

Application of a Multispectral SPOT Image for Land Use Classification in Sampean Watershed

Januar Fery Irawan¹ and Indarto²

Research Center of Water Resource Development, Research Institute, University of Jember. Jl. Kalimantan No. 37, Kampus - Tegalboto, Jember 68121, Indonesia, e-mail: januar_ir@yahoo.com¹ and ppsa@lemlit.unej.ac.id²

Received 14 May 2009 / accepted 10 May 2011

ABSTRACT

This article described the process of land use classification at Sampean Watershed. The research was conducted in Sampean watershed to calculate the land use area using a multispectral SPOT image. Two SPOT image scenes were used to identify and classify the main nomenclature of land use. The research applied level 2A of SPOT image raw data which were obtained during 2004. Research methodology consisted of geometric correction of Image; image enhancement using high sharpen filter; un-supervised classification and supervised classification. The classification algorithm used the maximum likelihood in which pixels was classified based on their spectral signature. Several training areas were identified to define the region area. Supervised classification could classified 9 class of land uses, the classification of land use consist of irrigated paddy field (56.05%), rain fed paddy field (0.89%), forest (10.75%), urban area (8.69%), plantation (4.22%), barren land (11.19%), river (0.05%), cropland (7.98%), and bushes (0.19%). The overall classification accuracy was 84.21%. This work will be useful for hydrological modelling and management planning of the Watershed.

Keywords: Classification, supervised, Sampean watershed, SPOT Image, unsupervised

INTRODUCTION

In the watershed areas, water resources management is related to the information of land use in watershed area themselves. Land use change occurred on the area may have effect on the runoff discharge flowing into the water courses region. Therefore, the rigorous land use map should be demanded in taking policy for watershed management. SPOT image has high resolution and it can cover plane section widely, so that it is able to be used for land use classification process either using multispectral or panchromatic channel. Studies and printed works concerning land use classification have been done by some researcher such as Hill and Sturm (1991); Liew *et al.* (1998); Lohnertz (2006); Atkinson *et al.* (1997); Kanello Poulos *et al.* (1992); Cross *et al.* (1991); Kang *et al.* (2001); and Zhao *et al.* (2003).

According to Curran (1985), land use classification method can be performed by using likelihood maximum algorithm which assumes that the probability of all class have the same chance. In fact, not all class can be treated with equal

probability to be viewed on the image. A training cluster which has much smaller one than other training clusters will have lower probability to appear, so that it needs a burden factor for every class coming up on the image. This small training cluster can be applied into a lower value comparing with other clusters. Decision maker which takes maximum likelihood classifier into account can be expressed by the following equation:

$$D = \ln(a_c) - [0.5 \ln(|Cov_c|)] - [0.5(X - M_c)^T (Cov_c^{-1})(X - M_c)] \quad (1)$$

where, D = distance with probability; C = a certain class; X = classified pixel vector; M_c = mean vector of class sample; a_c = percentage of probability for any pixel to be a member of class c, which is default value is 1.0 from assumed information, Cov_c = covariant matrix of pixels on class sample c; $|Cov_c|$ = determinant; Cov_c^{-1} = matrix inverse of Cov_c .

By using equation (1), one pixel will be included as class c, if D value for class c is the lowest one. Theoretically, this maximum likelihood algorithm will work well, if the histogram shape of every channels involved in the classification process presents the normal distribution appearance, since this algorithm considers the most statistic variable than other techniques. In its practice other than its histogram shape factor, the training cluster shape

