MAPPING AND CHANGE DETECTION FOR BOREAL WETLANDS OF NORTH AMERICA BASED ON JERS AND PALSAR DATA

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1. INTRODUCTION

The impacts of anthropogenic global warming are expected to be most intense at high latitudes. A leading concern is that global warming will melt the permafrost enough to drain its saturated organic soils and many thousands of thermokarst ponds. This could transform extensive permafrost peatlands into major sources of atmospheric carbon, greatly altering net fluxes of carbon dioxide and methane with far-reaching consequences to global carbon budgets. Due to concerns such as this, an ability to monitor long-term changes in northern wetlands is of great value. We have, therefore, been developing high-resolution thematic maps of wetlands throughout the North American boreal regions and using them to assess wetlands changes over the past decade.

2. METHODOLOGY

Space-based L-Band synthetic aperture radar (SAR) offers high-resolution visibility over wide swaths and is sensitive to vegetation structure, biomass, and moisture content. It can be used to map various wetlands classes throughout extensive ecoregions. Previously, we used 1997-1998 Japanese Earth Resources Satellite (JERS) SAR imagery to develop a wetlands map of Alaska [1] and now we are using 2007 Phased Array L-Band SAR (PALSAR) imagery to develop a second wetlands map. Comparison with the JERS-based classification reveals wetlands changes occurring over the 1997-2007 decade.

2.1. Input Data Layers

Our 1997-1998 JERS SAR imagery is taken from the summer and winter mosaics produced by the Global Boreal Forest Mapping (GBFM) project. The JERS data are at L-band (1.275 GHz), horizontal transmit, horizontal receive (HH) polarized, and provide 100 m resolution. They were collected over a wide range of swath collection dates; this, in some places, results in abrupt transitions in brightness that complicate the classification process.

Our 2007 PALSAR SAR imagery is assembled from (summer-only) individual swath imagery. The data are at L-band (1.270 GHz) for both HH polarization and Horizontal-transmit, Vertical-receive (HV) polarization. They have been radiometrically corrected, orthorectified to a DEM, and sampled to a resolution of 100 meters. The PALSAR data exhibit geometric and radiometric calibration far superior to those of JERS.

Our classifications also rely on a set of ancillary data layers, including SAR image texture, image collection dates, a digital elevation model (DEM), a slope model, an open water mask, a proximity to water map, and geographic latitude. These are described in more detail in [1].

2.2. Classification Approach

Our classifications are based on a decision-tree classifier known as "Random Forests" [2]. Random Forests first generates a large number of decision trees based upon training pixels from within the ground reference regions, then classifies each pixel by running it through every decision tree and assigning it to the class selected by the most decision trees. We have developed a PCI Geomatica software suite to enable this program to perform SAR image classification. Pixels are initially classified into a set of narrow wetlands/uplands subclasses according to morphology, vegetation structure, and water regime, after which the subclasses are aggregated into broad categories. Subclasses follow the Cowardin wetlands classification system [3] with the addition of two uplands classes. They are also mapped into the Canadian Wetland Classification System [4] for Canadian classifications.

Ground reference data are lacking in some areas of Canada. When such regions are sufficiently close to the US border, we classify them using decision tree forests saved from classifying nearby US regions. This approach yields acceptable results if the US classification has good accuracy and large-scale maps of North American ecosystems indicate that the ecosystem of the Canadian region is similar to that of the nearby US region.

2.3. Ground Reference Data

Random Forests requires ground reference data for both training and validation. For Alaskan classifications, our ground reference data are as described in [1]. For Canadian classifications, our ground reference data are assembled from Canadian wetlands study sites, such as BOREAS and Mer Bleue. For regions of Canada in the vicinity of US borders, we augment this with data from the National Wetlands Inventory (NWI), the National Land Cover Database (NLCD), and the Alaska Geospatial Data Clearinghouse (AGDC).

2.4. Error Assessment

Our accuracy assessment is based on confusion matrices generated by Random Forests. These reflect the classification performance achieved for validation pixels (i.e., ground reference pixels not used for decision tree training) included in the run. We use them to calculate producer and user error statistics both for narrow wetlands/uplands subclasses and for aggregate wetlands/uplands categories. It is, inevitably, not possible to numerically assess the classification accuracy of classification runs in areas for which there are no ground reference data, i.e., classification runs based on saved decision tree forests.

