LAND COVER CLASSIFICATION OF ALOS AVNIR DATA USING IKONOS AS REFERENCE

Bambang Trisakti[1]* and Dini Oktavia Ambarwati[1]
[1]National Institute of Aeronautics and Space (LAPAN), Jakarta
*Email: btris01@yahoo.com

Abstract. Advanced Land Observation Satellite (ALOS) is a Japanese satellite equipped with 3 sensors i.e., PRISM, AVNIR, and PALSAR. The Advanced Visible and Near Infrared Radiometer (AVNIR) provides multi spectral sensors ranging from Visible to Near Infrared to observe land and coastal zones. It has 10 meter spatial resolution, which can be used to map land cover with a scale of 1:25000. The purpose of this research was to determine classification for land cover mapping using ALOS AVNIR data. Training samples were collected for 11 land cover classes from Bromo volcano by visually referring to very high resolution data of IKONOS panchromatic data. The training samples were divided into samples for classification input and samples for accuracy evaluation. Principal component analysis (PCA) was conducted for AVNIR data, and the generated PCA bands were classified using Maximum Likehood Enhanced Neighbor method. The classification result was filtered and re-classed into 8 classes. Misclassifications were evaluated and corrected in the post processing stage. The accuracy of classifications results, before and after post processing, were evaluated using confusion matrix method. The result showed that Maximum Likelihood Enhanced Neighbor classifier with post processing can produce land cover classification result of AVNIR data with good accuracy (total accuracy 94% and kappa statistic 0.92). ALOS AVNIR has been proven as a potential satellite data to map land cover in the study area with good accuracy.

Keywords: *ALOS-AVNIR, Maximum likelihood enhanced neighbor classifier, Confusion matrix*

1 INTRODUCTION

Land cover information is a main data for supporting many applications in various sectors, such as: agriculture, forestry, urban planning, water resources and so on. Therefore, land cover information is very essential for effective resource management and for developing sound policy on land utilization (Langford and Bell, 1996). Accurate land cover information can be mapped by direct field survey in the interest area. However the field survey is inefficient when the interest area is too wide. It spends much effort, cost, and time. Remote sensing technique can be the best solution of this problem, because the technique can be used to monitor earth surface in the wide scale and can be obtained periodically to map and identify the change of the earth surface, especially for land cover change (Prakosa and Wuryata, 2009).

Land cover mapping is one of the most successful applications based on remote sensing satellite data. Application of remote sensing satellite data for land cover mapping has been widely used. Many scientists have tried to map land cover using many kinds of satellite data that have difference in spatial and spectral resolution. In the remote sensing data, the colors in a digital image are merely a conventional transposition of numerical values, and it is also possible to classify the pixels by their numerical values that corresponding to objects' spectral properties. This is the basic principle of image classification. Classification is defined as a method to label all pixels based on spectral characteristic of the pixel, the labelling process can be done using a computer by giving prior training to the computer for recognizing the pixels with the same spectral (Buono *et al.*, 2004).

Various classification methods have been used to obtain more accurate land cover classification results. Recently, visual classification was the most widely used method in Indonesia for mapping land cover for satellite data with medium and high spatial resolution. This might be due to the visual classification is easy to be handled and it has high accuracy of classification result. However, the visual classification has some significant problems with the lack of consistency in the delineation process and different interpretation result due to different understanding of interpreters.

Digital classification can solve the problem of visual classification. One of the popular classification methods is maximum likelihood classification. The maximum likelihood classifier quantitatively evaluates both the variance and covariance of the category spectral response pattern when classifying an unknown pixel. To do this, an assumption is made that the distribution of the cloud of points forming the category training data is a Gaussian distribution (normally distributed). Under this assumption, the distribution of a category response pattern can be completely described by the mean vector and the covariance matrix. Then statistical probability of a given pixel value being a member of particular land cover class can be calculated (Lillesand and Kiefer, 1999). The maximum likelihood classification method has been widely used to map land cover and their change using various optical sensor data. Saha *et al.* (2005) mapped land cover using Indian Remote Sensing Linear Imaging Self Scanner (IRS LISS) III Image and Digital Elevation Model (DEM) for a rugged terrain area, Prakosa and Wuryata (2009) analized land cover change using Landsat ETM+ for Batanghari Hulu Tengah watershed area, and Trisakti (2012) clasified land cover and identified the change in the catchment area of Tondano Lake using SPOT-4. The maximum likelihood classification method was also used to classify land cover using integration data of Synthetic Aperture Radar (SAR) and optical data (Huang *et al.*, 2005).

