MAPPING COASTAL WETLANDS USING POLARIMETRIC ALOS PALSAR DATA IN NORTH CAROLINA

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ABSTRACT

The purpose of this study is to map wetlands using multi-polarimetric and polarimetric analysis of ALOS Palsar data in coastal North Carolina. Radar sensor offers reliable acquisition of wetlands which are mandated, by Congress, to be mapped every ten years. Radar data products were generated using Wishart supervised (HH-HV-VV) and Wishart unsupervised (entropy and dominant scattering mechanism) classification algorithms. Classifications were done within PolsarPro4.0 software (ESA, 2009) and accuracy assessment done in ArcGIS 9.3. To meet the goal of mapping wetlands, this study assessed Palsar 10 m data discrimination potential based on (a) vegetation community classes as determined by the North Carolina Division of Coastal Management (NCDCM), and (b) to structure-based classes as determined by U.S. Fish and Wildlife Service (FWS).

1. INTRODUCTION

Wetlands play a vital role in ecological and socioeconomic functions of environment-human interrelationships (e.g., store floodwaters, protect shorelines, water quality, habitat, fisheries, recreation) [1] [2]. Satellite remote sensing data offers advantages for the inventory and monitoring of wetlands to preserve biodiversity and ecosystem services. Advantages include repeat coverage, coverage of surrounding land-cover, and digital integration with other data in a GIS [3]. Research also shows the limitations of satellite data for wetland mapping which includes cloud cover as well as coarse spatial (30 m), spectral and temporal resolutions of the most common satellites [3]. Because of these limitations, the NC-DCM and US-FWS chose to use aerial photographs instead of satellite data for the wetland inventories. However, the use of labor-intensive visual interpretation of aerial photographs for mapping wetlands means that maps are not being created every ten years to meet Congress-mandated timeline (e.g., FWS wetland map is circa 1980s and NC-DCM wetland map is circa 1990s).

Satellite radar data overcomes some of the limitations of optical satellite data as it can be acquired in most all weather conditions, has 10 m spatial resolution options (Radarsat-2, ALOS Palsar), and provides complimentary data compared to visible-infrared data. L-band multi-polarization data has been shown to provide good distinction between flooded and non-flooded forests, and between forests and marsh vegetation [4] [5]. Wetland vegetation communities can be distinguished using C-band multi-polarization data based on canopy structure, soil moisture and the presence or absence of flooding [6]. Bourgeau-Chavez et al., [6] show that L- and C-band are both necessary for the detection of flooding beneath vegetated canopies with HH images better than VV images for discrimination, and cross polarization images are needed to discriminate wood versus herbaceous vegetation. With the launch of Radarsat-2 and ALOS Palsar satellite sensors, there is now the ability to also do polarimetric analysis for mapping and monitoring wetlands [7] [8].

The purpose of this study is to map wetlands using 10 m ALOS Palsar polarimetric data in coastal North Carolina. Both multi-polarization (HH-HV-VV) and polarimetric data products (entropy and dominant scattering mechanism) are generated using Wishart supervised and Wishart unsupervised classification algorithms, respectively. The classification procedures were done using PolsarPro4.0 software (ESA, 2009) and accuracy assessment done in ArcGIS 9.3. Results of the radar classifications are compared to both the NC-DCM community-wetland map and the US-FWS structure-wetland map to assess L-band contribution for State and National wetland inventory programs. This paper presents the classification results compared to the NC-DCM community-wetland types and concludes with a brief outline of work to be completed by June on the comparison of classifications to the FWS structure-wetland types.