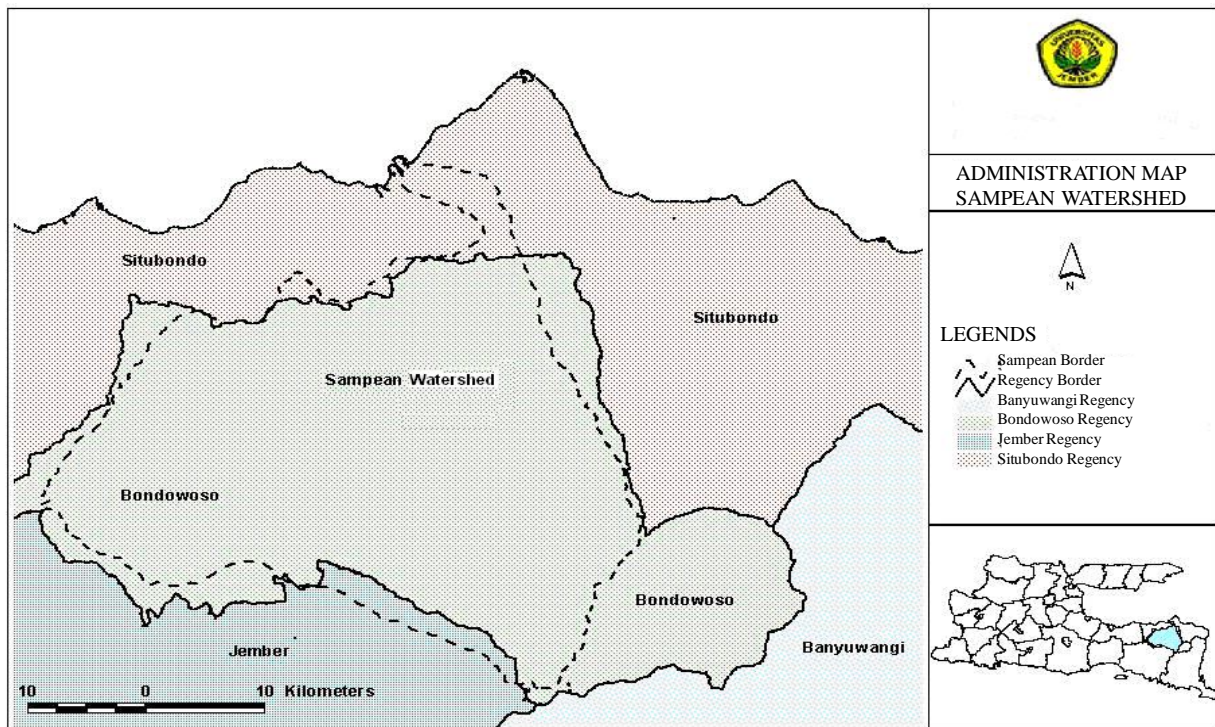


Figure 1. Location of the study area is indicated by the dashed region (Source: Water Resources Research Center, University of Jember).

which tends to form ellipsoid will be accurate as well, if classification also employs this algorithm.

This research aimed to compare between classification result of land use class using SPOT image and field study data in Sampean Watershed, East Java by applying maximum likelihood algorithm.

MATERIALS AND METHODS

Study Site

Sampean watershed was considered as research study area which covers Situbondo regency and Bondowoso Regency in East Java as shown in Figure 1. Spatial data for study used digital map database obtained from Water Resources Research Center of University of Jember. Field investigation and SPOT image which were categorized into level 2A of satellite data were taken in September and December 2004.

Image Processing

The image was prepared before they were classified. The raw image of SPOT was received in Geotif format in CD-ROOM. SPOT image used in this study were derived from type of product which characterized from 2A product type which means these products had been corrected geometrically and

radiometrically. Image data were consisted of 2 SPOT scene, one scene was based on the local datum projection of SUTM 49 and another scene was the projection of SUTM 50. Then, both scenes were registered on the coordinate of UTM Zone 50. Furthermore, these scenes had spatial resolution 2.5 meter with natural color consisting of Band 1= red, Band 2 = green and Band 3 = blue.

Three stages have been applied to process data *i.e.*: pre-classification, classification and post-classification, as shown in Figure 2. Pre-classification stage was carried out by image filtering in order to make image more realistic compared to true colour by eliminating some unnecessary parts. Geometric correction was also adopted with transformation to locate a pixel, expecting to see digital image as object appearance on the earth surface recorded by a sensor. Before coming into classification stage, transformation process was done to change pixel values systematically to lead the effect of image contrast sharper than the previous one. The change of pixel values includes contrast enhancement to gain the higher image contrast.

