THE CONTRIBUTION OF CHRIS/PROBA DATA FOR TROPICAL PEAT SWAMP LANDSCAPE DISCRIMINATION PURPOSES

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1. INTRODUCTION

Natural tropical peat swamp forests are important for their rich biodiversity and because they represent a huge carbon pool [1]. However, peat swamp forests have been decreasing due to conversion into managed land cover types, ecosystem degradation and uncontrolled exploitation. These issues increase the interest in mapping such environments because they are recognized as an important source of carbon released in the atmosphere. In this study, the contribution of multispectral and multi-angular Compact High Resolution Imaging Spectrometer (CHRIS) data collected over a Peat swamp landscape in Central Kalimantan (Indonesia) was evaluated as a function of viewing geometry (anisotropy). CHRIS is one sensor on board the European Space Agency Project for On Board Autonomy (PROBA) [2]. We aimed to demonstrate the Sun-view effects on the discrimination of a typical forest succession stages and peat swamp classes, using a scene collected under very clear sky conditions during the monsoon.

2. STUDY AREA

The location of the study area is a 7km x 12km subset bounded by the Sebangau and Kahayan rivers and close to Palangkaraya, the capital city in Central Kalimantan province (Indonesia; between -02°18'S/113°57'E and -02°21'S/114°05'E). The site shows a humid tropical climate (type Af in the Köppen system) with an annual rainfall of 3500mm and an annual mean air temperature of 25°C. The area is very flat, the maximum altitude above sea level being 30m and the mean peat average thickness 4m. Eight major classes occur in the peat swamp environment of the study area: Peat Swamp Forest (PSF), Advanced Secondary Forest (ASF), Dense Regrowth (DRG), Sparse Regrowth (SRG), Wetland (WTL), Grassland (GSL), Burnt areas (BRT) and Shrubland (SHL) [3].

3. METHODOLOGY

CHRIS/PROBA data was acquired on May 18, 2004 in 18 bands (415-1050 nm) with a spatial resolution close to 20m at nadir and four different nominal view zenith angles (-36°, +0°, + 36°, +55°). Striping effects were reduced and atmospheric correction was performed using the fast line-of-sight atmospheric analysis of spectral hypercubes (FLAASH) radiative transfer code. The geometric correction was performed using the Ground Controls Points methodology. For each physiognomy, 440 pixels (40 pixels as training and 400 pixels as validation) were selected with approximately similar position at each camera image based on the combined analysis of available vegetation maps [3] and K-Means unsupervised classification results. Attention was given for neighbor pixels to avoid spatial correlation. The training dataset was normalized to the nadir response and related to MODIS Level 2 Land Surface Products. Data analysis included the use of Principal Components Analysis (PCA) applied separately at each view angle (-36°, nadir, +36°, +55°) using the reflectance value of the 18 bands as input variables. This technique was applied in order to reduce data dimensionality at each dataset, enhance separability between the classes, and to provide input variables for Multiple Discriminant Analysis (MDA), respectively. After, PCA was applied over all dataset (four view angles). Principal Components (PC) with eigenvalues greater than 1 were retained. The total set of retained PC scores was used as input candidate variables for MDA and the best variables were selected from stepwise procedure. Finally, classification accuracy results from MDA using the validation set of pixels were compared between both approaches and Kappa coefficients were calculated as a measure of classification accuracy with McNemar and Z-test.

4. RESULTS AND DISCUSSION

For a given view angle, the near infrared reflectance increased from burnt areas to shrub, grassland to peat swamp forest and then in order to the successional stages and they presented also large reflectance values in this spectral region with decreasing LAI and canopy cover. Non-linear relationship between the red (683 nm) and near infrared reflectance (863 nm) showed some improvement from the forward scattering and nadir view to the backward scattering direction. The strongest differences from the nadir were noticed in the backward scattering direction (positive view angles) with the predominance of illuminated vegetation components viewed by the sensor. The red band presented a more anisotropic behavior than the near-infrared band as indicated by the wider range of normalized reflectance data in the backward direction [4]. On the other hand, directional effects were less pronounced at extreme viewing in the near-infrared due to the predominance of multiple scattering processes that reduce the spectral contrast between shadowed and illuminated components [5].

Classification accuracy results from MDA with the first two PC scores as input variables at each view angle confirmed that the only $+55^o$ view angle was statistically different at a 0.05% level of significance in comparison with nadir view angle. Kappa statistics ranged from 0.74 (at nadir view angle) to 0.81 ($+55^o$ view angle). In general, there was an improvement for six of the eight classes under study.

The use of the discriminant function to classify a separate set of pixel spectra showed an overall classification accuracy improvement from 77.1% (nadir) to 90.4% (multiangular approach). Kappa statistics ranged from 0.74 to 0.89. Results from both McNemar and Z-test confirmed that the multiangular approach produced statistically different classification values at a 0.05% level of significance to better differentiate the peatland classes than the single view angle approach (either nadir or $+55^o$ view angle). The most interesting result was the differentiation between primary forest and secondary forest using multiangular data that are reported as the most difficult to be mapped in the tropical rain forest environments [6], [7].

5. CONCLUSION

In relation to nadir view angle, the strongest anisotropy was observed in the backward scattering direction in which great amounts of sunlit canopy components were viewed by the sensor and in the visible bands. In the backward scattering direction Primary Forest and Grassland were more anisotropic than the remaining classes, especially for the red band. The two more spectrally similar classes were Dense and Sparse regrowth which were better differentiated at $+55^o$ view angle using PCA and MDA. In comparison with the single view angle approach (nadir), the multiangular approach produced an overall discrimination improvement. MDA-derived overall classification accuracy was statistically significant using a separate set of pixels and it increased from 77.1% to 90.4% (Kappa statistics from 0.74 to 0.89).

6. REFERENCES

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