

LAND-COVER CLASSIFICATION IN KALIMANTAN BY POLARIMETRIC PALSAR

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ABSTRACT:

The need for accurate estimation of forest cover information in Kalimantan is currently increasing because of the growing recognition of the potential role of forests in helping mitigate effects of climate change and global warming. Synthetic aperture radar (SAR) technology with different polarizations has been widely used for large-scale forest monitoring and land cover mapping. This study investigates the ability of ALOS PALSAR L-band data at quad polarization (four different polarizations: HH, HV, VH, and VV) and 15m resolution to provide useful information on forest and other land cover types for the purpose of accuracy mapping land cover types. The powerful source of polarimetric information allows us to more accuracy mapping the land-cover types. Several scenes of PALSAR level 1.1 Single Look Complex (SLC) data have been acquired in 2009 and 2010 for the south Kalimantan, Indonesia. In addition, two scenes of ALOS AVNIR-2 were also acquired for ancillary data set. Two land cover classification methods: maximum likelihood classification (MLC) method and subspace method were employed for land cover mapping. Our results indicate that when combining the polarimetric coherency T3 matrix with intensity images, the classification accuracy is higher than that using only four bands (HH, HV, VH, and VV) polarization data.

1. INTRODUCTIONS

Kalimantan Forest biomes are presently under intensive land cover conversion from natural vegetation to oil palm and agriculture (Sandker et al., 2007). Timely detection of recent land cover through remote sensing is a critical requirement for an operational land cover monitoring system in order to provide information to the regulatory systems and decision makers (Santos et al., 2008). Synthetic aperture radar (SAR) technology provides an effective solution to mapping land cover at typical lowland rainforest region both speed and flexibility because of its independence from weather conditions.

Phased-Array L-Band Synthetic Aperture Radar (PALSAR) on the Advanced Land Observing Satellite (ALOS), include several imaging modes and one of them is fully polarimetric mode (Shimada et al., 2009). The PALSAR fully polarimetric decives are able to transmit and receive both the orthogonal components (H and V) of an electromagnetic.

For investigate the potential of using fully polarimetric PALSAR for land cover classification, we use the both intensities of HH, HV, VH, and VV polarizations, and combining intensities of HH, HV, VH, and VV polarizations with polarimetric coherency T3 matrix (Cloude, 2009; Lee and Pottier, 2009), respectively, for land cover mapping. Recently, many advanced classification algorithms have been developed for remote sensing data classification including maximum likelihood classification (MLC) method; decision tree classifier; support vector machine (SVM); and neural network methods. In this study, we adopt the recent developed subspace method (Oja, 1983) and commonly used MLC for two sets of PALSAR data land cover classification.

2. SUBSPACE METHOD

Subspace approach is classifying and representing patterns given as elements of a vector space. The use of subspaces as class models is based on the assumption that the data within each class approximately lies on a lower-dimensional subspace which tend to be more easily interpretable. Here, each class is represented by a subspace spanned by a group of basis vectors, the Karhunen-Loève transform (also known as the principal component analysis) used as tool for obtaining orthogonal basis vectors and fixing subspace. Subspace method projects high-dimensional input data onto a low-dimensional feature space. The difference between subspace and SOM is that subspace has many low dimension subspaces, whereas SOM has only one low dimension feature map (Kohonen, 1982). After computing the projection lengths between pixel x and each subspace, pixel x is placed in the class that has the largest projection length (Bagan et al., 2008).

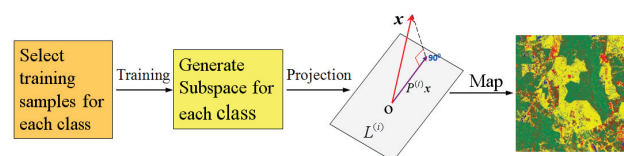


Figure 1. Process flow diagram of subspace method used in the study for land cover classification.

Recent study shows that the subspace method provides better classification accuracy than the MLC, SOM, and SVM methods when classifying high dimensional data set. Hence, we adopt the improved modified subspace method for land cover

classification which described in Bagan and Yamagata (Bagan and Yamagata, 2010).

3. STUDY AREA AND DATA

3.1 Study area

Figure 2 shows the study area in south Kalimantan, Indonesia. The Borneo contains some of the richest and most unique ecosystems on the planet. The pressure from increased population has resulted in the uncontrolled conversion of rainforests to oil palm or agricultural use. As a result, south Kalimantan is one of the most environmentally threatened places on Earth.

