A Comparison of Neural Networks and Maximum Likelihood Remotely Sensed Data Classifiers to Detect Logged-Over Tropical Rain Forest in Indonesia

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Abstract

Selective logging has been applied in the Indonesian tropical rain forest since the 1960. This has resulted in thousands of hectares of logged-over forest. In Labanan, Berau, East Kalimantan, selective logging will enter the second rotation in 2010. A comprehensive analysis of the forest condition should be made before harvesting the logged over forest. One aspect that should be considered is the forest structure. The objective of this study is to compare two classification techniques (Maximum Likelihood and Neural Network Classifiers) in characterizing the condition of the logged over and unlogged tropical rain forest using satellite remotely sensed data, namely: Landsat-7 ETM, JERS-1 SAR, ERS-2 SAR and Radarsat-1 SAR images. The results indicated a significant difference in structure condition between logged over and unlogged forest. The canopy closure, stem density, and basal area of logged over forest in the study area are 84%, 511 trees/hectare (ha), and 26 m2/ha, respectively. The corresponding results for the unlogged forest are 90%, 583 trees/ha, and 32 m2/ha, respectively. The use of a neural networks classifier is found to improve the accuracy of classification result, compared to the maximum likelihood classifier. Moreover, using neural networks, it is possible to classify two classes of logged over forest with significant difference in stem density and basal area per hectare.

1. Introduction

The increasingly rapid destruction of tropical rainforests through deforestation and degradation is now at the centre of world attention, prompting professional foresters and politicians alike to find ways to control, stop, and even reverse this process. Given the speed of the process, two issues are clear: actions are needed without undue delay, and a sustainable effect of such actions can be expected only if the causes are tackled. The problem thus needs to be examined from a cause-effect point of view.

Forest degradation and deforestation emerged as important issues in the latter half of the 20th century. Deforestation and forest degradation led to loss of forest cover, loss of biodiversity, climate change, desertification and watershed degradation.

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Although efforts have been made to combat tropical rain forest degradation and deforestation, there are many indications that the reduction and degradation of tropical rain forest have continued and even accelerated. According to the Food and Agriculture Organization of United Nations (FAO), in a report published in 1993, between 1981 and 1990 the average annual deforestation in the tropical forest was estimated to be 15.4 million hectares (ha), representing an annual loss of 0.8% (FAO, 1993). Nearly half of the deforestation occurred in the Americas (48%), with the remainder divided between Asia (25%) and Africa (26%) (Whitmore, 1997).

Logging is one factor that contributes to forest degradation. Data from the FAO shows that about 5.6 million ha were logged each year from 1981 to 1990. The figure represents 0.3% of the annual rate of logging for that period. In South and Central America 2.6 million ha of tropical forest were logged, followed by Asia (2.1 million ha) and Africa (0.9 million ha). Again, Asia had the highest rate (0.7%), followed by Americas (0.3%) and Africa (0.2%).

Logging activities cause two types of damages to the forest. Firstly, the passage of vehicles, which move logs, results in both physical disruptions of the soil and destruction of vegetation directly on the path of the roads. Secondly, indirect damage to the vegetation occurs during road construction and the felling of commercial trees. The felling of trees for road construction or harvesting purposes will knock over more trees, which probably will create more damage.

Major exploitation of the Indonesian rain forest for logging started in the 1960s (Riswan and Hartanti, 1995). The need for economic growth encouraged the government to start commercial logging by introducing forest concession holder. However, improper logging activities and lack of control from the government increased deforestation and forest degradation rate significantly. The situation was worsened by (i) large and uncontrolled forest fires, (ii) forest conversion to mining, transmigration (settlement schemes), and large-scale agricultural plantation, (iii) slash and burn cultivation by both migrants and traditional shifting local cultivators.

Many logging activities are now entering the second rotation. Soon, therefore, logging activities will, for the first time, take place on areas which were previously logged. Logging in the second rotation should therefore consider the current forest structure condition. Sustainable forest management requires that logging be regulated so that timber extraction from the forest does not exceed the productive and regenerative potential of that forest. Information on forest structure condition after the first harvesting should be known before the second harvesting takes place. The information should be quickly gathered and normally cover large area. Remote sensing has been proven to be an effective tool to generate information for large areas in an efficient way.

