DECADAL CHANGE IN NORTHERN WETLANDS BASED ON DIFFERENTIAL ANALYSIS OF JERS AND PALSAR DATA

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1. INTRODUCTION

Wetlands are among the most productive of the Earth's ecosystems and play a key role in the global carbon cycle. Northern peatlands, in particular, are believed to have hitherto served as important sinks of atmospheric carbon, but the warmer, drier conditions expected throughout the Arctic as a consequence of global warming may cause them to evolve into major sources of atmospheric carbon. Given the risk of far-reaching alterations such as this, an ability to monitor long-term changes in the locations, types, and extents of northern wetlands would be of great value.

Space-based L-Band synthetic aperture radar (SAR) offers high-resolution visibility over wide swaths, is unimpaired by clouds or lack of solar illumination, and is sensitive to vegetation structure, biomass, and moisture content. Due to this unique set of features, space-based L-Band SAR can be used to efficiently locate, distinguish, and thematically map various wetlands classes throughout extensive ecoregions. We have, consequently, been developing a continental-scale map of the North American boreal wetlands based on L-Band SAR imagery collected in 1997-1998 by the Japanese Earth Resources Satellite (JERS) [1]. The map currently covers the entire state of Alaska, identifying up to nine wetlands classes and two uplands classes. We have also recently obtained and classified a region of L-Band SAR imagery collected in 2007 by the Advanced Land Observing Satellite (ALOS) Phased Array L-Band SAR (PALSAR). Herein, we compare the results of the PALSAR classification to those of the JERS classification in order to detect changes in wetlands type or extent during the decade-long interval between the two sets of SAR imagery.

2. METHODOLOGY

Our 1997-1998 JERS data is taken from the summer and winter mosaics produced by the Global Boreal Forest Mapping (GBFM) project. It is Horizontal-transmit, Horizontal-receive (HH) polarized and provides 100 meters resolution. Our 2007 PALSAR mosaics are assembled from (summer-only) individual swath imagery. The data are both HH and Horizontal-transmit, Vertical-receive (HV) polarized and provide a resolution of 0.00028 degrees. The 2007 data exhibit geometric and radiometric calibration far superior to that of the 1997-1998 data.

All processing is implemented within PCI Geomatica application software. To produce each classified wetlands map, the SAR imagery is supplemented with 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. Image texture, which provides a measure of SAR brightness variability, is calculated as the coefficient of variation within an approximate 100 meter window. Week and year of image collection rasters, which allow adjustment for temporal differences between swaths, are formed from header file information. The DEM, which accounts for local terrain altitude, is taken from the USGS National Elevation Dataset (NED), reprojected and resampled to the PALSAR resolution. The slope model, which provides local orientation of the terrain surface, is calculated from the DEM using the standard algorithm provided in PCI. The open water mask, which indicates regions of open water, is currently calculated based on the 1997-1998 imagery, and will soon be computed based on the 2007 imagery. Proximity to water, which allows adaptation for waterside ecosystems, is calculated as a count of pixels to the nearest body of water. Geographic latitude, which captures the effects of geographic location, is calculated based on georeferencing data included in the imagery.

Our classification scheme is based on a decision-tree classifier known as “Random Forests” [2]. The algorithtm classifies by randomly generating a large number of decision trees based upon training data of known characteristics, implementing the decision trees, and setting each pixel’s classification code equal to the class selected by the most decision trees.

Our wetlands training data are imported from the National Wetlands Inventory (NWI). The NWI categorizes wetlands according to the Cowardin wetlands classification system; it covers about 15% of Alaska. Additional training data are imported from the Alaska Geospatial Data Clearinghouse (AGDC). This data set, which is used to represent several upland classes, covers most of Alaska. The AGDC data set is also used to eliminate areas of NWI/AGDC discrepancy. The NWI and AGDC training data sets offer the most systematic land cover representation available in Alaska. Data from them are geographically co-registered to the imagery, and merged into a single reference set.

Additional classification tasks include co-registering the JERS imagery and its associated products to the PALSAR imagery and masking out areas of high slope (i.e., greater than 3 deg inclination) and open water. For both the JERS imagery and the PALSAR imagery, we write all SAR image, ancillary, and truth reference data into correctly formatted files for the classification run, select run parameters, run Random Forests, extract the resulting class codes and form a thematic map. Finally, we detect and categorize differences between the JERS and PALSAR thematic maps, assembling the difference categories into a thematic map of wetlands changes.

3. PRELIMINARY RESULTS

Initial classifications performed by Random Forests sort each pixel in the imagery into one of 47 narrow wetlands/uplands subclasses according to morphology, vegetation structure, and water regime. The resulting subclasses are then aggregated into a small number of broad aggregate classes, which greatly improves classification performance. Our aggregate classes are: emergent, scrub/shrub, forested, barren. Even based on the relatively poor quality 1997-1998 JERS data, the overall aggregate accuracy for the state of Alaska is 89.5%, a result that is significantly better than can be achieved using standard classification algorithms. The preliminary classification accuracy for the small subset of the state of Alaska computed so far is 86%, but because of the superior PALSAR data quality we expect the overall aggregate accuracy based on the 2007 PALSAR data to be better once the entire state has been classified.

Preliminary results of our change analysis suggest that the most prevalent change to take place during the decade 1997 to 2007 is expansion of scrub/shrub into areas that were previously emergent. There are less prevalent, but still significant, regions in which scrub/shrub transitioned to emergent or forested transitioned to scrub/shrub and small areas in which barren transitioned to emergent or emergent transitioned to forested. The extent of each such category of wetlands change will be quantified in our final product. The accuracy of the thematic map of wetlands changes will be verified using ground reference data from wetland validation sites.

4. CONCLUSIONS

We are developing a thematic map of wetlands changes based on 1997-1998 JERS data and 2007 PALSAR data. Our preliminary results demonstrate the utility of multi-platform satellite SAR observations for monitoring long-term changes in northern wetlands. Once completed, our thematic map of wetlands changes will offer a valuable new tool for carbon modeling of northern wetlands.

In the near future, we plan to augment our data set with optical imagery in order to help distinguish herbaceous wetlands from agriculture and other non-wetlands regions. Further, once fully polarimetric PALSAR data becomes available, we plan to incorporate it into our PALSAR classification algorithm and then evaluate any improvements to our thematic map of wetlands changes based on those data.

5. REFERENCES

[1] Whitcomb et al., “Mapping vegetated wetlands of Alaska using L-band radar satellite imagery,” C. J. Remote Sensing, 2008, in press.

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