Classification

After enhancement, the following process was divided into supervised and unsupervised classification. Unsupervised classification classifies

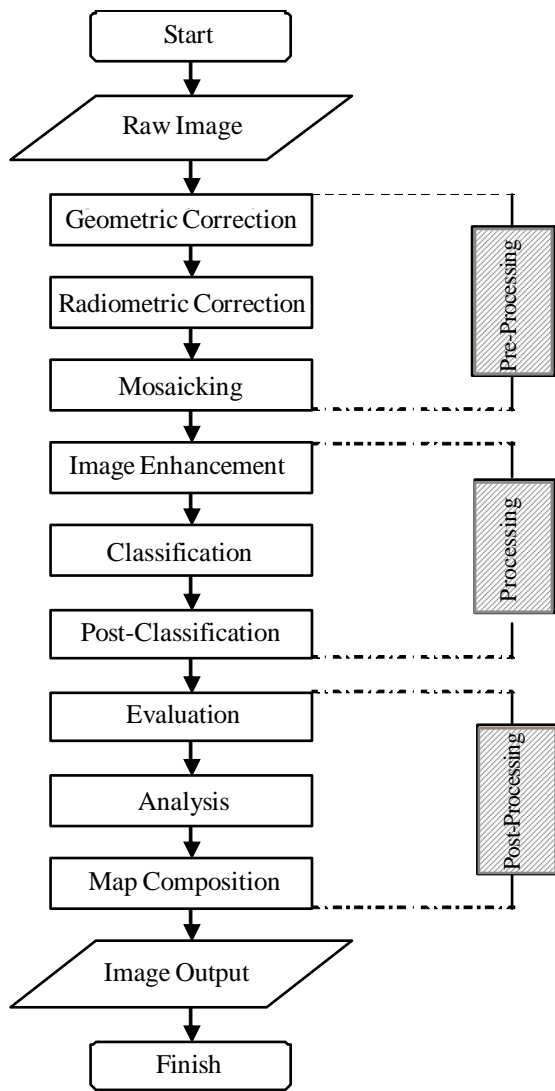


Figure 2. Diagram of SPOT Image Processing.

pixels based only on digital value of the pixels without reference available on the field. On the other hand, supervised classified was carried out by grouping data based on training area.

In the image processing stage, the available pixel values on the image were transferred to the thematic information. This process was usually consisted of band combination and classification process in which it was performed by picking the same pixel values relatively to be several land cover classes. In addition to these process, the categorisation was made automatically to all image pixels lead to the specific theme.

Unsupervised classification was taken by using cluster analysis automatically and recalculate class mean iteratively. While supervised classification process proposed maximum likelihood algorithm to classify land use classes. Assuming that homogenous object always presents histogram with normal distribution (Bayesian).

For supervised classification, the procedure followed 5 steps: (1) making ground control point (GCP) through field survey, (2) defining training area, (3) computing sampel statistically, (4) evaluating class with Scatergram, and (5) classifying image. After defining training area, the thing to do was statistic sampel calculation in all bands of SPOT image to identify the probability of each class with the whole region. Statistically, the chosen band to define training region in scattergram is the one with a small deviation standard because it has a high homogenity pixel and the grouping training regions. Bands adopted from statistic calculation result are spectral band 2 and 3 (Figure 5).

Post-classification was intended to improve accuracy of classification result. This reclassification was necessary to apply based on the information of the accepted ground check to get better information on the classification result.

RESULTS AND DISCUSSION

The Pre-Processing performed was comprised of geometric correction, radiometric calibration and mosaic. After correction process, the scene data was sharpened by applying the type of sharpen filter in order to observe pixels more clearly, so that they can be differentiated to other pixels. Radiometric correction aimed to improve image quality visually and the pixels value which were not appropriate with spectral reflection and refraction of the real object.

The another improvement of visual image quality could be refilling the empty rows due to either the drop-out row or scanning start error problem. Radiometric correction intended to build up pixels value enabling to reach the true pixel values commonly concerns disturbance factor of atmosphere as a major mistake source. Both scene data of SPOT image had already processed radiometrically so that the raw data were categorized as image with level of 2A. Finally, image was joined to obtain the whole picture concerning the study area. Before mosaicking, image should be registered in the same coordinate reference.