Many studies have been carried out to assess *deforestation* using remote sensing data. Assessment of forest *degradation* caused by logging activities using remote sensing data is, however, rare. Visual interpretation was used to detect selective logging using Landsat-TM images (Stone and Lefebvre, 1998). Visual interpretation is limited in its ability to define the limits between logged and unlogged forests since the disturbance zone is not always clearly visible. This problem leads to the inconsistencies and inaccuracies during the delineation of boundaries.

The objective of image classification is to replace visual analysis of the image data by quantitative techniques. Frequently, image classification uses spectral information as inputs for parametric classification algorithms, such as maximum likelihood, parallelepiped, and minimum distance classifiers. Image classification of tropical forest using only spectral information has usually been found to be successful in classifying forest and non-forest, but subdivision of forest is still difficult. The relatively homogeneous reflection characteristics of forest vegetation are usually considered to be the main factor that makes the digital subdivision in the forest difficult.

On digital images, the pixel representation of a forested area is a combination of many factors including the presence of different vegetation types, bare soil, and water. Selective logging will create gaps in the forest. However, these gaps do not always give different spectral reflectance since the presence of understorey vegetation and the canopy closure recovery may give a spectral reflectance similar to that of primary forest. Therefore, an alternative method that uses ancillary data should be implemented instead of using spectral information alone.

Despite the wide use of parametric classifiers, non-parametric classifiers such as neural network (NN) classifiers have also been developed. The reason for using neural networks classifiers in remote sensing is because neural networks use the powerful learning algorithm that can give better classification results (Atkinson and Tatnall, 1997). Unlike the maximum likelihood classifier, neural networks classifiers do not require data that has a normal distribution. Also, NN can integrate data from different sources, such as data from Geographic Information Systems (Ardo et al., 1997), which standard parametric classification cannot cooperate with. However, despite the powerful algorithm of neural networks for classifying remotely sensed data, some researchers have found that the use of neural network classifiers did not improve the accuracy of classification compared to maximum likelihood classifiers (Solaiman and Mouchot, 1994; Skidmore et al. 1997).

The objective of this study is to compare two classification techniques (Maximum Likelihood and Neural Network Classifiers) in characterizing the condition of logged over and unlogged tropical rain forest using satellite remotely sensed data, namely Landsat-7 ETM, JERS-1 SAR, ERS-2 SAR and Radarsat-1 SAR images (Table 1).

Table 1: Images used in the research

	Images	Data acquired
1	Landsat-5*	August 7, 1996
2	Landsat-7	August 26, 2000
3	ERS-2	May 12, 1998
4	Radarsat standard beam 2	October 5, 1998
5	Radarsat standard beam 5	October 5, 1998
6	Radarsat fine beam-1	November 14, 1998
7	JERS	July 12, 1998

* used only in pre-field data collection

2. Materials and Methods

The study area is located in Labanan concession forests in Berau regency, one of four regencies in East Kalimantan province, Indonesia. The boundaries of the study area are between latitude 2° 10' N and 1° 45' N and longitude 116° 55' E and 117° 20' E (Figure 1). The study area covers about 81,000 ha of production forest, which is managed by Inhutani I, a state owned forest concession company. Inhutani I have been applying selective logging since the 1970s.

The forest type of Labanan is often called by lowland mixed *Dipterocarp* forest because of the dominance in the canopy and the emergent stratum of the family of the *Dipterocarpaceae*. It contributes about 25% of the total tree density, 50% of the total tree basal area and 60.2% of the stand volume (Sist and Saridan, 1998). On average, the tree density, basal area and standing volume in the unlogged forest are 530.7 trees/ha, 31.5 m^2/ha and 402 m^3/ha, respectively (Sist and Saridan, 1998).

There were four main activities in this research. These activities were: (1) pre-field data collection, (2) field data collection, (3) field data analysis, and (4) remotely sensed data analysis. This paper will concentrate on the methods employed for remote sensing image analysis. The general research methodology for image analysis is shown in Figure 2.