Advanced Land Observation Satellite (ALOS) is a Japanese satellite equipped with 3 sensors, i.e. PRISM, AVNIR and PALSAR. The Advanced Visible and Near Infrared Radiometer (AVNIR) provides multi spectral sensors ranging from Visible to Near Infrared to observe land and coastal zones. It has 10 meter spatial resolution, which can use to map land cover with a scale of 1:25000 (JAXA, 2008). Therefore, ALOS AVNIR data is one of the potential satellite data which can be used to produce a detail scale of land cover for Indonesia area. On other hand, the spatial resolution of AVNIR data is better compared to Landsat ETM+ and SPOT-4 which are commonly used data in Indonesia. The aim of this research was to analyze the utilization of ALOS AVNIR data to map land cover using maximum likelihood classifier. The classification strategy was studied and developed to reduce misclassification and to improve accuracy of the classification result.

2 MATERIAL AND METHODS

2.1 Data and Location

The main data in this research was ALOS AVNIR of 27th June 2009 acquisition date obtained by Japan Aerospace Exploration Agency (JAXA) (Figure 1). Almost all of the AVNIR image scene was covered by thin cloud (haze) except around the Bromo vulcano (Figure 1, left). The relatively clear part of image was used for study area. The study area was located in Bromo volcano and its vicinity (Figure 1). Another data was IKONOS image of 2004 acquisition year downloaded from Google Earth (Figure 2) and Landsat ETM+ ortho image of 27th June 2002 acquisition date. IKONOS image covered only area surrounding volcano caldera. Landsat ETM+ ortho image was used as a reference data for geometric correction (rectification). On other hand, IKONOS was used as a reference data to identify and verify land cover types in AVNIR image.

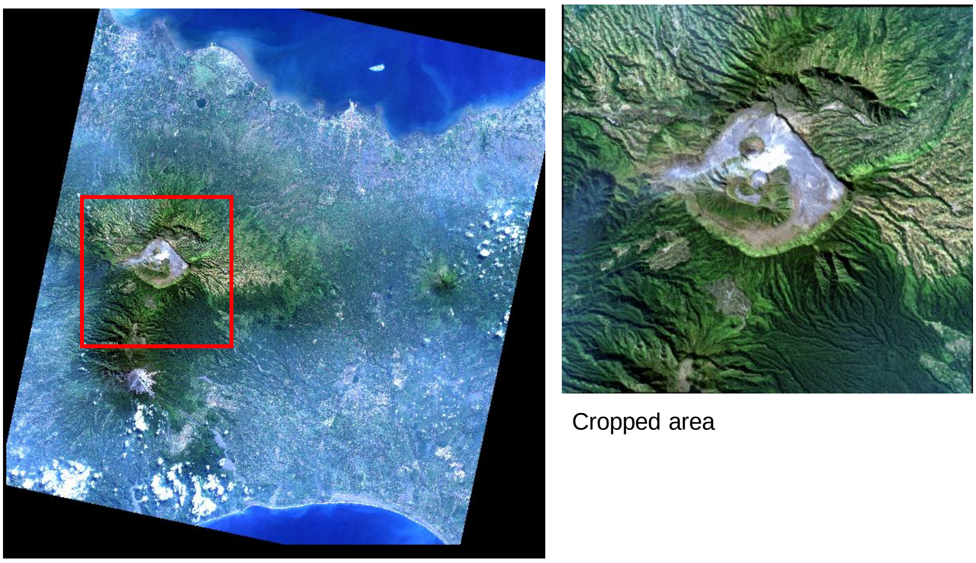
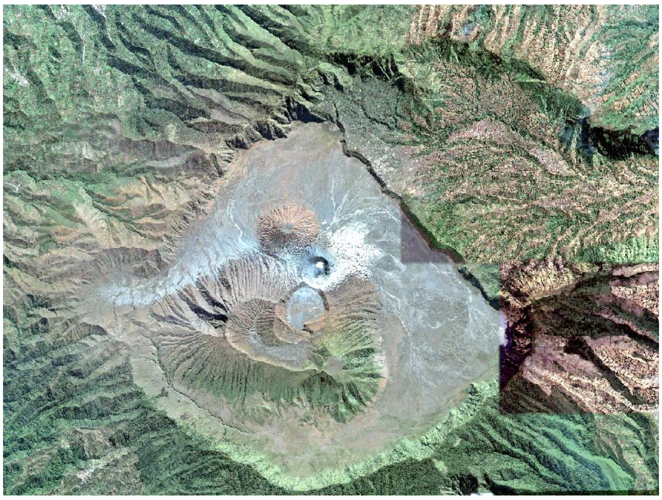
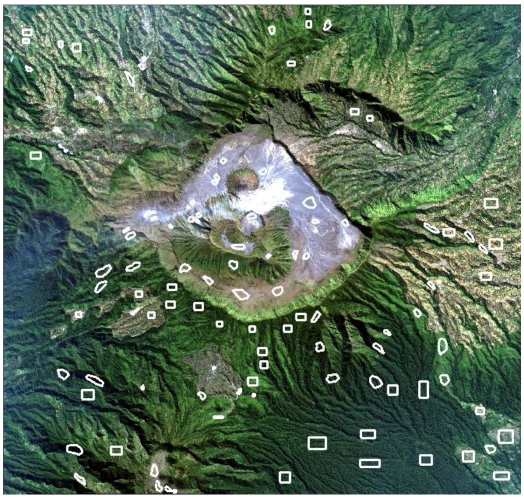