The result of mosaicking and registration are illustrated in Figure 3. Image processing stage was consisted of image enhancement and classification. The last scene was taken for Sampean watershed border to make it focus in the research area.

In the supervised classification, identification and training sites were found through observation in the field. Training location in the field was

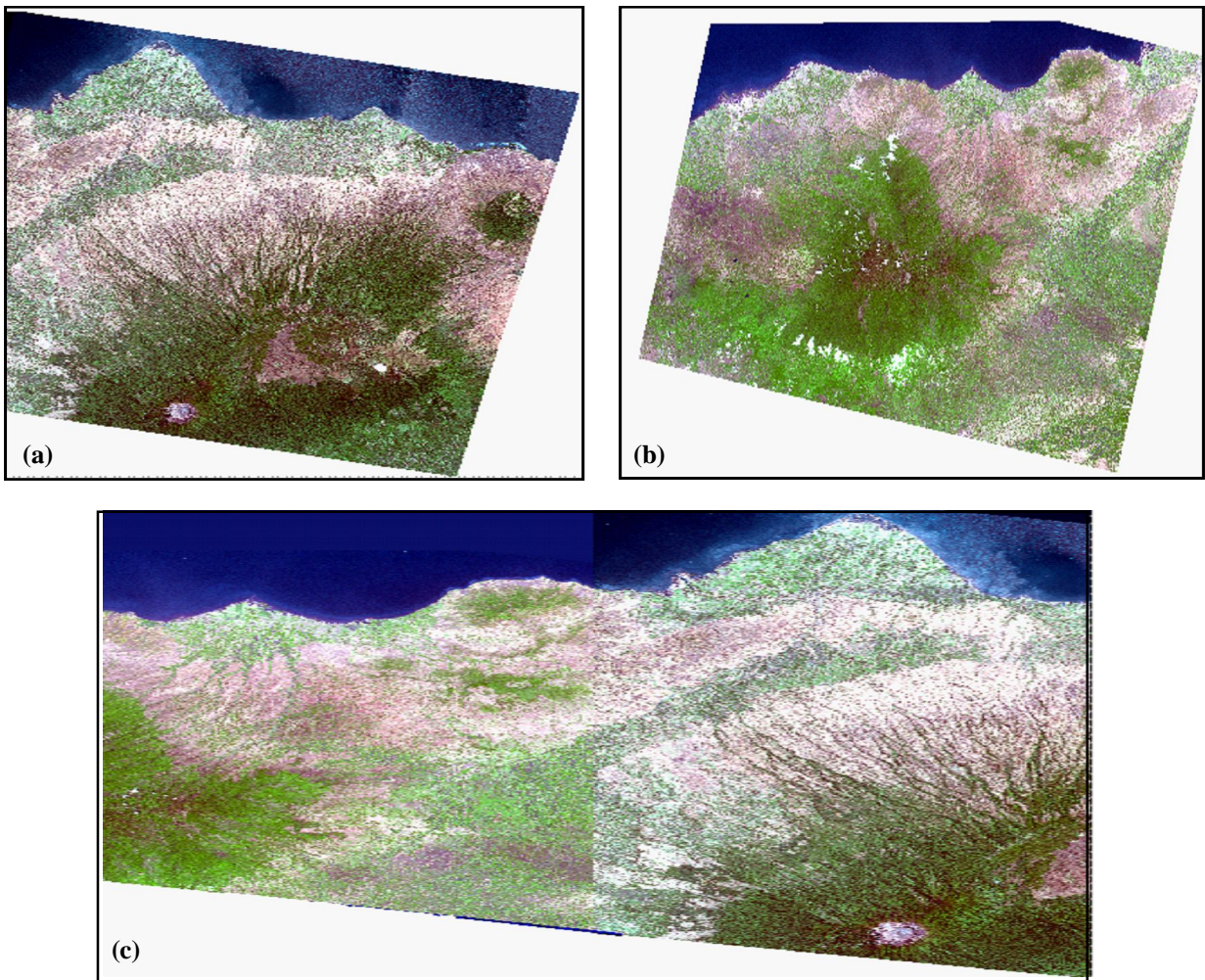


Figure 3. The image before registration (a), after registration (b), and image mosaicking (c).

divided into 9 land use classes : river, cropland, rain fed paddy field, irrigated paddy field, barren land, bushes, plantation, forest and urban area as shown in Figure 4.