3. Results

Selective logging activities create gaps in the forest canopy. Therefore, the presence of the gaps can be used to differentiate between un-logged and logged over forest. Statistical analysis proves that forest canopy closures in un-logged forest are significantly higher than canopy closures in logged over forest (t-test, T = 3.44 P = 0.0006 DF = 51, For computation see Table 3).

Image classification was performed using band 2,3,4,5, and 7 of Landsat-7 ETM+. Bands 1 and 6 were not used, as the signature separability on these two bands was low. The first method of classification was the maximum likelihood classifier. After the classification, 18 land cover classes were merged into 8 land cover classes. The second method of classification used was the Neural Network Classifier. The neural network configuration used three layers i.e. 1 input layer, 1 hidden layer, and 1 output layer. The network components, (the hidden node, learning rate, momentum, minimum error, and iteration number) were set to 20, 0.2, 0.5, 0.01, and 10000, respectively. Seven types of input were applied to perform neural network configuration. Those inputs were:

1. Landsat-7 ETM+ (band 2,3,4,5,7) image
2. Landsat-7 ETM+ (band 2,3,4,5,7) image and digital elevation model (altitude, slope, aspect)
3. Landsat-7 ETM+ (band 2,3,4,5,7) and Radarsat standard beam-2 image
4. Landsat-7 ETM+ (band 2,3,4,5,7) and Radarsat standard beam-5 image
5. Landsat-7 ETM+ (band 2,3,4,5,7) and Radarsat fine beam image
6. Landsat-7 ETM+ (band 2,3,4,5,7) and ERS-2 image
7. Landsat-7 ETM+ (band 2,3,4,5,7) and JERS image

Qualitative assessment of the maximum likelihood classification result reveals that the logged over forest which was logged 10 years ago is misclassified as unlogged forest (see the white circle in Figure 3(a)). The area of recent logging activity is successfully classified as logged over forest (see the red circle in Figure 3(a)). The unlogged forest (see the green circle in Figure 3(a)) is classified correctly as unlogged forest. Another successful result is found in classifying the non-forest areas such as water, bare soil, and agriculture.

Qualitative analysis of the neural network classification result shows that the neural network using input from Landsat-7 ETM+ gave almost the same result as maximum likelihood classifier (Figure 3(c)). Neural network also failed to detect forest which was logged 10 years ago. Recent logging activities and unlogged forest are well classified.

A better result is achieved by adding digital elevation model (DEM) into the network system. The forests, which were logged 10 years ago, are classified correctly as logged over forest, while the other forests like recent logged over forest and unlogged forest are also well classified (Figure 3(d)). The incorporation of a DEM into the network also reduces the scattered pixels of the logged over forest class, which are found in the maximum likelihood and neural network (NN) using input from Landsat-7 ETM+ alone. The land cover classes in Figure 3d are more compact compared to Figures 3(b) and 3(c). In general, the incorporation of the DEM into the network increases the pixels classified as logged over forest class, which is actually true in the study area, as compared to the use of Landsat-7 ETM+ alone as input to the maximum likelihood classifier and the neural network classifier.

Figure 3(e) presents the result of using images from Landsat-7 ETM+ and Radarsat standard beam-2 as inputs into the neural network classifier. It shows more pixels classified as logged over forest than using input from Landsat-7 ETM+ alone. The 10 years logged over forest areas are identified, but are slightly different from the result of NN using Landsat-7 ETM+ and DEM. The unlogged forest is also well identified as in the