Figure 1. AVNIR data for study area, full scene (left) and cropped image (right)



IKONOS



AVNIR image with training sample

Figure 2. IKONOS for Bromo volcano (left), and AVNIR image with training sample for input classification (right)

2.2 Data Analyses

The general procedure of the research is shown in Figure 3. AVNIR image was cropped for haze clear images in study area, and then the clear image was rectified using around 15 control points collected Landsat ETM+ ortho image. IKONOS has detail spatial resolution (1 m), so it can easily identify land cover types. Based on the reason, AVNIR image was verified using IKONOS image, and then the training samples were taken from the verified AVNIR image and used as input samples of classification process and accuracy evaluation. By observing the AVNIR image, it was found that actual number of land cover class identified in study area was eight classes (shrub, bush, forest, agriculture, water, bareland, urban and sand), and then the classes were added three more classes for land cover affected by shadow in terrain area. Terrain generates shadow which affects spectral value of the land cover pixels, (spectral value of pixel under terrain shadow becomes lower than the original value). So, those objects must be sampled separately. Finally, the total land cover classes in the training sample were 11 classes. Training samples were collected for each class in homogeneous area by visually identifying from IKONOS images. The training samples were divided into samples for classification input (128 samples) as shown in Figure 2 and samples for accuracy assessment (64 samples).

Principal component analysis (PCA) was conducted for AVNIR data which consist of four bands (blue, green, red and near infrared band). The generated PCA bands were classified using Maximum Likehood Enhanced Neighbor method. This method showed good performance for land cover classification in the previous research (Trisakti, 2012). The classification result was filtered using filter median 3x3, and then was re-classed into eight classes of land cover.

The next stage was carried out to identify the misclassification pixels on the classification result, and then correct those misclassification pixels by doing post processing method. In the post processing, some steps were done to create regions around the misclassification pixels, develop algorithm, and convert the class of those pixels into the actual class using the algorithm. Finally, the accuracy of classification results before and after post processing were checked using confusion matrix, and then the result was evaluated to know the effect of the post processing process.