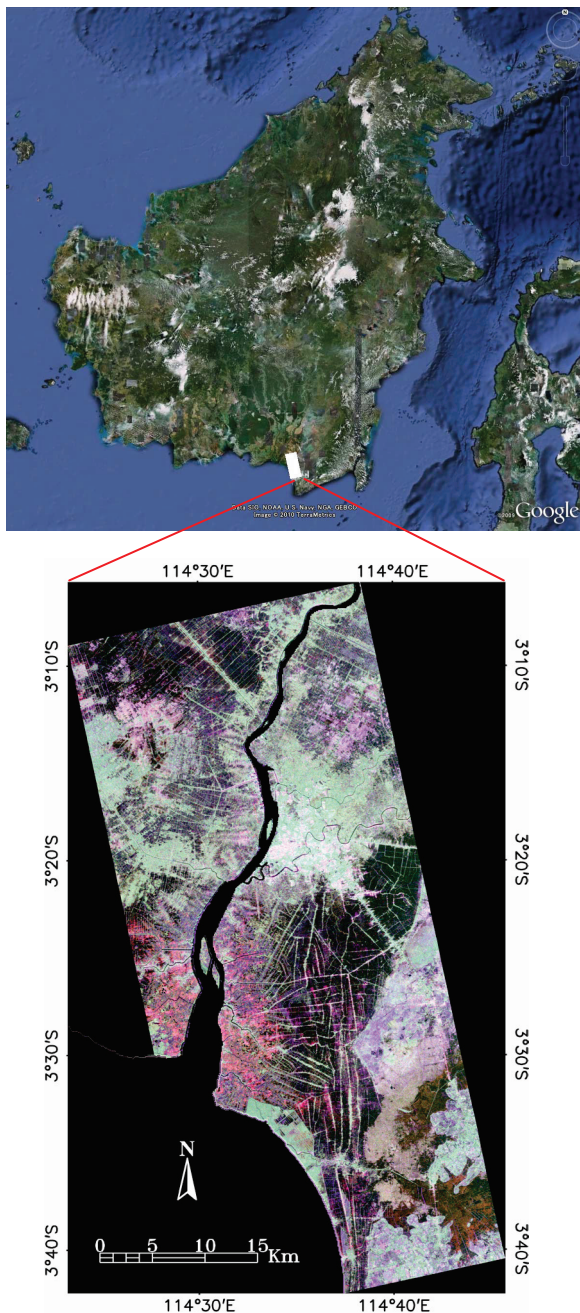


Figure 2. Location of the study area in south Kalimantan, Indonesia. The top image shows the location of the study area in Borneo Island (extracted from © Google Earth). The bottom

image is the full scene PALSAR image acquired on 25 March 2010 (RGB = HH, HV, and VV).

3.2 Data

We used two fully polarimetric PALSAR level 1.1 Single Look Complex (SLC) satellite data with amplitude and phase of the south Kalimantan area. One was acquired on 22 March 2009, and the other was acquired on 25 March 2010 as shown in figure 2. We used the PALSAR image of 25 March 2010 for land-cover mapping, and the 22 March 2009 PALSAR image for visual comparison with the classification results.

PALSAR SLC polarimetric image, its pixel spacing is 9.37m in range direction, and it is 3.56m in azimuth direction. The main PALSAR data processing steps are multi-looking, speckle filtering, geocoding (include ortho-rectification), Radiometric Calibration and Radiometric Normalization. The final pixel spatial resolutions are 15m. Here, we use the 90m SRTM-3 Terrain DEM data for Ortho-rectification process.

In addition to the two PALSAR images, we acquired and utilized numerous ancillary data for determination of typical land-cover classes and field training sites: two ALOS AVNIR-2 (three visible and one near-infrared) images with a 10m multispectral spatial resolution acquired on 25 April 2009, and 26 July 2009, respectively, were used for reference data; Land-use/Land-cover Datasets of Indonesia for the area; and high resolution IKONOS images from Google Earth. Since the main purpose of the experiment was to map forest distribution, only six broad categories were digitized for the study site (Table 1).

Land cover class	Samples	
	Training	Testing
Forest	709	533
Water	587	452
Urban	625	563
Cropland 1	587	424
Cropland 2	563	381
Cropland 3	437	309
Total	3508	2662

Table 1. Description of the land-cover classes and their pixel counts in study area

4. RESULTS AND DISCUSSION

Our experiments showed that for four bands of HH, HV, VH, and VV data classification, the MLC method provides better classification accuracy than the subspace method. However, for all 13 bands of HH, HV, VH, VV, and polarimetric coherency T3 matrix data, the subspace method results are better than those of the MLC method. Thus, the MLC method was chosen for four bands of HH, HV, VH, and VV data classification, and subspace method was chosen for all 13 bands of HH, HV, VH, VV, and polarimetric coherency T3 matrix data classification.

4.1 Results by four bands of HH, HV, VH, and VV

We made this Supervised Classification using the MLC acting on four bands of HH, HV, VH, and VV.