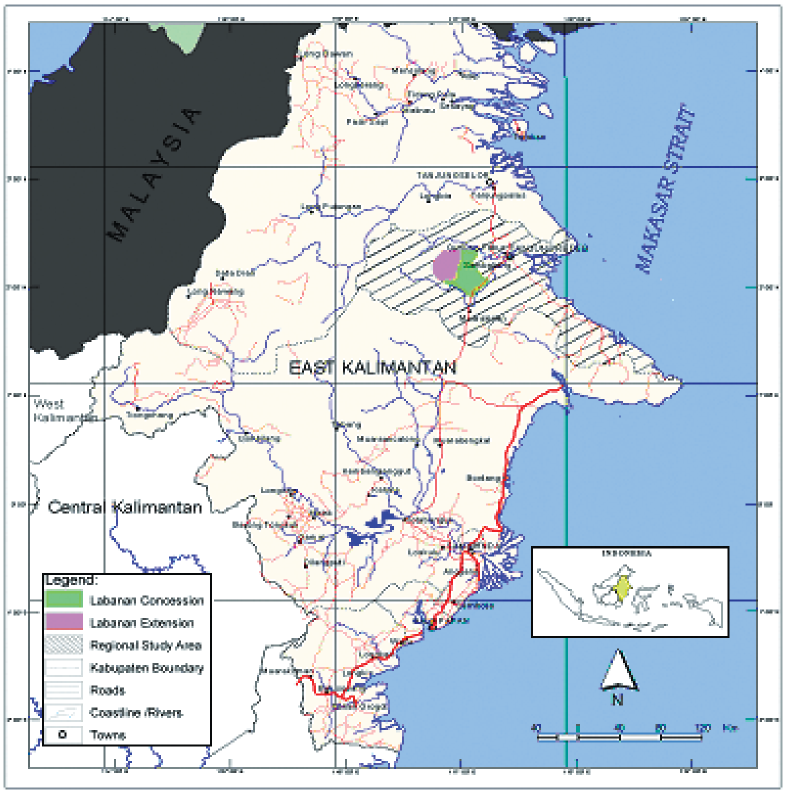

Figure 1: Location of the study area (Steenis and Verhoeven, 2000)

