Korean Journal of Remote Sensing, Vol.27, No.3, 2011, pp.315~328

Assessing the Extent and Rate of Deforestation in the Mountainous Tropical Forest

Eko Pujiono*, Woo-Kyun Lee*†, Doo-Ahn Kwak and Jong Yeol Lee***

*Department of Environmental Science and Ecological Engineering, Korea University, Seoul, 136-713, Republic of Korea

**Environmental GIS/RS Center, Korea University, Seoul, 136-713, Republic of Korea

Abstract : Landsat data incorporated with additional bands-normalized difference vegetation index (NDVI) and band ratios were used to assess the extent and rate of deforestation in the Gunung Mutis Nature Reserve (GMNR), a mountainous tropical forest in Eastern of Indonesia. Hybrid classification was chosen as the classification approach. In this approach, the unsupervised classification-iterative self-organizing data analysis (ISODATA) was used to create signature files and training data set. A statistical separability measurement-transformed divergence (TD) was used to identify the combination of bands that showed the highest distinction between the land cover classes in training data set. Supervised classification-maximum likelihood classification (MLC) was performed using selected bands and the training data set. Post-classification smoothing and accuracy assessment were applied to classified image. Post-classification comparison was used to assess the extent of deforestation, of which the rate of deforestation was calculated by the formula suggested by Food Agriculture Organization (FAO). The results of two periods of deforestation assessment showed that the extent of deforestation during 1989-1999 was 720.72 ha, 0.80% of annual rate of deforestation, and its extent of deforestation during 1999-2009 was 1,059.12 ha, 1.31% of annual rate of deforestation. Such results are important for the GMNR authority to establish strategies, plans and actions for combating deforestation.

Key Words : deforestation, Landsat, band ratios, hybrid classification, mountainous forest

1. Introduction

In recent years, many forest areas around the world tend to decrease gradually. In their latest assessment-Forest Resources Assessment 2010, Food Agricultural Organization (FAO) reported that in the period of 1990~2000, the net global forest loss was estimated about 8.3 million ha/year and in the period of 2000 ~2010, deforestation rate was estimated at 5.2 million ha/year (FAO, 2010). In country level, Indonesia is an example of a particular country experiencing large-scale of deforestation. Sunderlin *et al.*, (2005), reported that Indonesia ranks third in its endowment of tropical forest after Brazil and Zaire. In 1996, total forest cover in Indonesia was 120.6 million ha or 69% of total land in Indonesian territory, while in

Received May 7, 2011; Revised May 25, 2011; Accepted May 26, 2011.

† Corresponding Author: Woo-Kyun Lee (leewk@korea.ac.kr)

2003, it decreased to approximately 90 million ha, equivalent to 46% of total land (Government of Indonesia-FAO, 1996).

In order to avoid and reduce such deforestation, the deforestation areas and their rates should be monitored and assessed. The deforestation assessment is intended to be used: (a) to identify priorities for action in combating deforestation, (b) as a framework and source of tools for forest planning and management, (c) as a benchmark for future forest or environmental assessment, and (d) to guide future research.

One of the several approaches to assess deforestation has been Remote Sensing (RS) techniques. The main distinction of RS techniques for deforestation assessment is its ability to provide detailed quantitative land surface information at large spatial coverage and at frequent temporal intervals when compared with other approaches such as traditional land inventorial surveys (Prenzel, 2004). The other advantages are the repetitive acquisition on issued and inaccessible area with visible and invisible wavelength based on near-real time (FAO, 2007). Bonfour and Lambin (1999) also reported that RS data is cost-effective based on their study using economic approach and benefit cost analysis in tropical deforestation cases. In other word, previous study emphasized that RS is an approach that is technically and economically advantageous for assessing deforestation.

Several studies based on RS techniques have been conducted in Indonesia. Most of previous forest assessments in Indonesia used Landsat and supervised classification method as input data and classification method respectively (Forest Watch Indonesia-FWI, 2003; Gaveau *et al.*, 2007; Gaveau *et al.*, 2009; Mulyanto and Jaya, 2004). According to Bauer *et al.* (1994), supervised techniques were determined to be inadequate for a number of reasons: extreme forest complexity, narrow cover type spectral separability, and limited potential for automated processing. For alternative techniques, he suggested to use guided clustering that combines the training from unsupervised technique and classification process with supervised techniques. This technique was highly automated in processing, so this method was ideal for large area application (Bauer *et al.*, 1994) as same as Indonesian forest areas. Therefore, guided clustering was employed as classification method in this study.

Although several studies on deforestation assessments using RS technique have been conducted in Indonesia, little studies have been conducted in small islands. Almost studies have focused on assessing deforestation process in big islands that have large forest areas such as Sumatra (Broich *et al.*, 2011; Gaveau *et al.*, 2007; Gaveau *et al.*, 2009; Linkie *et al.*, 2004; Mulyanto and Jaya, 2004), Kalimantan (Broich *et al.*, 2011; Fuller *et al.*, 2010), Irian Jaya (FWI, 2003; FWI & CIFOR, 2006) and Sulawesi (Macdonald *et al.*, 2011; Prenzel and Treitz, 2004). In the other hand, Timor located in East Nusa Tenggara (ENT) Province is a small island which has less forest cover when compared with others big islands. The assessment of forest cover change in Timor Island was only performed by government agencies whereas there are little studies on deforestation by organizations or individuals. Monitoring and assessment of deforestation in small island is important because deforestation on small islands and areas of less forest cover will be expected in greater impact because of the limitation of existing nature resources, high dependence on forest resource and the fragility of ecological systems in small island (Tole, 2002).