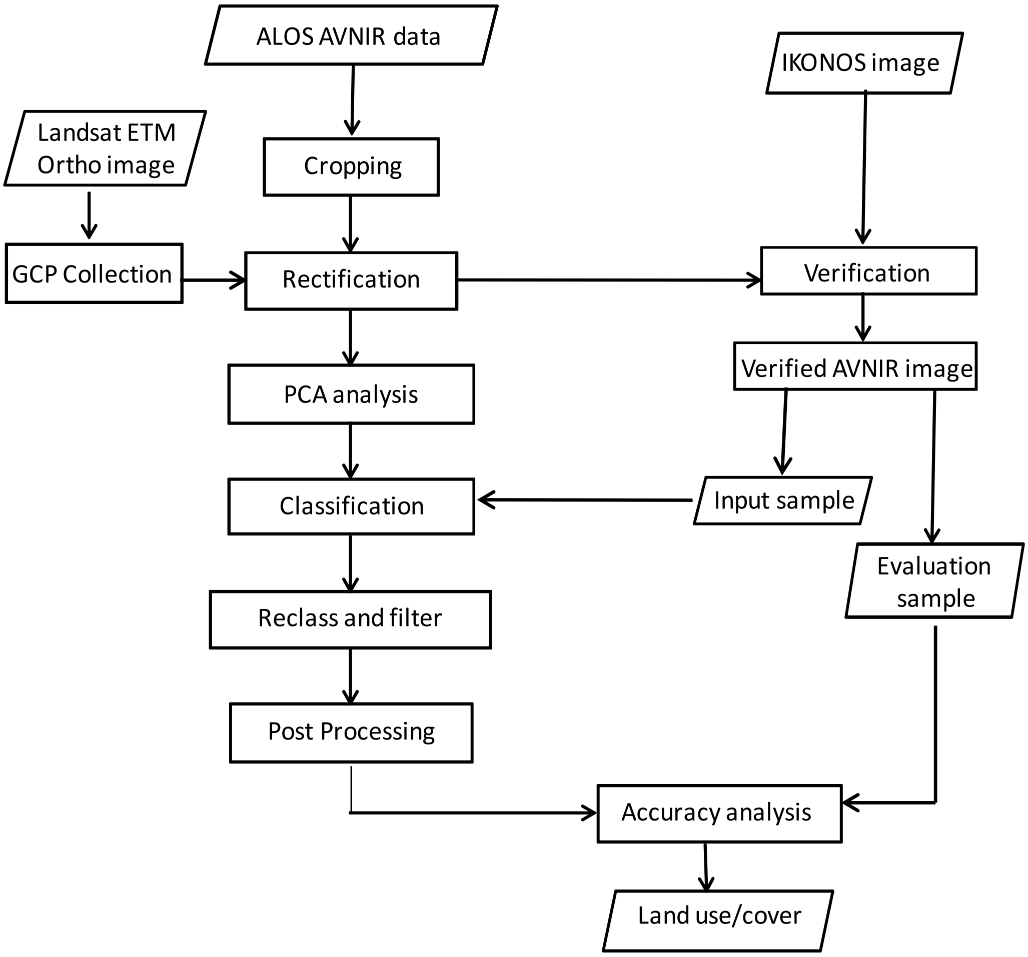


Figure 3. Flowchart of general research method

3 RESULT AND DISCUSSION

Before doing the classification, the AVNIR image was processed for PCA to obtain a smaller number of artificial bands that will account for most of the variance in the observed band. The result of PCA image (RGB 321) is shown in Figure 4. The image has different performance with the natural color composite (RGB 321) in Figure 1 and 2. The color difference between each class in PCA image is clearly recognized, especially for some classes such as agriculture area in red, sand in dense and light blue, forest in dense green and shrub in light green. Therefore, the PCA image can be good method for increasing the separation capability of maximum likelihood classifier to accurately classify land covers in the study area.

The land cover classification result of ALOS AVNIR data is shown in Figure 5. This result was re-classed from 11 classes into 8 classes and was filtered using median 3x3.

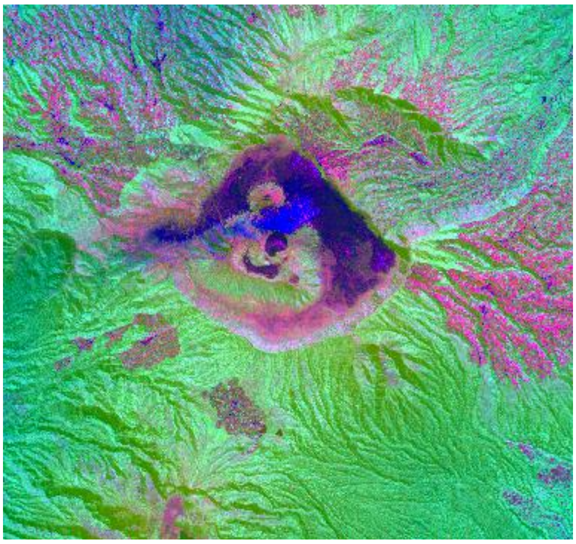


Figure 4. PCA Image of AVNIR data

Re-class was done to combine 2 different classes to become 1 class. Two classes for agriculture located on flat area and on shadow area were re-classed to become 1 class of agriculture, two classes for forest located on flat area and on shadow area were re-classed to become 1 class of forest, and two classes for bareland located on flat area and on shadow area were re-classed to become 1 class of bareland.

The classification result showed that land covers surrounding study area (Bromo volcano) were dominated by agriculture, forest, and bareland land respectively. Caldera of Bromo volcano was covered by sand, bareland land, and bush, but some misclassifications were easily identified in caldera of Bromo volcano, such as agricultural and urban class. It means that pixel values of bush and sand were relatively similar with pixel values of agricultural and urban, the similarity of pixel values of different land cover resulted the misclassification or mixing class happened in the classification result.

