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Random forest wetland classification using ALOS-2 L-band, RADARSAT-2 C-band, and TerraSAR-X imagery

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ABSTRACT

Wetlands are important ecosystems around the world, although they are degraded due both to anthropogenic and natural process. Newfoundland is among the richest Canadian province in terms of different wetland classes. Herbaceous wetlands cover extensive areas of the Avalon Peninsula, which are the habitat of a number of animal and plant species. In this study, a novel hierarchical object-based Random Forest (RF) classification approach is proposed for discriminating between different wetland classes in a sub-region located in the north eastern portion of the Avalon Peninsula. Particularly, multi-polarization and multi-frequency SAR data, including X-band TerraSAR-X single polarized (HH), L-band ALOS-2 dual polarized (HH/HV), and C-band RADARSAT-2 fully polarized images, were applied in different classification levels. First, a SAR backscatter analysis of different land cover types was performed by training data and used in Level-I classification to separate water from non-water classes. This was followed by Level-II classification, wherein the water class was further divided into shallow- and deep-water classes, and the non-water class was partitioned into herbaceous and non-herbaceous classes. In Level-III classification, the herbaceous class was further divided into bog, fen, and marsh classes, while the non-herbaceous class was subsequently partitioned into urban, upland, and swamp classes. In Level-II and -III classifications, different polarimetric decomposition approaches, including Cloude-Pottier, Freeman-Durden, Yamaguchi decompositions, and Kennaugh matrix elements were extracted to aid the RF classifier. The overall accuracy and kappa coefficient were determined in each classification level for evaluating the classification results. The importance of input features was also determined using the variable importance obtained by RF. It was found that the Kennaugh matrix elements, Yamaguchi, and Freeman-Durden decompositions were the most important parameters for wetland classification in this study. Using this new hierarchical RF classification approach, an overall accuracy of up to 94% was obtained for classifying different land cover types in the study area.

1. Introduction

Wetlands are soil saturated areas with water long enough to provide suitable ecosystems for hydrophytic vegetation and various kinds of biological activity, which are associated with a wet environment (Hardisky et al., 1986). Wetlands are important ecosystems with a variety of environmental services, including flood storage, shoreline stabilization, carbon sequestration, water-quality renovation, and, more important, a desirable habitat for both animal and plant species (Gallant, 2015). Despite the benefits, wetlands are being destroyed at increasing rates due both to natural processes, such as climate change, coastal processes, erosion and human interferences, such as road construction, installation of water-control structures, and oil spills (Tiner et al., 2015).

Traditional approaches for wetland mapping and monitoring have been mainly based on ground surveys of water and vegetation patterns to gather information about wetland ecosystems, which are time and cost consuming techniques. These traditional approaches have been gradually replaced with aerial photography (Cox, 1992) and, later, with satellite remote sensing tools (Rundquist et al., 2001). The advent of remote sensing technology has greatly changed the applied techniques for wetland monitoring by providing data from inaccessible wetland ecosystems in multi-

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temporal dimensions that facilitated long term monitoring of wetland complex. The use of remote sensing approaches for wetland monitoring have been well demonstrated in different applications such as classification (Chopra et al., 2001), change detection (Munyati, 2000), and water level monitoring (Wdowinski et al., 2008; Mohammadimanesh et al., 2016b).

Optical satellite images have been demonstrated to be useful for wetland classification if free cloud cover images are available (Adam et al., 2010; Li et al., 2013). However, optical images are less-useful in tropical, subtropical, and northern latitudes regions due to near permanent cloud cover (Evans and Costa, 2013). In contrast, Synthetic Aperture Radar (SAR) images are the preferred alternative for wetland monitoring when the capability of optical remote sensing imagery is hampered by either cloud cover or sun illumination (Dobson et al., 1996; Whiteside and Bartolo, 2015). In addition to being an independent of weather and day-night time conditions, the capability of SAR images to penetrate to soil, water, and vegetation canopies has caused them to gain increasing attention for wetland monitoring during the past two decades (Kasischke et al., 1997; Schmitt and Brisco, 2013; Whiteside and Bartolo, 2015; Mohammadimanesh et al., 2016a).

Though single SAR polarized data have been less investigated for wetland classification, they represented great potential for monitoring open water surfaces in different applications, including waterbody extraction (Silveira and Heleno, 2009; Gessner et al., 2015), flooding, and inundation mapping (Dellepiane and Angiati, 2012; Refice et al., 2014). Since satellite SAR sensors have a side-looking geometric data acquisition and transmit signals in off-nadir look angle, most of the signals transmitted to calm water surfaces are scattered away from the SAR sensor. Particularly, open water acts like a mirror and, as a result, open water appears dark in a SAR image with no or an extremely low SAR backscatter making it distinguishable from surrounding land. C- and X-band SAR data have been examined for open water mapping in several studies (Brisco et al., 2009, 2011; Martinis et al., 2015).