The Gunung Mutis Nature Reserve (GMNR) is a mountain tropical forest in Timor Islands that tends to decrease gradually because of wood collection, boundary and land disputes, livestock grazing and agriculture expansion (Eghenter, 2000; Fisher *et al*, 1998; Fisher *et al*, 2003; Lentz *et al*, 1998). This study would demonstrate how to measure decreased forest area or deforestation using RS techniques within the GMNR area. Based on the consideration that study area is mountainous area, we would use band ratio as additional bands in image classification process. Application of band ratios make spectral variability caused by some constraints to image classification in mountainous regions such as sun illumination difference, elevation diference and presense of shadow due to topographic variation (Shrestha and Zink, 2001; Zhang *et al.*, 2011) be reduced (Lillesand *et al.*, 2004; Jensen, 2005). Therefore, this study attempts to assess the extent and rate of deforestation in the mountainous tropical forest (the GMNR) area using multi-temporal Landsat data incorporated with band ratios and hybrid classification technique for the period of 1989-2009.

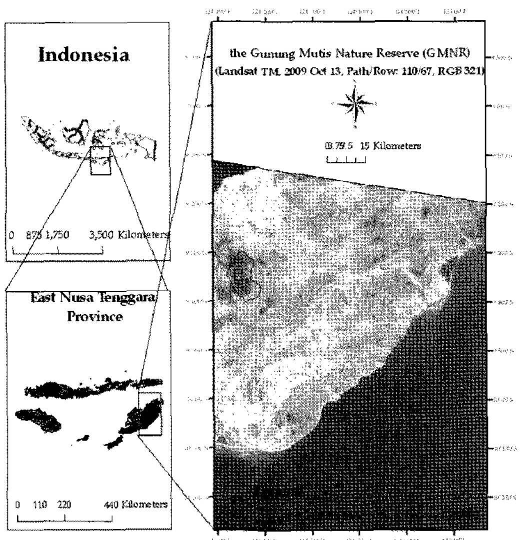

Fig. 1. Study area.

2. Materials and methods

1) Study area

The GMNR is administratively located at East Nusa Tenggara Province, Eastern part of Indonesia and geographically located between 124°10'-124°20'E and 9°30'- 9°40'S (Fig. 1). Overall topography in the GMNR area is hilly as a large part of its territory has a slope of 60% or above. The highest peak is Gunung (mount) Mutis with elevation 2,427 m above mean sea level. The GMNR areas consist of unique mountain forest dominated by homogenous stands of Timor mountain gum (*Eucalyptus urophylla*), grasslands and several small rivers draining in all directions.

The GMNR's forests are important at the local, regional and international levels (Lentz *et al.*, 1998). At a local level, communities use forest areas as grazing lands for livestock as well as a source of income supplements, building materials, and fuel wood. At regional level, forests in the GMNR area play a critical role as water catchment areas, especially given their location in the steep and mountainous interior. At international level, the unique ecology of forested areas and their high levels of species endemism and biodiversity lend international importance to their conservation. Therefore, the GMNR was employed as the study area.

2) Data

Landsat satellite images acquired by United State Geological Survey (USGS) and GIS data were used in this study as following Table 1.

Three different band ratios (band 4/band 3, band 4/band 5 and band 7/band 2) and Normalized Difference Vegetation Index (NDVI) were used as additional bands. The advantage of that using band ratio as an additional data is based on their ability to reduce many form of multiplicative noise such as sun illumination difference and some topographic

Table 1. List of data used

Data	Date of acquisition	Source
Landsat TM, Path 110 Row 67, L 1G[1], resolution 30m	1989/09/20	USGS
Landsat ETM, Path 110 Row 67, L 1G[1], resolution 30m	1999/09/08	USGS
Landsat TM, Path 110 Row 67, L 1G[1], resolution 30m	2009/10/13	USGS
Topographic Maps, scale: 1:25,000	1993, 1999, 2001	NCSMA[2]
The GMNR Vector Boundary	1999	MoF[3]

[1]L 1G = level 1G (systematic correction) data provided systematic radiometric and geometric accuracy
[2]NCSMA = National Coordinator for Survey and Mapping Agency, Indonesia
[3]MoF= Ministry of Forestry, Indonesia

variations (Lillesand *et al.*, 2004; Jensen, 2005).

The ratio of band 4 and band 3, known as simple ratio (Lillesand *et al.*, 2004), can be useful to distinguish forest and water body. Forests or vegetations appear in lighter tones because of their relatively highly reflectance in band 4 (near-infrared band) regions and low reflectance (strong absorption) in band 3 (red band) regions (Lillesand *et al.*, 2004). Water bodies appear in darker tones because of their relatively highly reflectance in band 3 regions and low reflectance in band 4. The ratio of band 4 and band 5 (mid-infrared band) enhances vegetation and presence of moisture content in the croplands/ agriculture (Rahman, 1997). In this ratio, vegetation generally appears in lighter tones because of high reflectance in band 4 and its comparatively lower reflectance in band 5. Band 7 (mid-infrared band) and band 2 ratio separates forests and croplands/ agriculture. It enhances built-up areas, soils and agriculture areas. All of them appears as lighter tone (Rahman, 1997), whereas dense vegetation/forest appears as darker tones.