The misclassifications were evaluated visually by checking all land cover classes of the classification result. It was found that the main misclassifications were caused by:

- Pixel values of urban and sand were relatively similar with pixel values of agriculture and bareland land in the volcano caldera (Figure 6).
- Haze or thin cloud cover in forest area increased pixel values of the forest to be similar with pixel values of bareland and agriculture (Figure 7).

Terrain shadow decreased pixel values of agriculture to be similar to forest pixels (Figure 8). Shadow affected the original pixel value which resulted misclassification in the classification result.

Post processing was conducted to correct the misclassification in the classification result. The method was simple and fast, but it was very effective to solve the misclassi-fication problem. The post processing procedure was consists of three main processes. The first process was to create regions in the misclassification area. Those regions can be made roughly surrounding the misclassification pixels. The second process was to develop algorithm, and the third process was to correct the misclassification using the developed algorithm. The algorithm converted pixels of the misclassification classes into the right classes.

The classification result after post processing is shown in Figure 9. The result shows that almost all misclassifications can be easily solved. Misclassification due to haze or thin cloud cover and terrain shadow could be corrected well. Agriculture and urban in the volcano caldera were converted to bush and sand respectively. On the other hand, misclassification in the forest area due to the haze cover was corrected, and the misclassification pixels were converted to be forest.