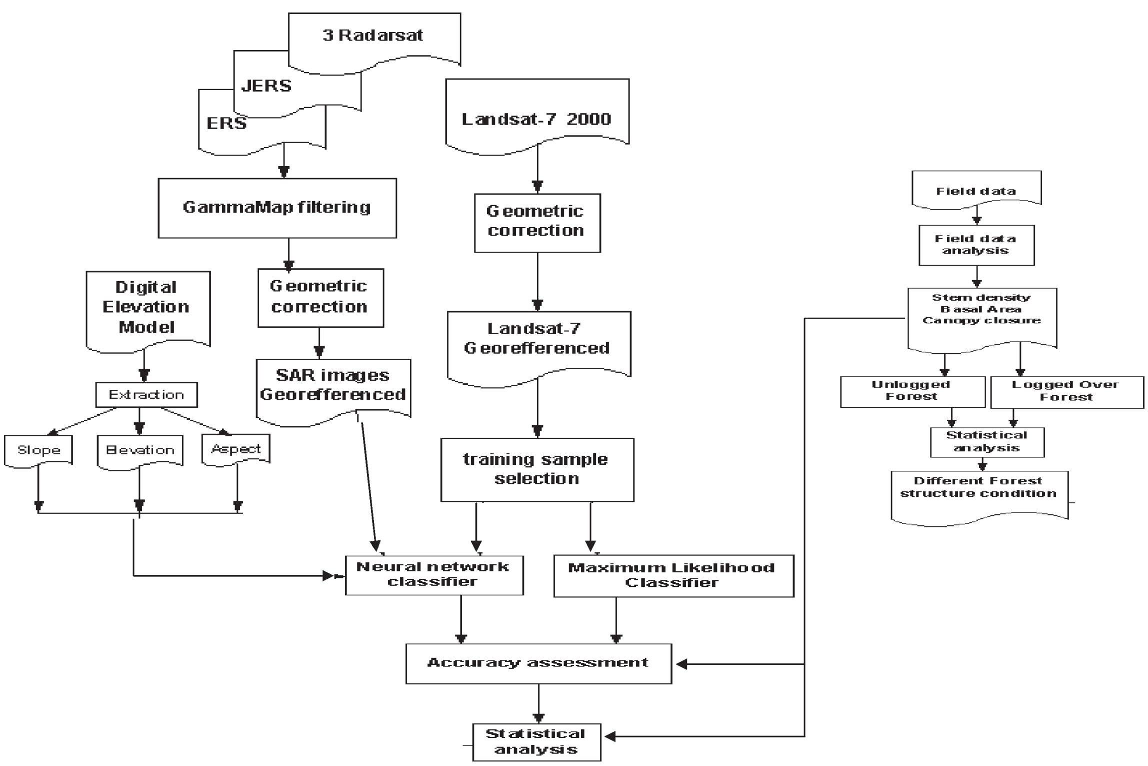

Figure 2: Research methodology

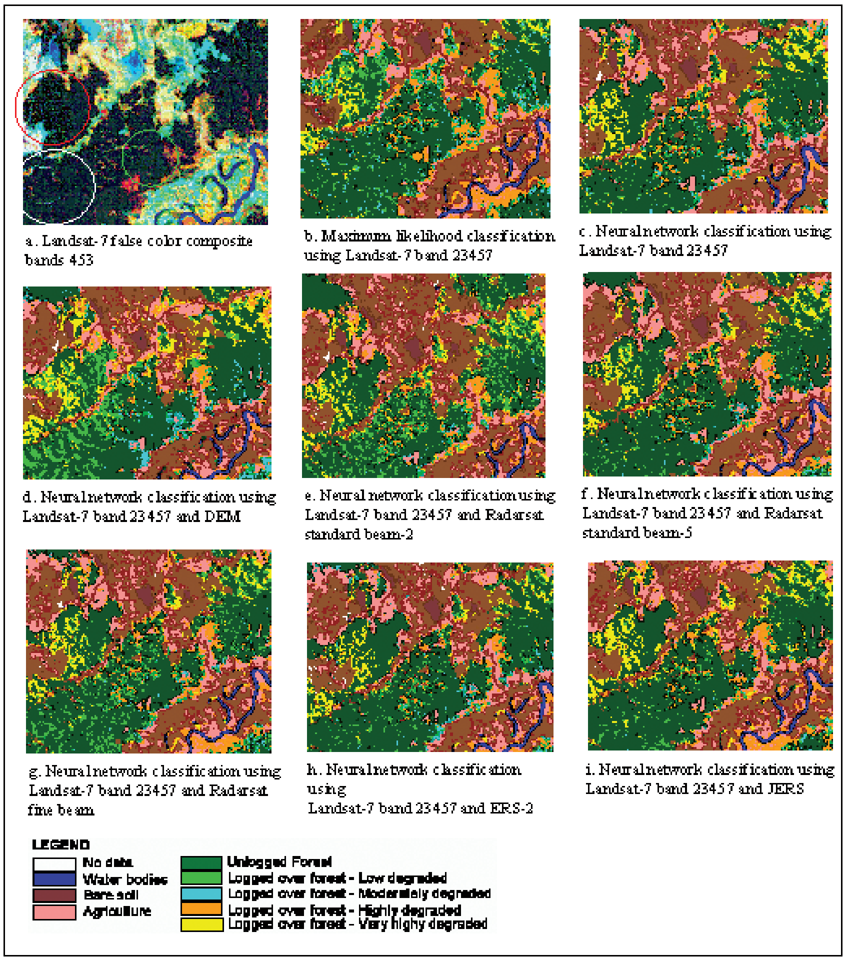

Figure 3: Subset of the classification results

previous classification methods. The scattered pixels of logged over forest are still found as in the classification result of maximum likelihood and neural network using input from Landsat-7 ETM+.

The use of Landsat-7 ETM+ and Radarsat standard beam-5 images, which has a different incidence angle than standard beam-2, gives slightly different results compared to use Landsat-7 ETM+ and Radarsat standard beam-2 images. The pixels, which are classified as logged over forest area, are reduced. The 10 years logged over forest area are miss-classified as unlogged forest. The recently logged over and unlogged forest are well classified. The incorporation of Radarsat standard beam-5 does not reduce the scattered pixels of logged over forest.