Because major part of study area was dominated by vegetation, NDVI was also used as additional band to enhance the separability among vegetation class, to reduce the shadow effect due to topography variations (Saha *et al.*, 2005) and to extract vegetated and non vegetated areas. The positive value of NDVI represented different types of vegetation classes whereas near zero and negative values indicated non-vegetation classes (Yacouba *et al.*, 2009). NDVI was computed from the equation developed by Rouse *et al.* (1974).

$$NDVI = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}} \tag{1}$$

where:
NIR = near-infrared radiant flux
RED = red reflected radiant flux

Totally, the image data set consisted of nine data layers (five original bands of Landsat-Band 2, 3, 4, 5, 7 and four additional bands-NDVI, ratio of band 4/ band 3, ratio of band 4/ band 5 and ratio of band 7/ band 2)

3) Image pre-processing

The image data set were geometrically corrected with World Geodetic System (WGS) 1984 datum and Universal Transverse Mercator (UTM) coordinate system. To do this, 1999-image was georeferenced using ground control points (GCPs) that were collected from 1999-topographic map. The 1989 and 2009 images were then registered to 1999-image using same reference of GCPs. The geometric transformation were performed using a second-order polynomial and nearest neighbour interpolation. The result of geometric correction on three images showed high geometric accuracy, with root mean square error (RMSE) of less than 0.02 pixels. The

Table 2. Land cover classification scheme used in this study

Land cover class	Description
Forests	Lowland, hilly or mountainous areas with mature trees; areas with estimated >70% of the existing crown covered by trees
Shrubs	Logged over areas with young regeneration of trees or small tress; degraded forest areas with estimated approximately 10% of the tree crown cover are also included
Grasslands	Non forest areas with grassland; non irrigated agriculture and dryland agriculture are also included

three images were then spatially resampled with nearest-neighbour techniques. Study area was determined by performing subset operation with guide of the GMNR vector boundary.

4) Image classification

(1) Land cover classification scheme

The selection of land cover classes to be considered for image classification was based on the land cover/land use classification system developed by Indonesian Ministry of Forestry (FWI & CIFOR, 2006). Based on Ministry of Forestry land cover classification system, our classification scheme comprised three land cover types representing the dominant land cover types in the study area (Table 2).

(2) ISODATA for creating training data set

The unsupervised classification with iteractive self-organizing data analysis (ISODATA) was used to create signature file and training data set. ISODATA enabled exploration of the spectral contents of an input image and automatically selects spectral cluster (Jensen, 2005; Abdulaziz *et al.*, 2009). This information was used to create signature file of image. A signature file is a set of data that defines a training sample or cluster (Leica Geosystems, 2005). In this study, 30 classes or spectral clusters would be obtained from ISODATA with 95% convergence threshold and 20 of maximum iteration number. The definition of 30 classes or clusters was the maximum number of clusters to be considered. In the first iteration of the ISODATA, the means of 30 clusters could be arbitrarily determined. After each iteration, a new mean for each cluster was calculated, and then a new mean was used for defining cluster in the next iteration. The process continued until there was a little change between iteration (Leica Geosystems, 2005). 30 classes obtained were then visually inspected, identified and matched with spesific landcover types derived from topographic map of study area. Classes corresponded to the land cover types in our classification scheme were then selected as training data set.

(3) Separability analysis for band selection

To identify the combination of bands that show the highest distinction between the land cover classes, a separability analysis was performed using the training data set derived from ISODATA. The separability is a statistical measurement devised on the basis of spectral distances computed for a combination of bands (Redy and Blah, 2009; Saha *et al.*, 2005). Divergence was one of the first measures of statistical separability used and it is still widely used as a method of band selection (Jensen, 2005). Divergence is computed using the mean and covariance matrix of the class statistic collected in the training phase. From several types of divergence, transformed divergence (TD) method was chosen in this study. It scaled the divergence values between 0 and 2000. A transformed divergence value of 2000 suggested excellent between-class separation, above 1900 provided good separation, while below 1700 was poor separation (Jensen, 2005). Divergence (D_{cd}) and transformed divergence (TD_{cd}) were computed as following equations (Jensen, 2005).

$$D_{cd} = \frac{1}{2} tr[(V_c - V_d)(V_d^{-1} - V_c^{-1})] + \frac{1}{2} tr[(V_d^{-1} - V_c^{-1})(M_c - M_d)(M_c - M_d)^T] \quad (2)$$

$$TD_{cd} = 2000\left[1 - \exp\left(\frac{-D_{cd}}{8}\right)\right] \quad (3)$$

where:

$tr[\,]$ = the trace of a matrix (i.e., the sum of the diagonal elements)

V_c and V_d = the covariance matrix for the two classes under investigation, c and d

M_c and M_d = the mean vector for classes c and d

(4) Supervised classification

By applying selected bands from separability analysis and the training data set derived from ISODATA process, Maximum likelihood classification (MLC) was performed to produce land cover map. MLC quantitatively evaluated both the variance and covariance of the category spectral response patterns when classifying an unknown pixel (Lillesand *et al.*, 2004; Redy and Blah, 2009). MLC has been found to be most accurate and commonly used classifier (Jensen, 2005; Saha *et al.*, 2005).

(5) Post-classification smoothing

Post-classification smoothing was used to reduce the salt and pepper due to inherent spectral variability encountered by a classifier when applied on a pixel-by-pixel basis (Lillesand *et al.*,2004). In this study, a 3×3 pixel majority filter was applied to the classified image.