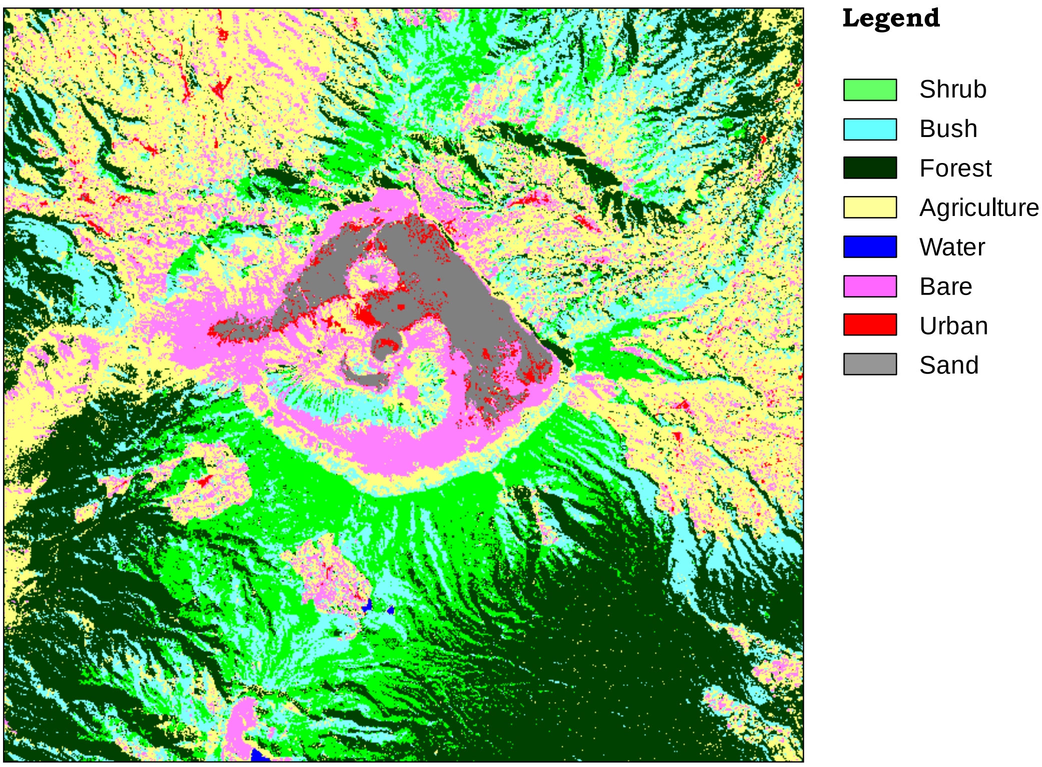


Figure 5. Classification result after filtered and re-classed

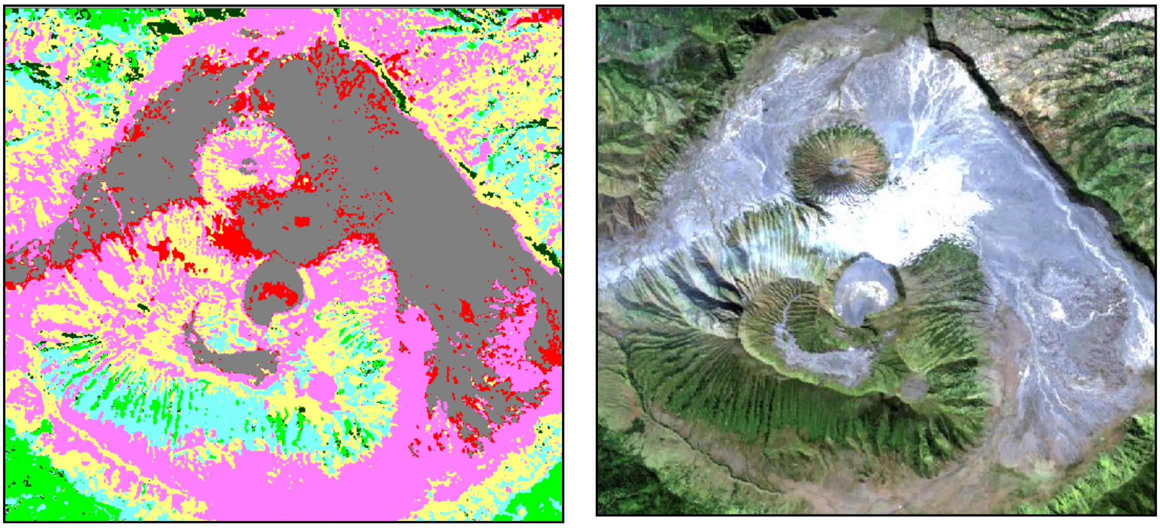


Figure 6. Misclassification of urban (red) and agriculture (yellow) in the volcano caldera.

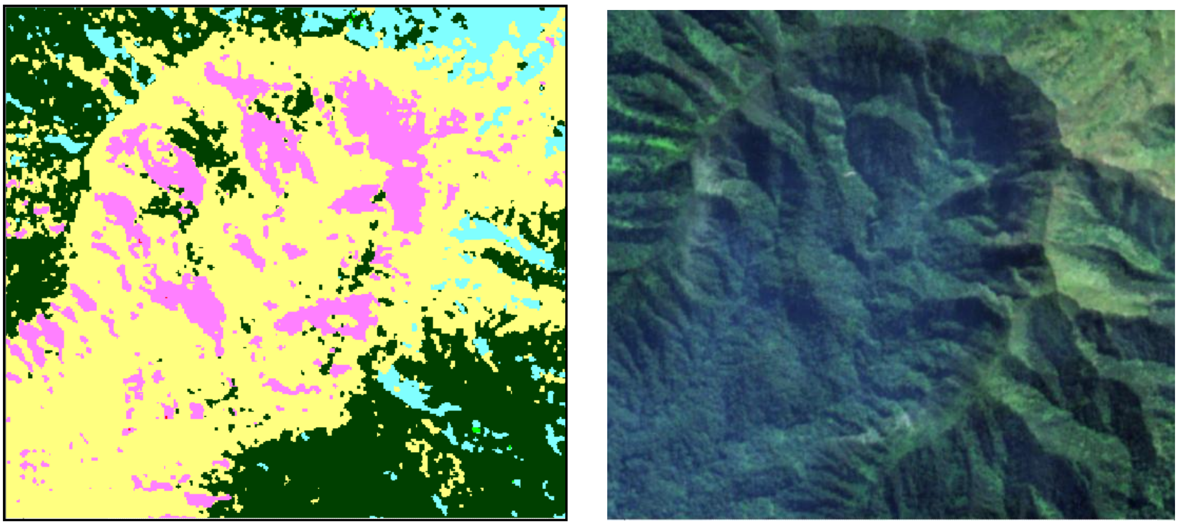


Figure 7. Misclassification of bareland (pink) and agriculture (yellow) due to haze cover