The comparison between satellite image and land uses of barren land (green), rain fed paddy field (merah tua), irrigated paddy field (yellow), cropland (white), bushes (blue), forest (violet), cropland (red), urban area (green) and paddy fields (red and yellow) appeared on the image after classification as described in Figure 6.

Shape, Size and Elipsoid orientation in Figure 7 were proposed to determine class group. This group was known as the maximum likelihood algorithm. In this regard, pixels were classified as the specific object based on their shape, size and elipsoid of the training area on their feature space forming in ellipsoid. To judge classification, the statistic information, such as mean, deviation of each training region, variation and covariation, was required. Mean and deviation for every sample will be otomatially stored when defining sample is held.

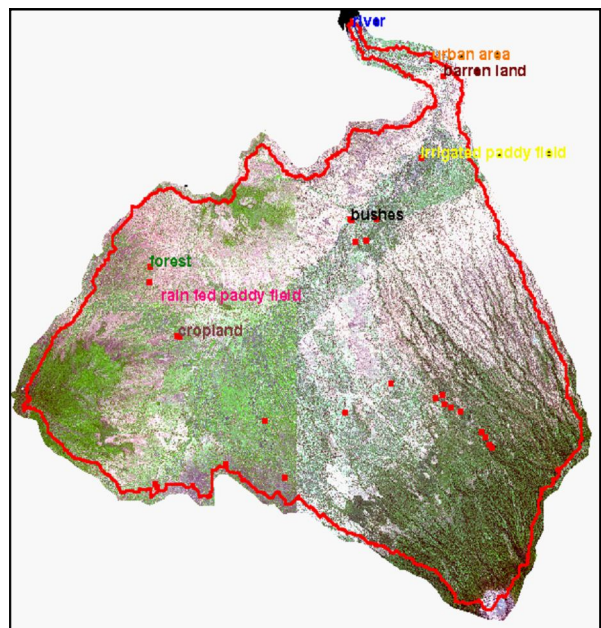


Figure 4. Determination of training regions as shown red dots on the image.

STATISTICS FOR DATASET: frame.ers				
REGION: All				
	Band1	Band2	Band3	Band4
Non-Null Cells	473193009	473193009	473193009	473193009
Area In Hectares	125401.553	125401.553	125401.553	125401.553
Area In Acres	309867.237	309867.237	309867.237	309867.237
Minimum	0.000	0.000	0.000	0.000
Maximum	255.000	255.000	255.000	8.000
Mean	71.005	71.889	62.127	0.001
Median	0.000	0.000	0.000	0.000
Std. Dev.	90.775	92.250	86.451	0.030
Std. Dev. (n-1)	90.775	92.250	86.451	0.030
Corr. Eigenval.	2.947	1.000	0.039	0.015
Cov. Eigenval.	23793.848	312.279	117.717	0.001

Figure 5. Statistic Report of all bands.