(6) Accuracy assessment

For accuracy assessment, the cross-tabulated matrix prepared arranged by comparing classified image and reference data (Congalton, 1991). 100 points on each 1993- and 1999-topographic map were used to assess the accuracy of 1989- and 1999-classified image, respectively. Combination of 12 points derived from 2009-ground truth data and 78 points from 2003-topographic map were used to verify the 2009-classified image. Kappa statistic and overall accuracy were calculated based on cross-tabulated matrix.

5) Deforestation assessment using change detection analysis

The extent and rate of deforestation areas could be computed by comparing the area under forest cover in the same region at two or more different times (Puyravaud, 2002). The extent of deforestation could be assessed by performing post classification change detection analysis that provide quantitative 'from forest to non forest' information. By applying a formula suggested by FAO (1995), the deforestation rate (R) could be calculated as following equation.

$$R = \left(\frac{A_2}{A_1}\right)^{1/(t_2 - t_1)} - 1 \quad (4)$$

where :

t_1 and t_2 = time 1 and time 2

A_1 and A_2 = forest area at time t_1 and t_2

Fig. 2 is a flowchart summarizing the steps involved in the assessment of the extent and rate of deforestation.

3. Results and discussions

1) Implementation of classification

We adopted the guided clustering or hybrid classification method for land cover classification. 30 classes for candidate of training data set were obtained from ISODATA analysis. Based on visual inspection and identification with the guide of the 1:25000 scale topographic map, we got some of classes corresponded to the land cover types in our classification scheme (Table2) that would be used as training data (Table 3). Separability analysis on the

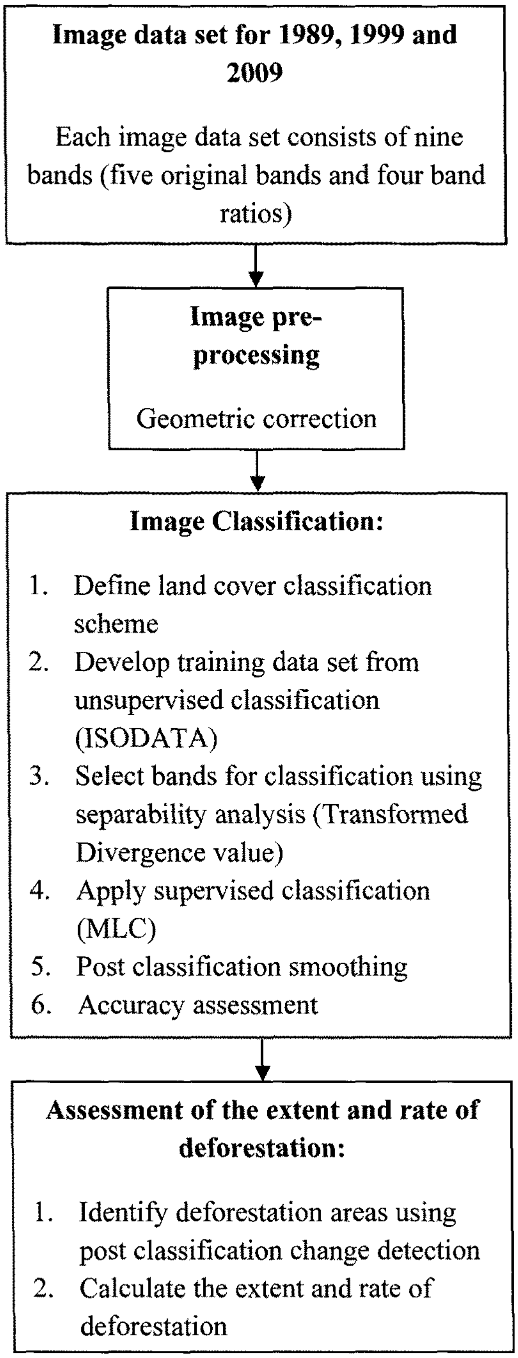

Fig. 2. Flowchart of the steps involved in the assessment of the extent and rate of deforestation.

three image data set using selected training data set showed that band combinations that consist of band ratio layer give the highest average of TD value

Table 3. Number of training pixels

Land cover class	Number of training pixels		
	1989 image	1999 image	2009 image
Forests	72929	91178	71750
Shrubs	12667	19984	13573
Grasslands	28600	29793	36346

Table 4. Optimum band combinations and TD values obtained from separability analysis

Images	Band combination	Average TD value
1989	2, NDVI, band ratio 4/3	2000
1999	2, band ratio 4/3, band ratio 4/5	2000
2009	2, 5, band ratio 4/3	2000

(Table 4). Selected training data and selected band combinations were used to perform supervised-MLC to produce land cover maps.

2) Land cover map

The land cover maps (Fig. 3) show the distribution of land cover classes within the GMNR area. Forest classes are commonly located in the middle of the GMNR area, shrub classes are commonly found in the transition of forest classes and grassland classes and grassland classes are commonly found along the GMNR boundary. The areal extent of land cover classes in the land cover map obtained from hybrid classification (Fig. 4) show that forest was dominant land cover type and covered 66% of the GMNR area in 1989, 61% in 1999 and 53% in 2009.