3. PRELIMINARY RESULTS AND NEXT STEPS

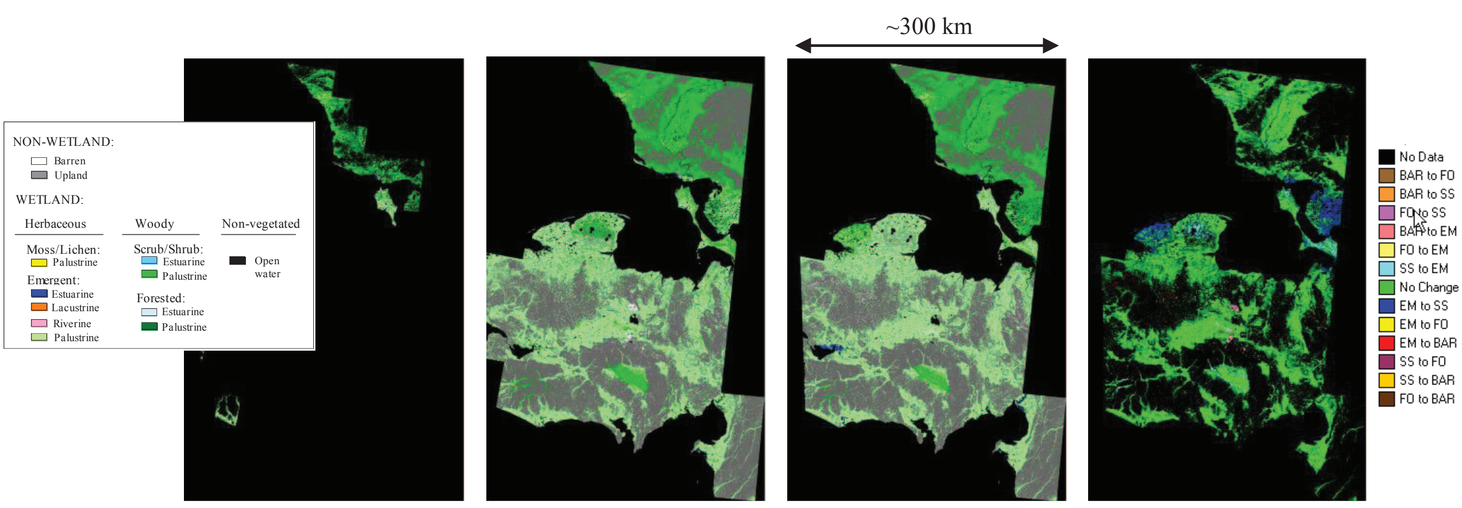
3.1. JERS Classifications

We have recently classified several broad strips of Canada adjacent to the Alaskan border. These runs were based on saved forests collected from a strip of Alaska just over the border from them [5].

We have also begun rerunning our Alaskan classifications due to inaccuracies discovered in our slope data layer, which was calculated using a commercial geospatial software package. In some areas, the new classifications differ from the previously published map, but overall they seem to exhibit fewer differences with our PALSAR classifications than were previously reported for some initial test regions [6]. Averaging results so far, our subclass classification accuracy is 80.4% and our aggregate category classification accuracy is 88.8%.

3.2. PALSAR Classifications

Results for a typical region around the Seward peninsula in northwestern Alaska are shown in Figure 1.



(a) (b) (c) (d)

Figure 1: Classification and change detection for a region around the Seward peninsula in northwestern Alaska
(a) Ground reference data, (b) JERS classification (corrected slope), (c) PALSAR classification, (d) Decadal change between JERS and PALSAR.

For this region, the PALSAR subclass classification accuracy is 84.6% and the aggregate category classification accuracy is 89.4%. We have also classified regions in and around the Kuskokwim delta and around Anchorage and the northern Kenai peninsula. Averaging results across all three regions, our subclass classification accuracy is 78.2% and our aggregate category classification accuracy is 88.6%.

3.3. Change Detection

As can be seen in Figure 1(d), most of the classified region is unchanged. The most prominent changes visible are emergent wetlands changing into scrub/shrub wetlands, but there are also a number of areas in which scrub/shrub wetlands have transitioned to emergent wetlands and small areas that have changed from barren to emergent or from emergent to barren. Similar observations have been made for other areas in Alaska. As PALSAR data continue to become available, we will extend the 2007-era wetlands classification and decadal change detection throughout Alaska and Canada. The results, indicating how and to what extent boreal wetlands have changed, are expected to enhance understanding of the feedbacks between wetlands and climate change.

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5. REFERENCES

[1] Whitcomb et al., 2009. “Mapping vegetated wetlands of Alaska using L-band radar satellite imagery,” C. J. Remote Sensing, 35, 54-72.

[2] Breiman, L., 2001. Random Forests. Machine Learning, 45, 5–32. Open source software available at www.stat.berkeley.edu/~breiman/randomforests.

[3] Cowardin, L.M., Carter, V., Golet, F.C., , LaRoe, E.T., 1979. Classification of wetlands and deepwater habitats of the United States. U. S. Department of the Interior, Fish and Wildlife Service. Available at: http://www.npwrc.usgs.gov/resource/1998/classwet/classwet.htm.

[4] National Wetlands Working Group, editors: Warner, B.A. and Rubec, C.D.A., 1997. The Canadian Wetlands Classification System, Second Edition. Available at: http://www.portofentry.com/Wetlands.pdf

[5] Whitcomb, et al., 2008. "Mapping Canadian wetlands using L-band radar satellite imagery", IGARSS 2008.

[6] Whitcomb, et al., 2008. "Decadal change in northern wetlands based on differential analysis of JERS and PALSAR data", IGARSS 2008.