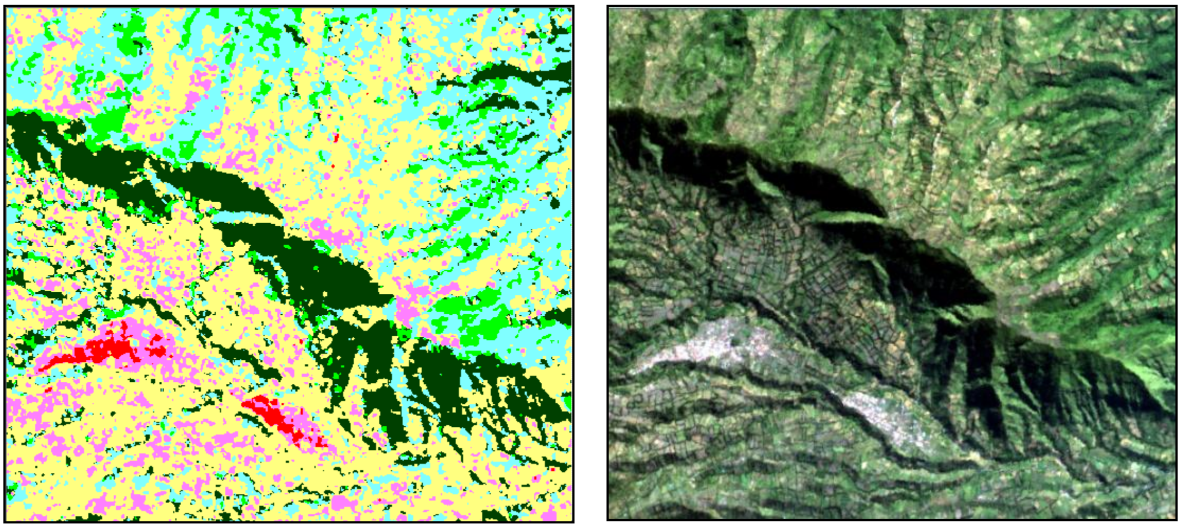


Figure 8. Misclassification of forest (dense green) due to terrain shadow.

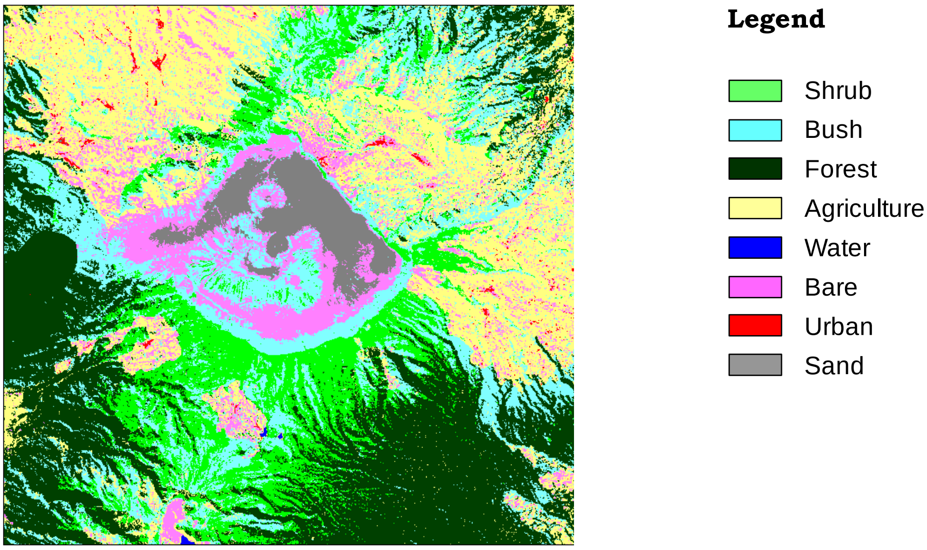


Figure 9. Land cover classification result after post processing

The accuracy of the classification results before and after post processing were evaluated using the same training sample for accuracy assessment. Total of the training samples used were 46 samples. Table 1 and Table 2 showed the result of confusion matrixs before and after post processing process. There are some types of accuracy in the confusion matrix, those are: user accuracy, producer accuracy, and overall accuracy. The user and producer accuracy are two widely used measures of class accuracy. The producer accuracy refers to the probability that a certain land cover of an area on the ground is classified as such, while the user accuracy refers to the probability that a pixel labeled as a certain land-cover class in the map is really this class. On other hand, the overall classification accuracy can be derived from confusion matrix table by counting how many pixels were classified the same in the satellite image and on the ground and dividing this by the total number of pixels. Comparison of confusion matrix results before and after post processing show that there are some significant improvements in user accuracy in forest (from 0.92 to 0.98), agriculture (form 0.72 to 0.99), bareland (from 0.64 to 0.72) and urban (from 0.88 to 0.90). There are also some significant improvements in producer accuracy in forest (from 0.59 to 0.99) and agriculture (from 0.82 to 0.87).