3) Accuracy assessment

The accuracy assessment for three classified image were shown in Table 5. Overall accuracy for 1989, 1999 and 2009-classified images were 82%, 86% and 84%, respectively. Previous studies with similar method-guided clustering reported that the overall accuracy ranged from 64-80% (Bauer *et al.*, 1994) and 70-84% (Reese *et al.*, 2002). The comparison of accuracy value between this study and previous

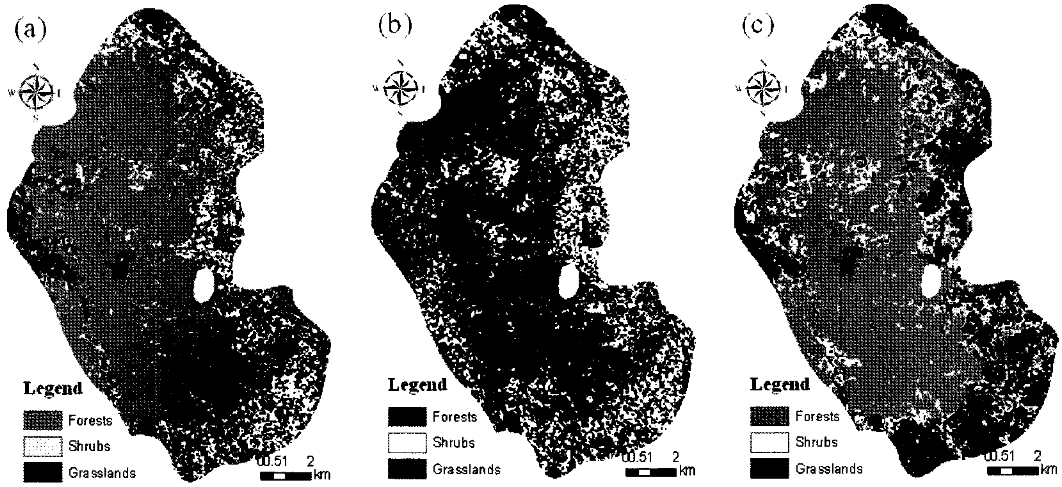

Fig. 3. Distributions of land cover classes within the GMNR area in three different year: (a) 1989, (b) 1999 and (c) 2009.

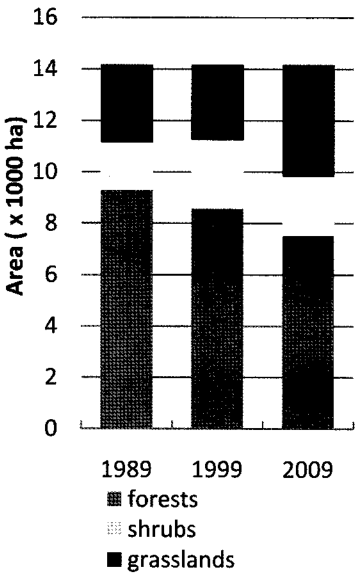

Fig. 4. Stacked histogram showing the areal extent (in thousand ha) of land cover classes in the land cover map obtained from hybrid classification.

studies indicate that the range of accuracy value of this study were slightly higher than those in previous study. This difference might be caused by data used-where this study used additional data, while previous study only used original band of Landsat data.

Kappa coefficients were estimated to be 0.72, 0.76 and 0.74 for 1989-, 1999- and 2009-classified image, respectively. Landis and Koch (1977) and Congalton (1996) stated that kappa values above 0.80 (80%) represent of strong agreement, a value between 0.40 and 0.80 (40% to 80%) represent moderate agreement and a value below 0.40 (40%) represent poor agreement. Therefore, the Kappa values of this study represent moderate agreement.

In Table 5, overall kappa statistic in 1999-classified image was higher than those in 1989- and 2009-classified image. It was attributed to the fact that the reference data used for 1999-classified image, 1: 25.000 topographic map derived from aerial photograph, were acquired in 1999, for 1989-classified image with 1993-topographic map and for 2009-classified image with 2001-topographic map. Temporal difference between classified image and reference data is possibly the source of error.

The accuracy assessment of individual categories (forest, shrubs and grasslands) was also represented with producer's and user's accuracy. For example, in 2009-classified image, the producer's and user's accuracy of forest was 91.30% and 94.23%

Table 5. Accuracy assessment of classified image for (a) 1989, (b) 1999 and (c) 2009

(a) 1989

Classified data	Reference data			Row total	User's accuracy (%)	Kappa
	Forest	Shrubs	Grasslands			
Forest	42	6	2	50	84.00	0.70
Shrubs	3	16	2	21	76.19	0.67
Grasslands	1	4	24	29	82.76	0.76
Column total	46	26	28	100		
Producer's accuracy (%)	91.30	61.54	85.71			
Total correct	82					
Overall accuracy (%)	82					
Overall kappa statistics	0.72					

(b) 1999

Classified data	Reference data			Row total	User's accuracy (%)	Kappa
	Forest	Shrubs	Grasslands			
Forest	53	5	0	58	91.00	0.81
Shrubs	1	15	3	19	78.95	0.72
Grasslands	0	5	18	23	78.26	0.72
Column total	54	25	21	100		
Producer's accuracy (%)	98.15	60.00	85.71			
Total correct	86					
Overall accuracy (%)	86					
Overall kappa statistics	0.76					

(c) 2009

Classified data	Reference data			Row total	User's accuracy (%)	Kappa
	Forest	Shrubs	Grasslands			
Forest	49	3	0	52	94.23	0.87
Shrubs	3	13	4	20	65.00	0.56
Grasslands	1	5	22	28	78.57	0.71
Column total	53	21	26	100		
Producer's accuracy (%)	92.45	61.90	84.62			
Total correct	84					
Overall accuracy (%)	84					
Overall kappa statistics	0.74					

respectively. It could be interpreted that 91.30% of forest area had been correctly identified to be forest, and 94.23% of forest areas were actually forest.