Surface water detection can also be conducted as an initial step for classification of flooded vegetation (Evans and Costa, 2013). Focusing on the suitable SAR polarization for water detection, HH-polarized data have been illustrated to be more useful due to their highest contrast between upland and open water (Brisco et al., 2009). Furthermore, it is less affected by wind-induced water surface changes than VV-polarization (Gstaiger et al., 2012; Wendleder et al., 2013). However, water surfaces affected by wind or current have higher SAR backscatter than calm water and can be challenging to detect using only single SAR polarized data. In the latter case, using the cross-polarization channel that is less sensitive to surface roughness is useful. Particularly, using the HH/HV ratio assures accurate water body delineation (Brisco et al., 2011).

The selection of appropriate SAR wavelength and polarization are two influential factors for land cover classification (Lee et al., 2001). Using Polarimetric Synthetic Aperture Radar (PolSAR) images with high capabilities to discriminate between different land cover classes (Qi et al., 2012) and, particularly, wetland classes (Touzi, 2007) is a more sophisticated approach. A fully polarimetric SAR sensor such as RADARSAT-2 acquires the full polarimetric scattering matrix, which provides comprehensive ground target information for each imaged pixel (Ainsworth et al., 2009). Different scattering mechanisms of ground targets can be detected by PolSAR data, including surface scattering (calm water surface), double-bounce scattering (man-made structure and flooded vegetation), and volume scattering (vegetation canopy). Different decomposition approaches of PolSAR data have been shown to be a promising tool for wetland classification (Touzi, 2007). In addition, wetland ecosystems are dominated by several distributed targets and may be better characterized using incoherent polarimetric decomposition techniques, such as Cloude-Pottier (Cloude and Pottier, 1996), Freeman-Durden (Freeman and Durden, 1998), van Zyle (van Zyl et al., 2011), and Kennaugh matrix (Kennaugh and Sloan, 1952). Thus, different polarimetric decomposition techniques have been used for wetland classification based on several classifiers in recent years (Schmitt and Brisco, 2013; Gallant et al., 2014).

In the case of fully polarimetric SAR data, the classification result would be sufficiently robust due to complete polarimetric information. However, recent studies have focused on using a combination of dual polarized SAR data that provides high classification accuracy, as close to that of fully polarimetric data as possible, for wetland classification (Schmitt and Brisco, 2013; Dabboor et al., 2015). Although the dual polarization mode obtains half the information of a fully polarimetric dataset, they have a wider swath width, and therefore, cover a larger area (Ainsworth et al., 2009).

While the suitability of using dual co-polarized (HH/VV) SAR data for monitoring flooded vegetation was demonstrated early in 1997 (Pope et al., 1997), it has not been further investigated due to a lack of SAR sensors operating in that particular polarization mode (Schmitt and Brisco, 2013). Later studies have demonstrated the sufficiency of information content of co-polarized SAR data for monitoring of flooded vegetation (Brisco et al., 2013; Schmitt and Brisco, 2013; Moser et al., 2016). Currently, SAR missions primarily operate in either dual (TerraSAR-X, Sentinel-1) or fully polarimetric (RADARSAT-2, ALOS-2) modes.

Another consideration for land cover classification is the fusion of multi-source data. In particular, a fusion of optical and SAR data for classification of flooded vegetation has been extensively examined (Li and Chen, 2005; Durieux et al., 2007; Grenier et al., 2008; Silva et al., 2008; Rebelo, 2010; Walker et al., 2010; Corcoran et al., 2013). The results demonstrated that integration of optical and radar data provides a promising tool in terms of classification accuracy. Furthermore, the combination of different SAR frequency bands has been found to improve the land cover classification accuracy (Lee et al., 2001; Li and Chen, 2005; Ainsworth et al., 2009; Turkar et al., 2012), particularly for wetlands (Costa, 2004; Costa and Telmer, 2006; Evans and Costa, 2013). Importantly, each wavelength has its own advantages in the context of land and wetland cover classifications. For example, longer wavelengths, such as L-band ($\sim$ 24 cm), have higher penetration depths through the vegetation canopy—necessary for discriminating between different wetland classes—while maintaining sensitivity to soil moisture and inundation (Li et al., 2013). Also, a number of studies have demonstrated that longer wavelengths are better suited for forested wetland due to their higher penetration capability (Li and Chen, 2005; Lang et al., 2008). However, shorter wavelengths, such as C-band ($\sim$ 5.6 cm) and X-band ($\sim$3.1 cm), are preferred to discriminate non-forested wetland classes (e.g., bog, fen, and marsh) as well as water (Brisco et al., 2009).

Concerning classification algorithms, the availability of high resolution SAR data has been combined with advanced image analysis techniques, such as Object-Based Image Analysis (OBIA), to further improve the accuracy of land cover classification (Benz et al., 2004; Blaschke, 2010). OBIA has been demonstrated to outperform pixel-based classification approaches because it fuses multiple sources of data with different spatial resolutions. OBIA employs object features as classification inputs, including the spectral, spatial, geometrical, textural, and contextual information of a group of neighboring pixels (objects), in addition to the original pixel values, and enhances input information for the classification procedure (Salehi et al., 2012). The capability of OBIA for wetland classification has been examined by a number of studies (Costa, 2004; Durieux et al., 2007; Grenier et al., 2008; Walker et al., 2010). OBIA is initiated with a Multi-Resolution Segmentation (MRS) analysis that generates objects of ground targets, which is