Mapping Land Cover Types in Amazon Basin Using 1km JERS-1 Mosaic

Sassan S. Saatchi[1], Bruce Nelson[2], Erika Podest[1], John Holt[1]
1. Jet Propulsion Laboratory, 4800 Oak Grove Drive , Pasadena, California 91109
2. Instituto Nacional de Pesquisas de Amazonia, CP 478, Ecologia, 69011-970, Manaus, Amazonia, Brazil

Abstract

In this paper, the 100 meter JERS-1 Amazon mosaic image was used in a new classifier to generate a 1 km resolution land cover map. The inputs to the classifier were 1km resolution mean backscatter and seven first order texture measures derived from the 100 m data by using a 10 x 10 independent sampling window. The classification approach included two interdependent stages: 1) a supervised maximum *a posteriori* Baysian approach to classify the mean backscatter image into 5 general land cover catagories of forest, savanna, inundated, white sand, and anthropogenic vegetation classes, and 2) a texture measure decision rule approach to further discriminate subcatagory classes based on taxonimc information and biomass levels. Fourteen classes were successfully separated at 1km scale. The results were verified by examining the accuracy of the approach by comparison with the IBGE and the AVHRR 1 km resolution land cover maps.

Introduction

Understanding the human or climate induced changes of a tropical landscape requires knowledge of the current status of the ecosystem, the extent of the land cover types susceptible to change, and the causes and impacts of such changes. Recent advances in remote sensing technologies have partially contributed in documenting and monitoring these land use changes. There are, however, several unresolved problems associated with mapping land cover types and monitoring the tropics on regional and continental scales. These derive from limitations of current remote sensing techniques and the methodologies used in both defining the land cover types and identifying the parameters to be monitored.

Optical remote sensing has been successfully used for classification of land cover types and the study of their changes on local to regional scales. High resolution (30 m) Landsat Thematic Mapper (TM) data has been the primary source for estimating the rate of deforestation by INPE (Instituto Nacional de Pesquisas Espaciais) and the Landsat Pathfinder Program (Skole and Tucker, 1993; Justice and Townshend, 1994). These studies have used visual interpretation and classification as their primary approach for extracting thematic information. Most large scale maps derived from these show few land cover types. This is due in part to difficulties in interpreting the spectral information of Landsat data acquired at different years or seasons.

During the past decade, several radar sensors have been deployed in space such as the shuttle imaging radar (SIR-A, SIR-B, and SIR-C/X-SAR), ERS-1,2, JERS-1, and Radarsat. Except the SIR-C/X-SAR system, all radar sensors have only one channel. Though none were designed specifically for land cover mapping, several investigations have demonstrated that the data provide unique information about the characteristics of tropical landscapes (Sader, 1987; Foody and Curran, 1994). First, the radar data can be acquired as frequently as possible due to insensitivity to atmospheric condition and sun angle. This allows continental scale high resolution data for systematic assessment of deforestation and regrowth processes. Second, depending on the wavelength, the radar backscatter signal carries information about forest structure and moisture condition by penetrating into the forest canopy. Few studies have addressed these characteristics by using the radar data for mapping tropical land cover and estimating the biomass of regenerating forests (Foody and Curran 1994; Luckman et al., 1997; Saatchi et al., 1997; Rignot et al., 1997).

During the Global Rain Forest Mapping (GRFM) project, JERS-1 SAR (Synthetic Aperture Radar) satellite was used to map the humid tropical forests of the world. The rationale for the project was to demonstrate the application of the spaceborne L-band radar in tropical forest studies. In particular, the use of data for mapping land cover types, estimating the area of floodplains, and monitoring deforestation and forest regeneration were of primary importance. In this paper, we examine the information content of the JERS-1 SAR data for mapping land cover types in the Amazon basin.

JERS-1 Amazon Mosaic

JERS-1 SAR is an L-band spaceborne SAR system launched by the National Space Development Agency of Japan (NASDA) in February, 1992. The system operates at 1.275 GHz with horizontal polarization for both transmission and reception. The spatial resolution of the system is 18 m in both azimuth and range. The swath width is 75 km and the incidence angle of radar at the center of swath is 38.5°. The single-look images have 4.2 m pixel spacing in azimuth and 12.5 m in range and the standard three look image has 12.5 m pixel spacing in both azimuth and range.

In late 1995, the JERS-1 satellite entered into its Global Rain Forest Mapping (GRFM) phase to collect high resolution SAR data over the entire tropical rainforest. In approximately 60 days, the satellite obtained wall-to-wall data over the Amazon basin. Because of cloud cover, similar coverage with high resolution optical data such as Landsat could only be provided on annual or decadal time frames. The JERS-1 coverage of the Amazon basin is shown in Figure 1.