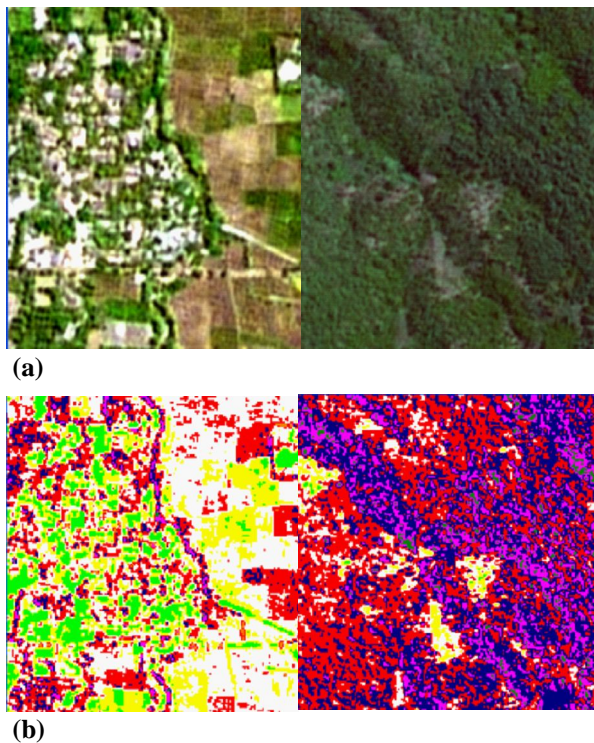


Figure 6. Comparison between the unclassified image (a) and the classified image (b).

The mean vector value governs the location of the training region ellipsoid on the feature space. The size of ellipsoid was affected by variation value in all spectral bands, whereas the shape and orientation of ellipsoid were influenced by their covariation (Shrestha and Dhruva 1991). Based on its mean, variation and covariation and probabilities of each pixel, it can be referred as the possession of a class to be able to calculate.

The classification result using this method can be seen in classification map of land use in Figure 8 which has total area of Sampean watershed as much as 1.254.016 Km per square.

Comparison of each area of land use class between classification and investigation result can be observed at Table 1.

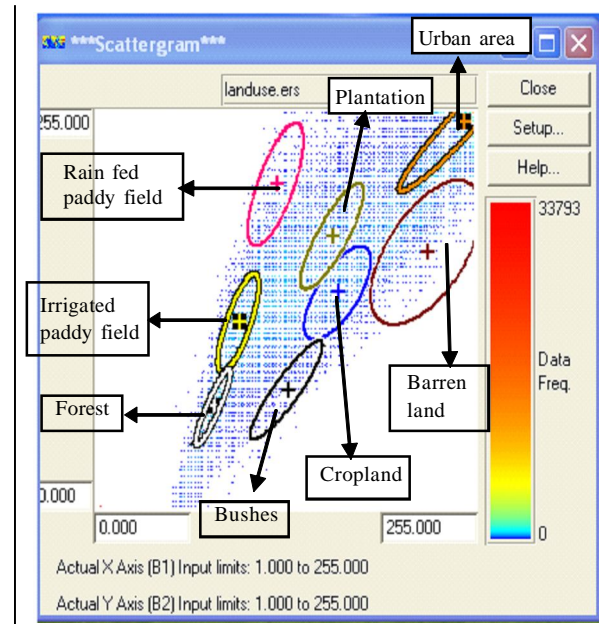


Figure 7. Scattergram of training regions using band 2 for y axis and band 3 for x axis.

There are two approaches to measure accuracy, *i.e.*, classification and thematic approach. Classification accuracy refers to the relation between a pixel and the true class area in which it can be noticed from a available reference map while thematic accuracy is frequently estimated from the sample defined arbitrarily (Janssen and van der Wel 1994). Moreover, Torkashvand (2010) described the corespondence between a pixel and area by using deviation value, whereas Perumal and Bhaskaran (2010) proposed Kappa value to determine thematic accuracy.

In this study, accuracy calculation of applied classification accuracy was indicated by deviation value of class area from a reference or survey map. The accuracy computation of all classes at Table 1 can obtain the overall accuracy which reached value at 84.21%. According to Janssen and van der Wel (1994), the analysis value of classification accuracy

