canada Committee on Ecological (Biophysical) Land Classification, 1988). Water source (precipitation, groundwater discharge, and lateral surface flow) is important for determining distinct types of wetlands (Brinson, 1993). Datasets derived from a Digital Elevation Model (DEM) can be used to model hydrogeomorphic criteria that influence the water source. Moreover, high sensitivity to surface water and soil moisture (due to a high dielectric constant) can make radar an efficient tool for determining hydrology (Kasischke and Bourgeau-Chavez, 1997; Rao et al., 1999).

For vegetative conditions it is necessary to distinguish different land cover. Spectral signatures, adequately resolved from optical imagery, can be used to infer the different land cover classes by automated image classification (Lillesand and Kiefer, 1994). Synthetic aperture radar (SAR) can penetrate vegetation canopy and, from backscatter mechanism identified, be used to characterize the vegetation and presence of flooding (Brisco, 2015). Wetland changes can be very good indicators of wetland characteristics, and so it is important that imagery be available at multiple stages in the growing season. Some sensors, like RADARSAT-2, have a higher capacity for this repeat cycle (Brisco, 2015). This pattern of changing water level is called the hydroperiod and is analogous to the wetland's unique hydrologic signature (Mitsch and Gosselink, 2007). Multi-temporal data will provide a crucial additional component to determining where wetlands are located (Brisco, 2015).

Single polarized SAR has been tested for mapping wetlands, such as in the studies being part of the Canadian Wetland Inventory (Li and Chen, 2005; Grenier et al., 2007; Fournier et al., 2007) or elsewhere (Ozesmi and Bauer, 2002). The nature of the polarimetric sensors allows transmission and receiving of signals in both horizontal and vertical polarization. The various combinations are described using the orientation of the transmitted signal first, followed by the received signal (e.g. horizontal transmission – vertical reception, or HV). Wetland classification can be improved using multiple polarizations because they can provide more information than single polarizations (Wang et al., 1998). The launch of fully polarimetric SAR X, C and L-band sensors (PALSAR in 2006 and TerraSAR-X and RADARSAT-2 in 2007) provides data that allow a complete description of the scattering properties because it provides the full scattering matrix. Such an advantage offers an additional opportunity to develop improved tools for mapping wetlands. These tools include polarization synthesis and computation of polarimetric variables and polarimetric decomposition parameters. Polarimetric data have already been shown to be effective for wetland mapping (Touzi et al., 2007).

Multiple polarizations can provide more information than a single polarization, especially when there is a specific orientation to an object or objects being detected. In the case of wetlands, when there is emergent vegetation within wetlands, L-VV backscatter is relatively low while L-HH and L-VH is high (Ramsey et al., 1999). C-HH data were found to be superior to C-HV or C-VV data in delimiting flood extent of the Elbe River in Germany, although C-HV data provide some information in regard to flood detection (Henry et al., 2006). According to Pope et al. (1997), C-HH data provided the highest accuracies for delineating sawgrass and cattails, but C-VV data are useful to separate cattails and low-density marshes. Co-polarizations (HH and VV) give a higher contrast backscatter between swamps and dry forest than cross-polarization for X- and L-bands that gives the ability to separate between flooded and non-flooded forests (Henderson and Lewis, 2008). However, some studies have noted that cross-polarization is better at separating between marsh and swamp classes for L-band (e.g., Henderson and Lewis 2008). Longer wavelength P- and L-bands have been useful in penetrating forest canopies to detect standing water, as the surface water results in a double bounce off the tree trunks, enhancing the signal response. C-band data have been useful in detecting standing water under short vegetation (Henderson and Lewis, 2008; Li and Chen, 2005). C-band and X-band data have also been shown to be favorable in some wooded wetlands with low density canopies, or leaf-off conditions (Henderson and Lewis, 2008; Townsend, 2002; Lang et al., 2008; Lang and Kasischke, 2008).

Resolution is a concept in remote sensing that will often determine the type of sensors used. Of the four types of resolution in remote sensing (temporal, spatial, spectral and radiometric (Lillesand and Kiefer, 1994)), spatial resolution determines the limits of feature size that can be detected and the precision of the edges. The Nova Scotia Department of Natural Resources wetland inventory shows wetlands that are greater than or equal to ½ ha (Nova Scotia Environment, 2009). The pixel spacing of 8 m for RADARSAT-2 SLC fine quad-pol is enough to accommodate a square of ½ ha but very narrow wetlands will be difficult to map. QuickBird multispectral bands have an even finer resolution of 2.4 m but were resampled to eight m. Spectral resolution, as in the case of QuickBird imagery, determines the ability to separate features based on potentially subtle differences in how they interact with the energy that is reflected. Vegetation condition shows a marked difference between the red band and the near-infrared band, and this can be used to distinguish between some vegetation types that may differ from class to class. Monitoring areas at different times can be especially valuable for wetland areas that may exhibit periodic flooding conditions (Brisco, 2015). LaRocque et al. (2014) have shown that flooding conditions, typically observed in the spring in eastern Canada and northeastern United States, were important for wetland classification in New Brunswick, Canada. Corcoran et al. (2013) also observed the importance of spring optical images in Minnesota, United States. Both locations are similar to Nova Scotia in terms of forest cover and topography.

Our study presents a method to map wetlands by applying a non-parametric classifier (Random Forests or RF), to a unique combination of RADARSAT-2 C-band polarimetric SAR images, QuickBird images (4 bands), and five variables derived from Lidar data in an area close to Halifax, Nova Scotia; that comprises forests, barrens and a chaotic topography (Neily et al., 2005). While most of the previous wetland mapping studies have used optical satellite images (see the review of Ozesmi and Bauer, 2002), some have also used radar images, mainly single-polarized images (Ozesmi and Bauer, 2002; Li and Chen, 2005; Grenier et al., 2007; Fournier et al., 2007) or dual-polarized images (LaRocque et al., 2014). More recently, radar polarimetric SAR (polSAR) images have been tested, but in a landscape that is less complex than ours and is mainly located over flat areas (Brisco et al., 2011; Millard and Richardson, 2013; Corcoran et al., 2011; Corcoran et al., 2013; van Beijma et al., 2014). Also, these polSAR studies assessed the accuracy of the resulting maps by comparing training areas with the equivalent classified areas in the imagery (Brisco et al., 2011; Millard and Richardson 2013; Corcoran et al., 2011; Corcoran et al., 2013; van Beijma et al., 2014), or against maps derived from aerial photography (Millard and Richardson, 2013); while in our case, we compare the classified image with GPS field data. Our study also identifies the sources of confusion errors with the upland classes and amongst the wetland classes for each wetland class. Our study shows that the combination of Random Forests classifier, lidar, optical, and polSAR data and specific variables derived from them, is beneficial to