The combination of Landsat-7 ETM+ and Radarsat fine beam, which has the finest spatial resolution of Radarsat images, as input for the neural network classifier, gave fewer scattered pixels of unlogged forest than standard beam-2 and 5. The 10 years logged over forest area is miss-classified as unlogged forest (Figure 3(g)). The recent logged over and unlogged forests are equally well classified using Radarsat standard beam-2 and 5.

ERS-2 image has the lowest spatial resolution of the radar images used in this study. Figure 3(h) presents the result of classification using Landsat-7 ETM+ and ERS-2 images as input for the neural network classifier. The result shows that the number of pixels classified as logged over forest is smaller than the other methods. The logged over forest area in the recent logged over forest are reduced. Misclassification is found in the 10 year logged over forest.

JERS images are acquired from satellite using the L-band. Theoretically, L-band has longer penetration into the forest. Therefore, the L-band should give more information than C-band, which is used by Radarsat and ERS-2. The result of classification using JERS and Landsat-7 ETM+ as input for neural network classifier is given in Figure 3(i). A qualitative analysis on the classification result reveals that this classification input does not give better results than using Radarsat data as an input. The pixels classified as logged over forest are reduced compared to use of Radarsat standard beam-2. The 10 years logged over forest is misclassified as unlogged forest. The scattered pixels of logged over forest are still found, as in the classification results using inputs from the other SAR images and Landsat-7 ETM+.

A quantitative accuracy assessment was performed in order to get more exact information on how accurately the various image classification methods detect logged over and unlogged forest. Quantitative accuracy assessment is performed by calculating the overall accuracy, user accuracy, producer accuracy, and KHAT statistics.

The overall accuracy of the maximum likelihood classifier (MLC) in detecting logged over and unlogged forest is 64.2% (Table 2). According to the standard of classification accuracy made by Anderson et al. (1976), this accuracy is poor. The KHAT statistics of the MLC is 0.33 (Table 2). According to Montserud and Leamans (1992) this value is also categorized as poor.

A closer look at the error matrix of the MLC explains that 95% of the unlogged forest sample plot was correctly classified (producer accuracy). However, user accuracy shows that only 39% of area that classified as unlogged forest actually is unlogged. The opposite situation is found in classifying logged over forest. Only 55% of the logged over forest sample plots are classified correctly. But, 97% of the areas classified as logged over forest are really logged over forest.

The accuracy assessment results in Table 2 indicates that the neural network classifier (NNC) with the same input as the MLC give better accuracy in detecting logged over and unlogged forest than the MLC. The accuracy was improved from 64.2%, using the MLC, to 66.7%, using the NNC.

Table 2: The overall classification accuracy and KHAT value

Code	Algorithm	Channel	Overall Accuracy	KHAT Values	KHAT variance
K1	Maximum Likelihood	Landsat-7 ETM+ (band 2,3,4,5,7)	64.2%	0.33	0.0146
K2	Neural Networks	Landsat-7 ETM+ (band 2,3,4,5,7)	66.7%	0.35	0.0139
K3	Neural Networks	Landsat-7 ETM+ (band 2,3,4,5,7), digital elevation model	74.1%	0.43	0.0125
K4	Neural Networks	Landsat-7 ETM+ (band 2,3,4,5,7), Radarsat standard beam-2	65.4%	0.31	0.0146
K5	Neural Networks	Landsat-7 ETM+ (band 2,3,4,5,7), Radarsat standard beam-5	64.2%	0.30	0.0151
K6	Neural Networks	Landsat-7 ETM+ (band 2,3,4,5,7), Radarsat fine beam	66.7%	0.33	0.0163
K7	Neural Networks	Landsat-7 ETM+ (band 2,3,4,5,7), ERS	61.7%	0.27	0.0163
K8	Neural Networks	Landsat-7 ETM+ (band 2,3,4,5,7), JERS	64.2%	0.30	0.0151

Table 3: Statistical T-test result on the forest structure of the logged and unlogged forest