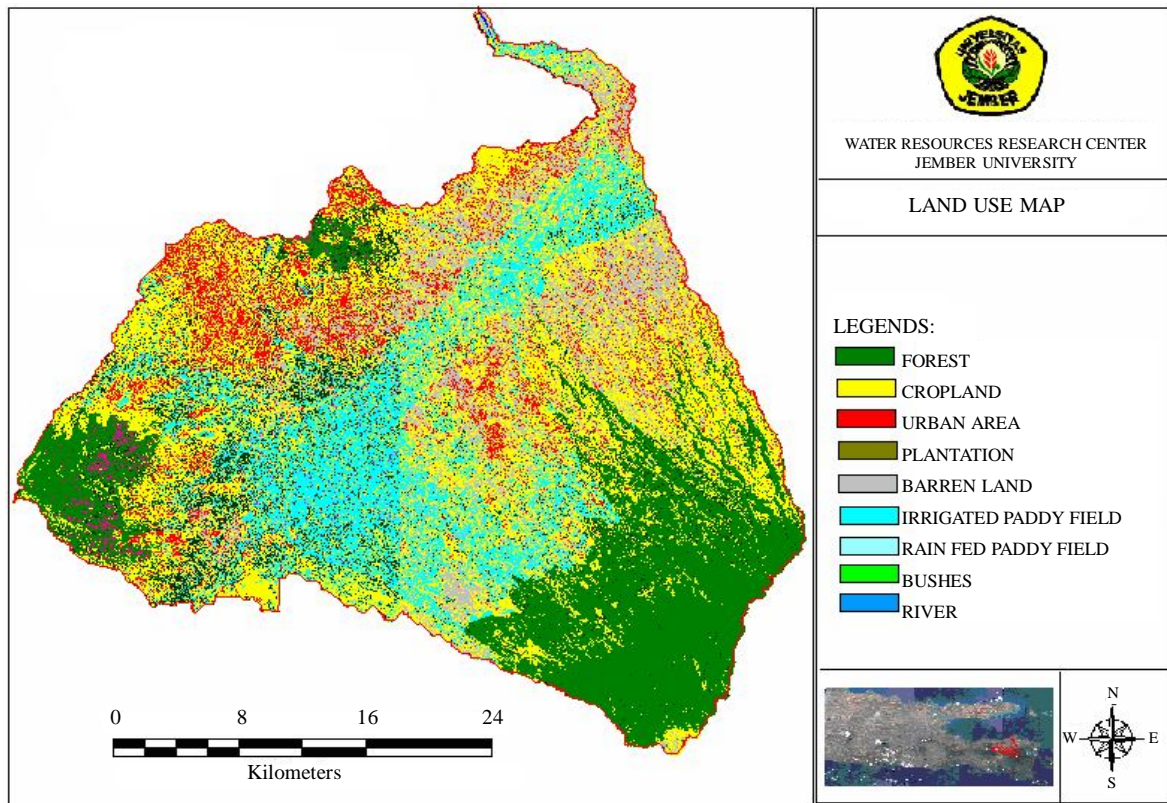


Figure 8. Land Use Map in Sampean Watershed obtained from supervised classification.

Table 1. Land use area in percentage and accuracy calculation.

No	Land Use Classes	Classification Result in Percentage	Classification Result in Square Km	Investigation Result in Square Km	Deviation	Accuracy in Percentage
1	Plantation	4.22	52.96	61.32	13.63	86.37
2	Irrigated Paddy Field	56.05	702.85	660.87	-6.35	93.65
3	Rain Fed paddy Field	0.89	11.17	10.91	2.37	97.63
4	Bushes	0.19	2.34	2.13	9.59	90.41
5	Cropland	7.98	100.03	213.69	-53.19	46.81
6	Barren Land	11.19	140.32	64.08	54.33	45.67
7	River	0.05	0.63	0.50	0.20	99.80
8	Forest	10.75	134.81	131.80	-2.28	97.72
9	Urban Area	8.69	108.91	108.72	-0.17	99.83
Total		100	1254.02	1254.02		84.21

over 80% has been accepted as a good result. Besides, based on accuration calculation, the highest accuracy level was urban area class which reached value at 99,83% and the lowest accuracy level was cropland and barren land with accuracy level ranged from 45 to 46%. This is happened because sample for these classes was only selected on the area with the gentle topography so that the classifier was difficult to define between cropland and barren land in the steep topography region.

CONCLUSIONS

The image classification outcome using supervised or unsupervised technique had suggested that the result was accurate enough and demonstrated the 9-class land use classification. This was supported by the 2.5-meter high resolution of SPOT image and with wide spectral band for band 2 and band 3. Supervised classification results the biggest land use area for irrigated paddy field 56.05%, whereas the lowest area which covers its

surface with vegetation was bushes class. Moreover, the percentage of forest area class was 10.75%.