Figure 3 shows the classification map, and Table 2 presents the accuracy assessment results. Classification results on the four bands of HH, HV, VH, and VV images showed an overall classification accuracy of 77.69%, with a κ statistic of 0.7306.

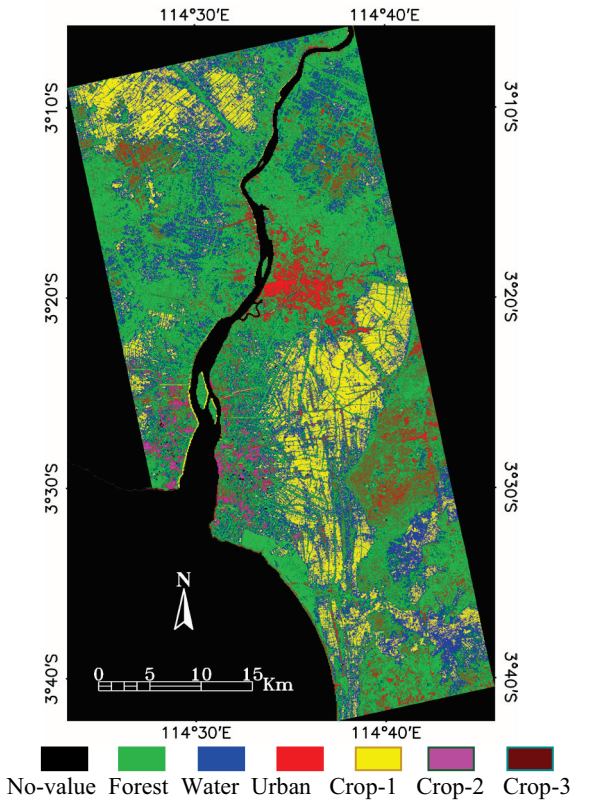


Figure 3. land-cover map of the study area derived from 4 band of PALSAR HH, HV, VH, and VV classified by MLC method.

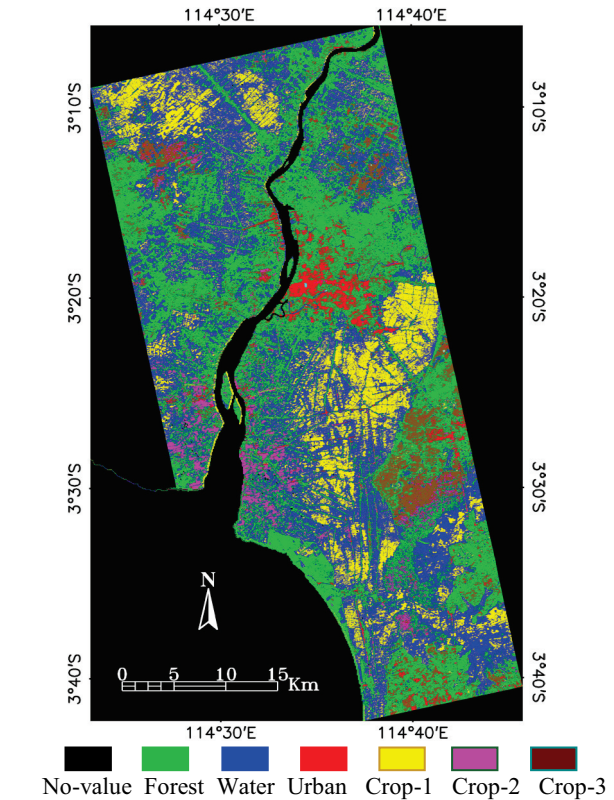


Figure 5. land-cover map derived from 13 band of HH, HV, VH, VV, and coherency T3 matrix classified by subspace method.

Class	1	2	3	4	5	6	User
1	503	26	27	12	0	10	87.0
2	0	140	0	71	0	0	66.4
3	6	0	474	0	1	53	88.8
4	0	286	0	341	0	0	54.4
5	0	0	9	0	364	0	97.6
6	24	0	53	0	16	246	72.6
Prod	94.4	31.0	84.2	80.4	95.5	79.6	(%)

Table 2. Confusion matrix obtained by application of subspace method to the test data set

4.2 Results by adding coherency T3

We add the polarimetric coherency T3 matrix into original four bands of HH, HV, VH, and VV images to perform land cover classification. The subspace dimension was fixed at 6, learning parameters are 0.00145, and MSM parameter is 0.0012. The maximum iteration is 485. Figure 4 shows the training process.

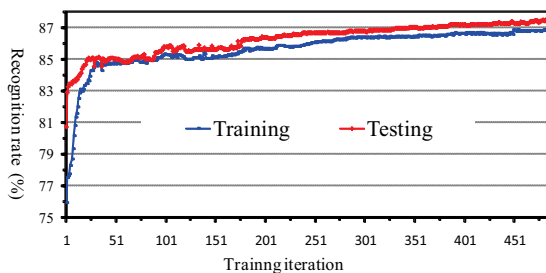


Figure 4. Recognition rate with training iterations.