We have used 100 m resolution JERS-1 data (8 by 8 averaging of high resolution 12.5 m three-look data) to generate a map of the entire basin from 1500 images. The spatial mosaicking technique is based on a mathematical wallpapering approach which minimizes the propagation of errors. The inter-scene overlaps both in the along-track and cross-track directions were used for individual scene geolocation. The scenes were placed on a global coordinate system with the flexibility of having scenes float freely with respect to one another. The locations of all scenes were calculated simultaneously, avoiding any directional errors. The result is an optimum seamless mosaic (Figure 2)

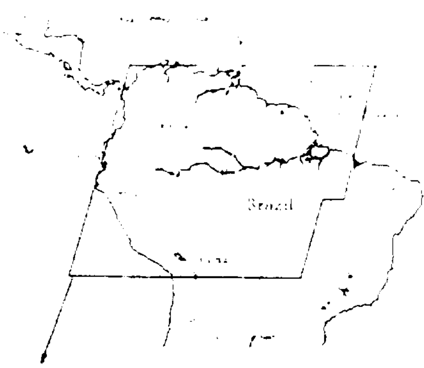

Figure 1. JERS-1 coverage map of the Amazon basin.

Figure 2. JERS-1 Amazon mosaic image during the dry season.

Methodology

In classifying the JERS-1 SAR data, we developed texture measures from the 100 m JERS-1 mosaic over a 10 x 10 window, resulting in 1 km resolution texture images with independent pixel information, as the windows were shifted in a blockwise fashion in a 10-pixel increments. These first order histogram statistics characterize the frequency of occurrence of grey levels within the window in the single channel radar data and are sensitive to window size which was determined a priori. The JERS-1 mosaic image in figure 2 shows orbital stripes which are due to slight radiometric discrepancy between the calibration of orbital data takes. These calibration discrepancies which are often less than 0.5 dB in

intensity do not affect the texture measures and the classification of the image at a resampled resolution of 1 km.
Eight texture measures were calculated for classification from the first order histograms (mean, variance, energy, entropy, contrast, kurtosis, skewness, coeffiecient of variation). Training areas were chosen from the mosaic image by consulting the RADAMBRASIL vegetation map of Amazonia. The class separability using all texture measures were calculated by using the B-distance (Bhattacharyya distance). The separability test helped us to identify the significance of texture measures in classifying each land cover types.

After choosing a list of texture measures, we employ a two stage approach to perform a supervised classification of the JERS-1 mosaic. In the first stage, we use a maximum *a posteriori* Baysian (MAP) classifier on the JERS-1 mean backscatter image at 1 km scale to select five general categories of land cover types (forest, nonforest, savanna, floodplain, open water)
In the second stage, the texture measures and the MAP classified image were used in a hierarchical decision rule based algorithm to further discriminate more specific vegetation types within each of five general land cover categories. The decision rules were derived by using predictor variables obtained from the multi-dimensional separability analysis of the backscatter and texture measures for each vegetation type. The rules for texture measures are calculated in a hierarchical fashion using the normal distribution for the statistics of training areas. This assumption was verified when using the B-distance separability test. Once the training data set was obtained and the MAP classified image was produced, the decision rules were determined in an automated procedure in order to guarantee the repeatability of the classifier. Note that the input texture images to the classifier and the training data sets are derived from the 100 m JERS-1 using a 10 x 10 window. The use of 100 m backscatter image rather than the 1 km images for collecting the training data, helps avoiding mixed pixel information in training data set.

Discussion

A total of twenty sites were chosen for each vegetation type, of which ten were used for training the classifier and ten for verifying the accuracy of classification. To make the selection of training and validation sites as accurate as possible, we registered the RADAM map with the JERS-1 mosaic and extracted the backscatter and texture measures for each land cover category as indicated on the map. During the selection of these, we avoided those cases where the RADAM vegetation types did not match with the general characteristics of the radar image suggesting a possible error in the RADAM data.
A total of 14 classes were separated JERS-1 mosaic. The accuracy of classification were calculated by developing a confusion matrix of classes, comparison with the RADAM map, and pixel-by-pixel comparison with the AVHRR land cover map. The results and detailed discussion are reported in Saatchi et al.(1999).

Acknowledgment
This work is performed at the Jet Propulsion Laboratory, California Institute of Technology, under contract from National Aeronautic and Space Administration.

References
Foody, G.M., and Curran, P.J., 1994, *J. of Biogeograhy.* 21:223-244.

Luckman, A., Baker, J., Kuplich, T.M., Yanasse, C., and Frery, A.C., 1997, *Remote Sens. Environ.*, 60:1-13.

Rignot, E., Salas, W., and Skole, D.L., 1997, *Remote Sens. Environ.*, 59:167-179.

Saatchi, S.S., Soares, J.V., and Alves, D.S., 1997, *Remote Sens. Environ.* , vol. 59: 191-202.

Saatchi, S., Nelson, B., Podest, E., Holt, J., 1999, *Int. J. Remote Sens.*, In press.
Sader, S.A., 1987, *Phtogramm. Eng. Remote Sens.* 53(2):193-202.

Skole, D.L. and Tucker, C.J., 1993, *Science* , 260:1905-1910.

Veloso, H.P., Rangel Filho, A.L.R.& Lima, J.C.A., 1991, IBGE. Rio de Janeiro. 123 pp.