Two sample T for canopy closure

CODE	N	Mean	StDev	SE Mean
LOF	62	84.12	8.46	1.1
UF	19	89.56	5.06	1.2

95% CI for mu (LOF) – mu (UF) : (–8.6, –2.3)
T–Test mu (LOF) = mu (UF) (vs <) : T = –3.44 P = 0.0006 DF = 51

Two sample T for stem density per hectare

CODE	N	Mean	StDev	SE Mean
LOF	62	511	176	22
UF	19	583	157	36

95% CI for mu (LOF) – mu (UF) : (–158, 14)
T–Test mu (LOF) = mu (UF) (vs <) : T = –1.70 P = 0.049 DF = 33

Two sample T for basal area per hectare

CODE	N	Mean	StDev	SE Mean
LOF	62	26.0	11.5	1.5
UF	19	32.4	13.8	3.2

95% CI for mu (LOF) – mu (UF) : (–13.6, 0.8)
T–Test mu (LOF) = mu (UUF) (vs <) : T = –1.84 P = 0.039 DF = 26

Note:
LOF = logged over forest
UF = unlogged forest

Table 4: The Z values of the classification methods

Code	K1	K2	K3	K4	K5	K6	K7
K2	0.70						
K3	5.14	4.55					
K4	0.92	1.64	6.13				
K5	1.63	2.36	6.79	0.73			
K6	0.14	0.81	4.97	0.72	1.40		
K7	2.92	3.65	7.93	2.05	1.33	2.64	
K8	1.63	2.36	6.79	0.73	0.00	1.40	1.33

The overall accuracy of 74.1% (Table 2) indicates that adding a DEM in the input layer significantly improves the accuracy compared to using the spectral information alone. Z-value of 5.14 and 4.55 (Table 4) give an indication that adding DEM in the input layers (K3) is significantly improves the accuracy than using input from spectral information alone (K1 and K2). This result confirms that digital elevation model are valuable inputs that give additional information in order to improve the accuracy of neural network classifier in detecting logged over and unlogged forest.

The combinations of Landsat-7 ETM+ with Synthetic Aperture Radar (SAR) images (ERS, JERS, and Radarsat) as input layers into the network do not improve the classification accuracy as compared to use Landsat-7 ETM+ image alone. Only a combination of Landsat-7 ETM+ and Radarsat fine beam images gives the equal result with classification using Landsat-7 ETM+. The low accuracy result of image classification using SAR images means that SAR images do not give additional information that can be used to improve the accuracy of neural network classification in distinguishing logged over from unlogged forest.

4. Conclusions

This research has found that there is a significant difference in the structure between logged over and unlogged forest (t-test T = 3.44 P = 0.0006 DF = 51). The canopy closure, tree density, and basal area in the logged over forest are 84%, 511 trees/ha, and 26 m^2/ha, respectively. The corresponding results for the unlogged forest are 90%, 583 trees/ha, and 32 m^2/ha, respectively. These findings indicate there is a significant difference in forest structure between logged over and unlogged tropical rain forest.

The use of a neural network classifier with input from Landsat-7 ETM+ and digital elevation model (topographic information) was found to improve classification accuracy, thus giving better results than the maximum likelihood classifier in detecting logged over and unlogged tropical rain forest (Z-test, Z = 5.14, P<0.05). The overall accuracies of the neural network and maximum likelihood classifier were 74.1% and 64.2%, respectively.

Neural network classifiers with inputs from an optical sensor (e.g. Landsat-7 ETM+) and a digital elevation model can classify two logged over forest classes, which are then called low and highly degraded, with significant differences in stem density and basal area per hectare. The mean stem density and basal area on highly degraded forest are 483 trees/ha and 23 m^2/ha, respectively. The mean stem density and basal area of low degraded forest are 570 trees/ha and 30 m^2/ha, respectively. These findings suggest that remotely sensed data (i.e. optical and or radar sensor) and image classification techniques (i.e. maximum likelihood classifier or neural networks classifier) can be used to successfully classify the logged over forest classes.

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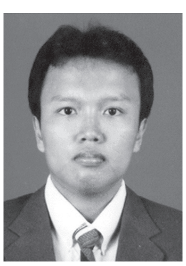

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