2. METHODOLOGY

2.1. Study Site Description

The study site for this project is located along the east coast of North Carolina. The ALOS Palsar images correspond with Beaufort, Carteret, Craven, Hyde, Pamlico, and Tyrrell counties. The NC-DCM (2002) method for extracting community-based wetland classes from aerial photography identifies wetlands based on vegetation type, visible hydrology and geography; the results are subsequently classified in accordance to Cowardin et al., [9] classification scheme. The most recent NC-DCM wetland map was generated circa 1999. Based on the NC-DCM wetland inventory, the wetland classes in our study area include swamp forest, bottomland hardwood, pocosin, pine flat, hardwood flat, managed pine, freshwater marsh, salt/brackish marsh, estuarine scrub shrub, estuarine forest, maritime forest, headwater swamp, and human impacted.

2.2. Data Description

Data used in this research are ALOS Palsar (Phased Array L-band Synthetic Aperture Radar) L-band (23.5 cm) data. The use of ALOS Palsar data for wetland mapping is affordable ($125 per scene) which makes it feasible for state and national governments to monitor wetland coverage distributions every ten years as mandated by Congress. This study used fully polarimetric (HH-HV-VH-VV) data at the 10 m spatial resolution in descending mode. The two images acquired are orientated from the southwest to the northeast along the coast of North Carolina and was acquired on April 3rd, 2007. The southern portion of the image extent (2,315 km^2) was used in the polarimetric analysis. Because supervised classification is more labor intensive, the multi-polarization analysis was done in Carteret County; this county has approximately 700 km^2 of wetlands which represents 53% of the county's land area. The NC-DCM wetland classes are salt-brackish marshes (26%), pocosins (18%), pine flats including pine flats, drained pine flats, and cleared pine flats, (16%), managed pineland (14%), and small amounts of estuarine scrub and cut over headwater swamp.

2.3. Radar Analysis

Radar analysis can use either multi-polarization or polarimetric data. PolsarPro4.0 software (ESA, 2009) was used for both analysis methods in this study. Wishart supervised classification was done using the multi-polarization (HH- HV-VV) data while Wishart unsupervised classification used the entropy [H] and dominant scattering mechanism [σ] images generated from polarimetric data. The multi-polarization data were extracted from the geo-referenced images (1.5 extensions) using the Sinclair matrix. Polarimetric analysis used the complex data (1.1 extension) which is not geo-referenced in order to the preserve calibration integrity of the data.

In the supervised classification of the multi-polarization data, three to five calibration sites were created for each NC-DCM wetland class (16 classes) resulting in a minimum of forty (40) pixels per wetland class (>10 pixels for each of the polarizations [10]). Wishart supervised classification algorithm uses the calibration sites to group the remaining image pixels based on Wishart distribution; this distribution is a generalization of multiple dimensions of chi squared distribution for non parametric data [11].

After the classified image was generated using HH-HV-VV polarization images, the classified image was imported into ArcGIS 9.3 to perform accuracy assessment. Within ArcGIS, one-hundred (100) validation sites were randomly generated to assess the accuracy of the supervised classification image. At each validation site, the wetland type was recorded on both the classified image and the NC community-based wetland inventory and a confusion matrix was created.

For the polarimetric analysis, the entire extent of the southern image was used for unsupervised classification as this process is less labor intensive compared to the supervised classification procedure described above. In PolsarPro, the complex data, extracted using the Coherency Scattering matrix, was batched processed. This batch processes includes filtering the data (Lee filter), generation of decomposition images (e.g., entropy (H), dominant scattering (σ), and secondary scattering (anisotropy)), followed by the unsupervised Wishart classification on the H and σ images. The entropy (H) image represents the randomness of the scattering mechanism (e.g., low, medium, high) and the alpha (σ) image represents the dominant scattering mechanism (e.g., surface reflectance, volume scattering, and multiple scattering).

The resulting Wishart unsupervised classification based on H and σ images was imported into ArcGIS and geo-referenced to an aerial photograph for comparison to the NC community-based wetland inventory. Fifteen control points were used to georeference the unsupervised classification image using Nearest Neighbor transformation with a RMS error less than one pixel. Using the NC-DCM wetland inventory data, only those areas that were delineated as wetlands were extracted on the unsupervised classification image. The unsupervised image was then converted into integer format (8 classes) and then converted from raster to vector polygons to enable the polygon feature class function. This function included the ability to "select by attributes" in order to identify where each wetland type (from the NC inventory) existed on the unsupervised classification image to identify its corresponding entropy-dominant scattering mechanism category.