In all of three classified image, the accuracy assessment of shrubs was low (approximately 60% of producer's accuracy). In 1989-classified image, where forest dominated land cover (Fig. 3 and Fig. 4), shrub classes were most often confused with forest classes (23% commission error; Table 5a). In some cases, especially in dense shrub areas, it was difficult to distinguish shrub and forest. This might have been due to similar spectral value between shrubs and forest. In 2009, when grassland classes (grasslands and agriculture areas) increased (Fig. 3 and Fig. 4), shrub classes were most often confused with grassland classes (24% commission error; Table 5c).

In some areas, it was also difficult to distinguish very sparse shrubs with grasslands areas. Therefore, it was reasonable if shrubs would be identified as grasslands. This result is in line with previous study that also had difficulties for classifying shrubs in particular (Reese *et al.*, 2002).

4) Deforestation assessment using change detection analysis

Change detection analysis results (Table 6 and Fig. 5) show that forest areas tend to decrease gradually during two time intervals of change detection analysis (1989-2009 and 1999-2009), whereas grassland/agriculture tend to increase, especially for 1999-2009. In time interval of 1989-1999, 85% of forest areas were unchanged, 11% of forest areas were converted to shrub and 4% of forest areas to grass/agriculture. Another time interval, 1999-2009, show that 81% of forest areas were unchanged, 11% and 8% of forest areas were converted to shrub and grass/agriculture, respectively.

As Table 7 indicates, the GMNR has the change of 720.72 ha in forest area during 1989-1999 with 0.80% of the annual deforestation rate. During 1999-2009, the deforestation rate was higher with 1.31% of annual deforestation rate and overall forest loss was estimated 1.059.12 ha. The difference on deforestation rate between two time intervals of assessment might be caused by the difference of political condition at those times. Some previous studies have highlighted the explosion of illegal logging caused by political instability in Indonesia during late of 1900s and early of 2000s period

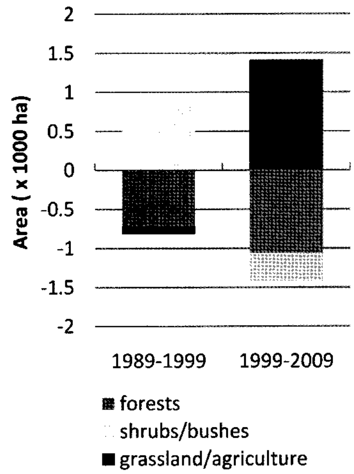

Fig. 5. The change in land cover classes obtained from change detection analysis.

Table 6. 'From-to' change detection statistic for the time intervals of (a) 1989-1999 and (b) 1999-2009

(a) 1989-1999 change detection statistics (ha)

1989-Class	1999-Class			Total 1989
	Forest	Shrubs	Grasslands	
Forest	7,940.16	1,001.70	353.97	9,295.83
Shrubs	355.05	981.45	523.17	1,859.67
Grasslands	279.90	689.94	2,037.42	3,007.26
Total 1999	8,575.11	2,673.09	2,914.56	14,162.76

(b) 1999-2009 change detection statistics (ha)

1999-Class	2009-Class			Total 1999
	Forest	Shrubs	Grasslands	
Forest	6,977.43	934.29	663.39	8,575.11
Shrubs	419.58	853.11	1,400.40	2,673.09
Grasslands	118.98	531.54	2,264.04	2,914.56
Total 2009	7,515.99	2,318.94	4,327.83	14,162.76

Table 7. The extent and rate of deforestation for the time intervals of 1989-1999 and 1999-2009

The extent and rate of deforestation	Time interval	
	1989-1999	1999-2009
Overall of deforestation (ha)	720.72	1,059.12
Annual deforestation (ha)	72.07	105.91
Annual deforestation rate (%)	0.80	1.31

(Burgess *et al.*, 2010; Casson and Obidzinski, 2002; Singer, 2009). Based on this fact, it is reasonable that the deforestation rate in 1999-2009 was higher than the deforestation rate in 1989-1999.

Another deforestation assessment developed by FAO in 2010 reported that annual rate of deforestation in Indonesia were 1.75%, 0.51% during the period of 1990-2000 and 2000-2010 respectively (FAO, 2010). Comparison between FAO's deforestation assessment with this study show that there are some differences in the rate of deforestation. Rate of deforestation during 1989-1999 in this study is lower than FAO's assessment in the case of 1990-2000. In contrary, the rate of deforestation in 1999-2009 was higher than FAO's assessment during 2000-2010. These differences are probably attributed to the temporal difference between those assessments and scope of coverage area. In their assessment, FAO used sampling and calculated average of deforestation in country scope, so it is possible that not all areas of this study are included in their assessment. Therefore, the rates of deforestation between FAO's assessment and this study assessment are different.

5) Comparison with previous studies

In order to prove the results of this study, we compared with previous studies that have similarity both in method used or study area condition. Saha *et al.* (2005) demonstrated multi source classification approach using original bands of RS data together with NDVI band to classify a mountain forest area in India. They found that there was an improvement in accuracy of classification when original bands of RS data and NDVI bands were used together in classification process. Bahadur (2009) used original bands of RS data, band ratios and hybrid classification approach to produce land cover map in a mountainous landscape in Nepal. He found that the use of band ratios in three bands combination showed higher accuracy value than the combination of original bands of RS data. Both of two previous study found that the accuracy of classification in mountainous areas could be improved by modification of original bands and integration of additional bands. In this study, it was found that the use of band ratios and NVDI as additional data have produced the best separability among land cover classes (Table 4) that will result in better accuracy in image classification process. So, this study is in line with previous studies which found that the additional bands, such as band ratios and NDVI could reduce the effect of shadow, which is a problem for satellite image interpretation in mountain area.