The user accuracy, producer accuracy, overall accuracy, and kappa statistic of the classification results before and after post processing are shown in Table 3. From the table, it is known that the land cover classification result after post processing has higher accuracy comparing to the classifi-cation result before the post processing. The overall accuracy signifi-cantly increases from 81% to 94%, and kappa statistic increases from 0.76 to 0.92. It means that the post processing process gives significant improvement of the classification result and also becomes very important step to produce good accuracy of the land cover classification based on AVNIR data.

Table 1. RESULT OF CONFUSION MATRIX BEFORE POST PROCESSING

Result/ reference	Shrub	Bush	Fores t	Agricul-ture	Water	Bare land	Urban	Sand	Accuracy
Shrub	761	10	2	14	0	0	0	0	0.97
Bush	0	857	0	101	0	0	0	0	0.89
Forest	152	0	3547	164	0	0	0	0	0.92
Agricul-ture	0	0	2037	5140	0	3	0	0	0.72
Water	0	0	0	0	420	0	0	0	1
Bareland	0	0	423	787	0	2514	13	198	0.64
Urban	0	0	1	55	0	0	529	13	0.88
Sand	0	0	0	0	0	0	16	3469	0.99
Accuracy	0.83	0.99	0.59	0.82	1	0.99	0.95	0.94	**0.81**

Table 2. RESULT OF CONFUSION MATRIX AFTER POST PROCESSING

Result/ reference	Shrub	Bush	Forest	Agricultur e	Water	Bare land	Urban	Sand	Accuracy
Shrub	770	10	2	14	0	0	0	0	0.97
Bush	0	857	0	101	0	3	0	0	0.89
Forest	143	0	5994	5	0	0	0	0	0.98
Agricultur e	0	0	13	5299	0	0	0	0	0.99
Water	0	0	0	0	420	0	0	0	1
Bareland	0	0	0	787	0	2514	13	198	0.72
Urban	0	0	1	55	0	0	529	0	0.90
Sand	0	0	0	0	0	0	16	3482	0.99
Accuracy	0.84	0.99	0.99	0.87	1	0.99	0.95	0.95	**0.94**

Table 3. ACCURACY COMPARISON OF LAND COVE RCLASSIFICATION RESULTS BEFORE AND AFTER THE POST PROCESSING

	Total producer accuracy	Total user Accuracy	Overall Accuracy	Kappa statistic
Classification accuracy before post processing	89%	87%	**81%**	**0.76**
Classification accuracy after post processing	94%	93%	**94%**	**0.92**

4 CONCLUSION

Post processing process produced significant improvement for the classification result and also became very important step to produce better accuracy of the land cover classification based on satellite data, moreover the process was simple and fast.

Maximum likelihood enhanced neighbor classifier with post processing can produce land cover classification from AVNIR data with good accuracy (total accuracy 94% and kappa statistic 0.92).

ALOS AVNIR has been proven as a potential satellite data to map land cover in the study area with good accuracy.

ACKNOWLEDGEMENT

Authors would like to thank to Japan Aerospace Exploration Agency (JAXA) for their data used in this research.

REFERENCES

Buono, A., Marimin, and D. Putri, 2004, Land use/cover classification from Landsat TM multispectral using Probabilistic Neural network, *Jurnal Ilmiah Ilmu Komputer*, 2(2):1-13.

Huang, H., J. Legarsky, and M. Othman, 2007, Land-cover Classification Using Radarsat and Landsat Imagery for St. Louis, Missouri, *Photogrammetric Engineering & Remote Sensing,* 73(1):37–43.

JAXA, 2008, ALOS User Handbook, NDX-070015, EORC-JAXA.

Langford, M. and W. Bell, 1997, Land cover mapping in a tropical environment: a case study in the Cauca region of Colombia, *Int. J. Remote Sensing*, 18(6):1289-106.

Lillesand, T.M. and R.W. Kiefer, 1999, Remote Sensing and Image Interpretation, John Wiley & Sons, New York.

Prakosa, D. dan A. Wuryata, 2009, Study of Land cover change using Landsat 7 ETM+ in Batanghari Hulu Tengah (Jambi) watershed, *Tekno. Hutan Tanaman*, 2(3):121-132.

Saha, A.K., M.K. Arora, E. Csaplovics, and R.P. Gupta, 2005, Land Cover Classification Using IRS LISS III Image and DEM in a Rugged Terrain: A Case Study in Himalayas, *Geocarto International*, 20(2):

Trisakti, B., 2012, Accuracy improvement of Land cover classification using Maximum Likelihood method, proceeding PIT MAPIN XIX, Makassar, June 2012.