

MAPPING TROPICAL FOREST USING ALOS PALSAR 50M RESOLUTION DATA WITH MULTISCALE GLCM ANALYSIS

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1. INTRODUCTION

This paper investigates the abilities and the limitations of ALOS PALSAR 50m resolution data for land cover classification in Tropical rainforest as part of the ALOS Kyoto and Carbon (K&C) Initiative Project. The K&C Initiative forms the continuation of the Global Rain Forest and Boreal Forest Mapping (GRFM/GBFM) project, in which 100m spatial resolution mosaics of the entire tropical and boreal zones using data acquired by the Japanese Earth Resources Satellite (JERS-1) L band HH SAR were generated. Since only two bands (HH and HV) have been proven to be limitation in land cover differentiation in SAR data, textures have been used as feature dimensions for classification [1, 2]. A large number of techniques for texture analysis have been investigated for SAR image classification. Among texture analysis methods, the most prevalent technique used for deriving texture is the use of the grey-level co-occurrence matrix (GLCM) [3]. This technique uses a spatial co-occurrence matrix that computes the relationships of pixel values and uses these values to compute the second-order statistical properties [4, 3]. This study focus on comparing various second-order texture parameters and features at multiple scales to demonstrate their contributions in land cover classification which are importance for ALOS K&C Initiative projects.

Incorporated with World Wildlife Fund (WWF), a part of Riau province, in central Sumatra, was selected as a test site. Riau hosts some of the most biodiversity ecosystems and unique species. It is covered by vast peat lands estimated to hold Indonesia's largest store of carbon. However, Riau have been under serious threat because of rapid large-scale deforestation. [5]

2. METHODOLOGY

2.1. Image texture

Second-order texture measurements based on Haralick's grey-level co-occurrence matrices (GLCM) [6] outline the distance and angular spatial relationships between pixels within the moving window. The GLCM compute the joint probability of occurrence of the pairs of grey levels separated by a given distance and direction [1, 7]. GLCM texture were calculated for all directions (omnidirectional) for more closely replicate variance measured within a window [4]. Several statistical measurements can be extracted form the GLCM which have been used effectively in many SAR application [7, 8]. In this research, six second-order texture measurements were calculated which are the angular second moment, contrast, correlation, entropy, inverse difference moment, and maximum probability

2.2. Classification

A maximum likelihood (ML) classification was used to classify all of the images produced in this study. However, we used *a priori* information about the expected distribution of classes to improve the classification accuracy. *A priori* information is incorporated though the use of *a priori* probability, i.e., probabilities of occurrence of classes that are based on separated, independent knowledge concerning the area to be classified [9]. Used in their simplest form, the probabilities weigh the classes

according to their expected distribution in the output dataset by shifting decision space boundaries to produce larger volumes in measurement space for classes that are expected to be large and smaller volumes for classes that are expected to be small.

The classification starts at the low resolution scale (400 m). At this scale, the *a priori* probability is assumed equal for all classes. The results of the classifier at this scale are used to develop *a priori* probabilities for the next scale. These are probabilities with which the class membership of a pixel could be estimated before classification. They are represented by the first term, $p(w_i)$, in the discrimination function for ML classification [2, 9]:

$$g_i(\mathbf{x}) = \ln p(w_i) - \frac{1}{2} \ln |\Sigma_i| - \frac{1}{2} (\mathbf{x} - \mu_i)^T \Sigma_i^{-1} (\mathbf{x} - \mu_i) \quad (1)$$

where μ_i is mean vector of class i , Σ_i is the covariance matrix, Σ_i^{-1} the inverse covariance matrices. T refers to the transposed matrix. The *a priori* probability when stepping from one scale to another is calculated for each pixel by [2]:

$$p(w_i) = \frac{g_i(\mathbf{x})}{\sum g(\mathbf{x})} \quad (2)$$

The denominator is the sum over all classes of the discrimination function for the pixel.

2.3. Feature Selection

For each resolution scale, the texture features used in the classification are selected by using Transformed divergence (TD) [10]. It evaluates the performance in land cover discrimination by calculating the statistic distance between land cover classes included in the image. This is an indirect and *a priori* estimate of the probability of correct classification. The transformed divergence for class pair (i,j) is given by

$$TD_{ij} = 2000(1 - e^{-\frac{D_{ij}}{8}}) \quad (3)$$

with

$$D_{ij} = \frac{1}{2} \text{tr}[(\Sigma_i - \Sigma_j)(\Sigma_i^{-1} - \Sigma_j^{-1})] + \frac{1}{2} \text{tr}[(\Sigma_i^{-1} + \Sigma_j^{-1})(\mu_i - \mu_j)(\mu_i - \mu_j)^T] \quad (4)$$

tr is the trace of the matrix in question (sum of the diagonal elements). Computation of TD_{ij} is based on the assumption that the classes follow normal distribution. High value indicates large separability and thus higher probability for correct classification.

3. CONCLUSION

From the feature selection result, we found that angular second moment with distance length equal to one at eight quantization bit scales was the best parameter in discriminate the class types. However, the ability in discriminate the class types is reduce when the resolution scale is increase. This is because of the higher resolution scale images were influenced by noise. This research also show that a multiscale texture-based classifier can provide accurate thematic information from ALOS PALSAR at 50 m. resolution by compared with the 2008 WWF map for Riau province.

4. REFERENCES

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