When comparing the result of accuracy classification with a reference map it was suggested that the map accuracy of classification was entirely acceptable with accuracy 84.21%. The highest accuracy level for urban area class was 99.83%, while the lowest accuracy level was cropland class and barren land with the value of 45 - 46%.

REFERENCES

- Atkinson PM, MEJ Cutler and H Lewis. 1997. Mapping sub-pixel proportional land cover with AVHRR Imagery. *Int J Remote Sens* 18: 917-935.
- Congalton RG. 1991. A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sens Environ* 35: 35-46.
- Cross AM, JJ Settle, NA Drake and RTM Paivinen. 1991. Subpixel measurement of tropical forest cover using AVHRR data. *Int J Remote Sens* 12: 1119-1129.
- Curran PJ. 1985. Principles of Remote Sensing, London: Longman. 282 p.
- Hall FG, DE Stiebel, JE Nickson and SJ Goetz. 1991. Radiometric rectification: towards a common radiometric response among multitude, multisensor images. *Remote Sens Environ* 35: 11-27.
- Hill J and B Sturm. 1991. Radiometric correction of multitemporal thematic data for use in agricultural land-cover classification and vegetation monitoring. *Int J Remote Sens* 12: 1471-1491.
- Janssen and van der Wel. 1994, Accuracy Assessment of Satellite Derived Land-Cover Data: A Review. *Photogram Eng Remote Sens* 60: 479-426.
- Kanellopoulos I, A Varfis, GG Wilkinson and J Megier. 1992. Land-cover discrimination in SPOT HRV imagery using an artificial neural network- A 20-class experiment. *Int J Remote Sens* 13: 917-924.
- Kang DJ, YS Huang and XZ Feng. 2001. Study on Water Bodies Extraction and Classification from SPOT Image. *J Remote Sens* 5: 214-219 (in Chinese).
- Liew SC, OK Lim, LK Kwoh and H Lim. 1998. A Study of the 1997 Forest Fires in South East Asia using SPOT Quick look Mosaics. Paper presented at the 1998 International Geoscience and Remote Sensing Symposium, July 1998, Seattle. Centre for Remote Imaging, Sensing and Processing (CRISP), National University of Singapore
- Lillesand TM and RW Kiefer, 1994. Remote Sensing and Image Interpretation. New York: John Wiley and Sons. 750p.
- Löhnertz M. 2006. Einsatz räumlich hochauflösender Satellitendaten (SPOT) zur multitemporalen Kartierung von Fruchtarten und Bedeckungsgraden als abflussgenetisch relevante Raumfaktoren. (Diplomarbeit, Universität Trier) (in German).
- Perumal K and R Bhaskaran. 2010. Supervised Classification Performance of Multispectral Images. *J Computing* 2: 124-129
- Projo D. 1993. The Use of Knowledge-based Approached in the Integration of Remote Sensing and Geographic Information System for Land Use Mapping-a Case Study of the Buffer Zone of Cibodas Biosphere Reserve, West Java, Unpublished, Enschede: International Institute for Geo-Information Science and Earth Observation (ITC)
- Projo D. 1996, Digital image Processing: Theory and its Application in Remote Sensing Field, Enschede: International Institute for Geo-Information Science and Earth Observation (ITC)
- Shrestha and BP Dhruva. 1991. Digital image Processing, Enschede: International Institute for Geo-Information Science and Earth Observation (ITC)
- Torkashvand AM. 2010, The possibility in providing soil surface erosion map by the supervised classification of ETM+ satellite images in a mountainous basin (Roodbar sub-basin, Guilan, Iran). *Sci Res Essays* 5: 343-348.
- Verhoeve J and R de Wulf R. 1999. An image processing chain for land covers classification using multitemporal ERS1 data. *Photo Eng Remote Sens* 65: 1179-1186.
- Zhao P, XZ Feng and GF Lin. 2003. The Decision Tree Algorithm of Automatically Extracting Residential Information from SPOT Images. *J Remote Sens* 7 (4): 310-315 (in Chinese).