4. Conclusions

This study has estimated that during the period of 1989-1999, the extents of deforestation were 720.72 ha and increased into 1,059.12 ha in the period of 1999-2009. During the period of 1989-1999, the GMNR lost on 0.8% of its forest cover per year and in the period of 1999-2009, 1.31% of its forest cover were lost annually. This loss will threaten the significant contribution of the GMNR forest to provide ecological and economical functions.

In line with other studies, this study found that original band of Landsat data incorporated with additional band, such as NDVI and band ratios, to be particularly useful for satellite image interpretation in the mountain forest area, when a hybrid classification is applied. The lack of reference data and ground truth data in this study may affect the result and accuracy of image interpretation. In order to improve the accuracy of classified image obtained from digital image classification in the mountainous regions, it is important to combine the method in this study with other methods such as topographic normalization or using ancillary data such as Digital Elevation Model (DEM) for further research. However, the extent and rate of deforestation resulted from satellite image interpretation in this study, could be important for the GMNR authority to formulate plans, strategies, and actions for combating deforestation.

References

Abdulaziz, A. M., J. M. Hurtado, and R. Al-Douri, 2009. Application of multitemporal Landsat data to monitor land cover change in the Eastern Nile Delta region, Egypt. *International Journal of Remote Sensing*, 30(11): 2977-2996.

Bahadur, K., 2009. Improving Landsat and IRS Image Classification: Evaluation of Unsupervised and Supervised Classification through Band Ratio and DEM in a Mountainous Landscape in Nepal. *Remote Sensing*, 1: 1257-1272.

Bauer, M. E., T. E. Burk, A. R. Ek, P. R. Coppin, S. D. Lime, T. A. Walsh, D. K. Walters, W. Befort, and D. F. Heinzen, 1994. Satellite Inventory of Minnesota Forest Resources. *Photogrammetric Engineering & Remote Sensing*, 60(3): 287-298.

Bonfour, A. and E. F. Lambin, 1999. How valuable is remote sensed information? The case of tropical deforestation modelling. *Space Policy*, 15: 149-158.

Broich, M., M. Hansen, F. Stolle, P. Potapov, B. A. Margono, and B. Adusei, 2011. Remote sensed forest cover loss shows high spatial and temporal variation across Sumatera and Kalimantan, Indonesia 2000-2008. *Environmental Research Letter*, 6.

Burgess, R., M. Hansen, B. Olken, and S. Sieber, 2010. *The political economy of deforestation in the tropics*. The University of Warwick, Coventry, UK.

Casson, A. and K. Obidzinski, 2002. From New Order to Regional Autonomy: Shifting Dynamics of 'Ilegal' Logging in Kalimantan, Indonesia. *World Development*, 30(12): 2133-2151.

Congalton, R., 1991. A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data. *Remote Sensing of Environment*, 37: 35-46.

Congalton, R., 1996. *Accuracy Assessment: A Critical Component of Land Cover Mapping*. Gap Analysis. Gap Analysis. American Society for Photogrammetry and Remote Sensing.

Eghenter, C., 2000. Mapping Peoples '*Forests: The Role of Mapping in Planning Community-Based Management of Conservation Areas in Indonesia*. Washington DC.: Biodiversity Support Program (BSP).

FAO, 1995. *Forest Resources Assessment 1990. Global Synthesis*. FAO, Rome, Italy.

FAO, 2007. *Manual on Deforestation, Degradation and Fragmentation using Remote Sensing and GIS*. MAR-SFM Working Paper 5/2007.Food and Agriculture Organization of the United Nations, Rome.

FAO, 2010. *Global Forest Resources Assessment 2010*. FAO Forestry Paper No. 163, the United Nations, Food and Agriculture Organization, Rome.

Fisher, L. M., 1998. Cattle, Cockatoos, Chameleons and Ninja Turtles: Seeking Sustainability in Forest Management and Conservation in Nusa Tenggara, *Indonesia. International CBNRM Workshop*. Washington D.C.

Fisher, L., I. Moeliono, and S. Wodicka, 2003. The Nusa Tenggara Upland, Indonesia: Multiple-site lessons in conflict management. In D. Buckles (Ed.), *Cultivating Peace - Conflict and Collaboration in Nature Resources Management* (p. 300pp). Ottawa, Canada: International Development Research Center (IDRC).

Fuller, D. O, E. M. Meijaard, L. Christy, and T. C. Jessup, 2010. Spatial Assessment of threats to biodiversity within East Kalimantan, Indonesia. *Applied Geography*, 30: 416-425.

FWI & CIFOR., 2006. *Analisa Kondisi Tutupan Hutan di Papua dan Irian Jaya Barat Sebagai Salah Satu Langkah untuk Mendukung Pengelolaan Hutan Alam dan Pembatasan Konflik di Sektor Kehutanan*. Laporan Updating Landcover Mapping Papua, Kerjasama: FWI-Bogor dan CIFOR, Bogor. (In Indonesian language)

FWI., 2003. *Pemetaan Land Use Land Cover (LULC) dari Penginderaan Jauh Landsat7 ETM+ untuk Wilayah Mamberamo dan Raja Ampat Provinsi Papua*. Laporan Proyek, Kerjasama: FWI, Baplan-Departemen Kehutanan dan Conservation International Indonesia-Papua Program, Bogor. (In Indonesian language)

Gaveau, D. L. A., M. Linkie, Suyadi, P. Levang, and N. Leader-Williams, 2009. Three decades of deforestation in southwest Sumatra: Effects of coffe prices, law enforcement and rural poverty. *Biological conservation*, 142: 597-605.