Figure 5 shows the classification map, and Table 3 presents the accuracy assessment results.

Class	1	2	3	4	5	6	User
1	524	14	17	0	0	0	94.4
2	1	299	6	122	0	0	69.9
3	0	0	472	0	0	0	100
4	0	139	0	302	0	0	68.5
5	0	0	27	0	381	0	93.4
6	8	0	41	0	0	309	86.3
Prod	98.3	66.2	83.8	71.2	100	100	(%)

Table 3. Confusion matrix obtained by application of subspace method to the test data set

Figure 4 shows the behaviour of the resulting accuracies as functions of iteration. To check the time complexity and the classification error in the subspace training iteration step, we computed the recognition rate for the training and test data set respectively. The training and test data set were classified by current subspaces.

Table 3 showed an overall classification accuracy of 87.49%, with a κ statistic of 0.8493. In all the 13 bands of PALSAR data, the classification accuracies and Kappa coefficients of the Subspace method are higher than those of the corresponding MLC classification. Therefore, when all HH, HV, VH, and VV bands and polarimetric coherency T3 matrix are used, the accuracy is higher than that using only four HH, HV, VH, and VV bands PALSAR data.

To visualize the differences in the classified regions more clearly, we extracted same region from two ALOS ANVIR-2 images which are acquired on 25 April and 26 July, 2009, respectively, over the study area. Figure 6 shows the original ALOS ANVIR-2 images at 10 m spatial resolution.

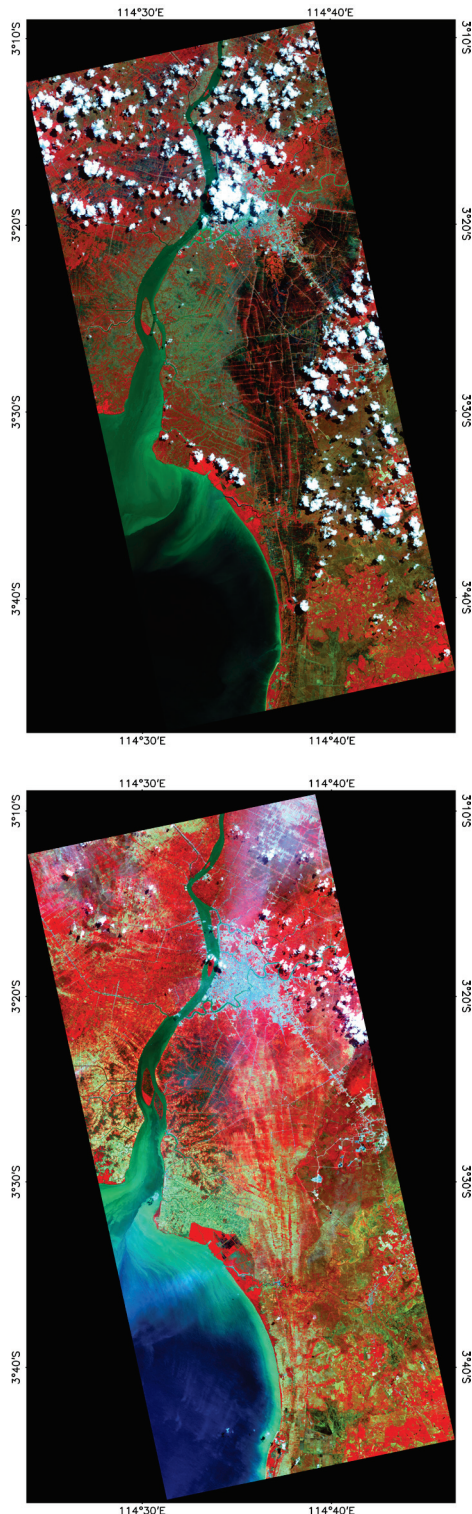


Figure 6. ALOS ANVIR-2 images (RGB = 4, 3, 1 Band) of the study area acquired on 25 April 2009 (top) and 26 July 2009 (bottom).

5. CONCLUSIONS

In this study, we use a fully polarimetric PALSAR level 1.1 SLC data for land-cover classification. We presented a subspace classification algorithm for fully polarimetric PALSAR remote sensing imagery. The polarimetric features of coherency matrix and intensity were investigated by classification of the whole

image. By integrate PALSAR intensity images with polarimetric coherency T3 matrix, we able to improve classification accuracy compared with 4-band PALSAR polarimetric intensity data. The classification results might be further improved by integrates polarimetric interferometric coherence information into classification process for our test site (Cloude et al., 2008).

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