3. RESULTS/CONCLUSIONS

Preliminary results are based on the mapping of wetlands using NC-DCM vegetation-community classes. The results were mixed for both the supervised (HH-HV-VV) and unsupervised (H and σ) classifications. In the supervised classification, the salt-brackish marsh was classified with 100% accuracy and water with a 98% accuracy. The remaining wetlands types did not meet the acceptable accuracy (80%) required [8]. Pocosin and cutover headwater swamp had 50% classification accuracy while the remaining wetland types were poorly classified (18% or 0% accuracy). Poor classification results were primarily due to an inability of radar data to separate structurally similar pine flats, drained pine flats, cleared pine flats and managed pine flats or separate estuarine scrub from headwater swamp class as per the NC-DCM wetland inventory scheme. In addition, transition zones between wetland types were not well delineating with the areas between two wetland classes often confused for a third category (e.g., transition zone between salt-brackish marsh and estuarine scrub was confused with agriculture).

The results of the unsupervised classification using H and σ images showed that pocosins and salt-brackish marshes can be discriminated using dominant scattering mechanisms. In addition, headwater swamps and managed pine flats can be discriminated using both dominant and secondary scattering mechanisms. Pocosins were dominated by surface reflectance (87%) and salt-brackish marshes by multiple scattering (83%) mechanisms allowing these two wetland types to be discriminated from other wetland classes. All pine flats classes were also dominated by surface scattering ranging from 48% for cleared pine flats to 77% for drained pine flats. However, headwater swamps and cut over headwater swamps also had this range of surface reflectance (55% and 76%, respectively) limiting the ability to discriminate these classes. Both managed pine flats and headwater swamps have unique secondary scattering mechanisms (e.g., 36% volume scattering for managed pine and 19% multiple scattering for headwater swamps) suggesting that these secondary mechanisms are required for discrimination of these two wetland categories.

3.1. *Proposed Research*

It was hypothesized from the NC-DCM wetland mapping results that ALOS radar data may be better at representing structural differences in wetlands (FWS) rather than the vegetation community groups. Radar response is determined by (a) topography, (b) surface target type and geometry, and (c) dielectric content (reflectivity due to water content and/or metallic content). Topography in coastal North Carolina is flat and thus will not vary for our targets. Surface targets (wetland classes), geometry of targets and water content are the determining factors of radar response.

The same supervised and unsupervised classifications described above will be applied using the FWS structural-based wetland inventory. Because the FWS data is over thirty years old, an additional step to generate a current validation map using FWS wetland classes and aerial photographs acquired in 2008 by the National Agriculture Imagery Program (NAIP) is required. The aerial photographs were acquired in 2009 with a one (1) meter spatial resolution, true-color composite (RGB) and divided into 3.75 minute tiles. NAIP's focus is agricultural mapping thus the waterways and adjacent wetlands are not available in coastal North Carolina. To compensate for the lack of data along coastlines, the multi-polarization classification will be done in Pamlico County which has 95% image area coverage and has the most wetland types represented by the FWS inventory.

Once the validation map has been created, an assessment of ALOS polarimetric radar ability to map structural-wetlands categories will be completed. The US-FWS wetland classes include estuarine and marine deepwater, estuarine and marine wetland, freshwater emergent wetland, freshwater forested/shrub wetland, freshwater pond, lake, and riverine. It is expected that ALOS data will map wetlands at an acceptable accuracy for state and national wetland monitoring based on estuarine and marine deepwater, estuarine and marine wetland, freshwater emergent wetland, freshwater forested/shrub wetland, freshwater pond, lake, and riverine classes.

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