Gaveau, D. L. A., H. Wandono, and F. Setiabudi, 2007. Three decades of deforestation in Soutwest Sumatra: Have protected area halted forest loss and logging, and promoted re-growth? *Biological Conservation*, 134: 495-504.

GoI-FAO, 1996. *National Forest Inventory of Indonesia : Final Forest Resources Statistics Report. Directorate General of Forest Inventore and Land Use Planning*, Ministry of Forestry Government of Indonesia and Food and Agriculture Organization of the United Nations, Jakarta.

Jensen, J., 2005. *Introductory Digital Image Processing: A Remote Sensing Perspective* (3rd ed.). Upper Saddle River, NJ: Pearson Education, Inc.

Landis, J. and G. Koch, 1977. The measurement of Observer Agreement for Categorical Data. *Biometrics*, 33: 159-174.

Leica Geosystems, 2005. *Erdas Field Guide*, Leica Geosystems Geospatial Imaging, LLC, Norcross, GA, USA.

Lentz, C., M. Malo, and M. Bowe, 1998. Environmental Management in Gunung Mutis. *International Association for the Study of Common Property*, 10-14 June. Vancouver, Canada.

Lillesand, T. M., R. W. Kiefer, and J. W. Chipman, 2004. *Remote Sensing and Image Interpretation* (5th ed.). Hoboken, NJ: John Willey & Sons, Inc.

Linkie, M., R. J. Smith, and N. L. Williams, 2004. Mapping and predicting deforestation patterns in the lowlands of Sumatra. *Biodiversity and Conservation*, 13:1809-1818.

Macdonald, E. A., M. Collins, P. J. Johnson, L. M. Clayton, Y. Malhi, J. B. Fisher, E. J. Milner-Gulland, and D. W. Macdonald, 2011. Wildlife conservation and reduced emission from deforestation in a case study of Nantu National Park, Sulawesi. *Environmental Science & Policy, article in press, doi: 10.1016/j.envsci. 2011.03.003*.

Mulyanto, L. and I. N. S. Jaya, 2004. Analisis Spasial

Degradasi Hutan dan Deforestasi: Studi Kasus di PT. Duta Maju Timber, Sumatera Barat. *Manajemen Hutan Tropika*, *X*(1), 29-42.(In Indonesian language)

Prenzel, B., 2004. Remote sensing-based quantification of land-cover and land-use change for planning. *Progress in Planning*, 61: 281-299.

Prenzel, B. and P. Treitz, 2004. Remote sensing change detection for a watershed in nort Sulawesi, Indonesia. *Progress in Planning*, 61: 349-363.

Puyravaud, J., 2003. Standardizing the calculation of the annual rate of deforestation. *Forest Ecology and Management*, 177: 593-596.

Rahman, M., 1997. *Identification of Land Use and Land Cover using Band Ratioing Tecnique*. Retrieved June 1, 2011, from http://www.murraystate.edu/qacd/cos/geo/gsc641/1997/rahman/

Redy, M. B. and B. Blah, 2009. Topographic normalization of satellite imagery for image classification in India. *Progress in Physical Geography*, 33(6): 815-836.

Reese, H. M, T. M. Lillesand, D. E. Nagel, J. S. Stewart, R. A. Goldmann, T. E. Simmons, J. W. Chipman, and P. A. Tessar, 2002. Statewide landcover derived from multiseasonal Landsat TM data: A retrospective of the WISCLAND project. *Remote Sesing of Environment*, 82: 224-237.

Rouse, J. W., R. H. Haas, J. A. Schell, and D. W. Deering, 1974. Monitoring Vegetation Systems in Great Plains with ERTS. *Proceedings, 3rd Earth ResourceTechnology Satellite (ERTS) Symposium*, 1: 48-62.

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. *Geocarto International*, 20(2): 33-40.

Shrestha, D. P. and J. A. Zink, 2001. Land use classification in mountainous areas: integration of image processing, digital elevation data and field knowledge (application to Nepal). *International Journal of Applied Earth and Geoinformation*, 3(1): 78-85.

Singer, B., 2009. *Indonesian Forest-Related Policies: A Multisectoral Overview of Public Policies in Indonesia's Forests since 1965*. PhD Thesis (Draft), Institut d'Etudes Politiques and CIRAD, France.

Sunderlin, W. D., A. Angelson, B. Belcher, P. Burgers, R. Nasi, L. Santoso, S. Wunder, 2005. Livelihoods, Forests, and Conservations in Developing Countries: An Overview. *World Development*, 33(9): 1383-1402.

Tole, L., 2002. An estimate of forest cover extent and change in Jamaica using Landsat MSS data. *International Journal of Remote Sensing*, 23(1): 91-106.

Yacouba, D., H. Guangdao, and W. Xingping, 2009. Assessment of Land Use Cover Changes using Ndvi and Dem in Puer and Simao Counties, Yunnan Province, China. *World Rural Observation*, 1(2): 1-11.

Zhang, Z., R. R. D. Wulf, M. B. V. Coillie, L. P. C. Verbeke, E. M. De Clercq, and X. Qu, 2011. Influence of different topographic correction strategies on mountain vegetation classification accuracy in the Lancang Wathershed, China. *Journal of Applied Remote Sensing*, 5: 1-21.