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A COMPARISON BETWEEN NEURAL NETWORKS AND MAXIMUM LIKELIHOOD REMOTELY SENSED DATA CLASSIFIERS TO DETECT TROPICAL RAIN LOGGED-OVER 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 thousands of hectare logged-over forest. In Labanan, Berau, East Kalimantan, selective logging will enter the second rotation in 2010. A comprehensive analysis on the logged over 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 between 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. 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 are 84%, 511 trees/hectare (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. The use of neural networks classifier is found to improve the accuracy of classification result as compared to maximum likelihood classifier. Moreover, neural networks classifier can classify two logged over forest classes 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. Deforestation and forest degradation led to loss of forest cover, loss of biodiversity, climate change, desertification and watershed degradation.

Forest degradation and deforestation have emerged as important issues in the latter half of the 20th century. Many efforts have been made to combat tropical rain forest degradation and deforestation. However, there are many indications that the reduction and degradation of tropical rain forest have continued and even accelerated. According to Food and Agriculture Organization of United Nations (FAO), in a report published in 1993, from 1981-1990 the average annual deforestation in the tropical forest was estimated to be 15.4 million hectares (ha), representing an annual loss of 0.8% annual rate of deforestation (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 FAO shows that about 5.6 million ha were logged each year from 1981 to 1990. The figure represents 0.3% 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, result in both physical disruptions of the soil and destruction of vegetation directly on the path of the roads. Secondly, the 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 Indonesia rain forest for logging started in the 1960s (Riswan and Hartanti 1995). The needs for economic growth encouraged the government to start commercial logging by introducing forest concession holder. Improper logging activities and lack of control from the government increased deforestation and forest degradation rate significantly. The condition was worsened by (i) large and uncontrolled forest fire, (ii) forest conversion to mining, transmigration (settlement scheme), and large-scale agriculture plantation, (iii) slash and burn cultivation both by migrants and traditional shifting local cultivators.

Many logging activities are now entering the second rotation. For the first time they are going to return to the area, which were previously been logged. Logging in the second rotation should consider the current forest structure condition. Sustainable Forest Management requires that logging be regulated so that timber extraction from forest does not exceed the productive and regenerative potential of that forest. Information on forest structure condition after first harvesting should be known before second harvesting take place. The information should be quickly gathered and normally cover large area. Remote sensing has been proven 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 has limitations 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 inaccuracy during 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 algorithm, such as maximum likelihood, parallelepiped, and minimum distance classifier. Image classification using only spectral information over tropical forest usually found successful in classifying forest and non-forest, but subdivision of forest is still difficult. The similar reflection of vegetation considered the main factor that makes the digital subdivision in the forest is difficult.

On digital images, the pixel representation of 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 similar spectral reflectance with primary forest. Therefore, an alternative method that uses ancillary data other than spectral image should be implemented instead of using spectral information alone.

Despite the wide use of parametric classifiers there are also development of using non-parametric classifier like neural networks (NN) classifier. The reason of using neural networks classifier in remote sensing is because neural networks use the powerful learning algorithm that can give better classification result (Atkinson and Tatnall 1997). Neural networks classifiers do not require data that has normal distribution as maximum likelihood classifier does. Also, NN can integrate data from different sources such as data from Geographic Information System (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 found that the use of neural networks classifier did not improve the accuracy of classification compare to maximum likelihood classifier (Solaiman and Mouchot 1994, Skidmore et al. 1997).

The objective of this study is to compare between 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.

2. MATERIALS AND METHODS

The study area is located in Labanan concession forests in Berau regency. It is one of four regencies in East Kalimantan province, Indonesia. The boundaries of the study area are between latitude 2º 10' N and 1º 45' N and longitude 116º 55' E and 117º 20' E. 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 402m^3/ha, respectively (Sist and Saridan 1998).

There were four main activities in this research. Those 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. General research methodology for image analysis shown in Figure 1.

Several remotely sensed images were used for this study (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

3. RESULTS

Image classification was performed using band 2,3,4,5, and 7 of Landsat-7 ETM+. Band 1 and 6 was not used, as the signature separability on these two bands was low. The first method of classification was using maximum likelihood classifier. After the classification, the 18-landcover classes were merged into 8-landcover classes. The second method of classification was using Neural Network Classifier. The neural network configuration was using three layers i.e. 1 input layer, 1 hidden layer, and 1 output layer. The network components such as 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

After the classification, the 18-landcover classes were also merged into 8-landcover classes.

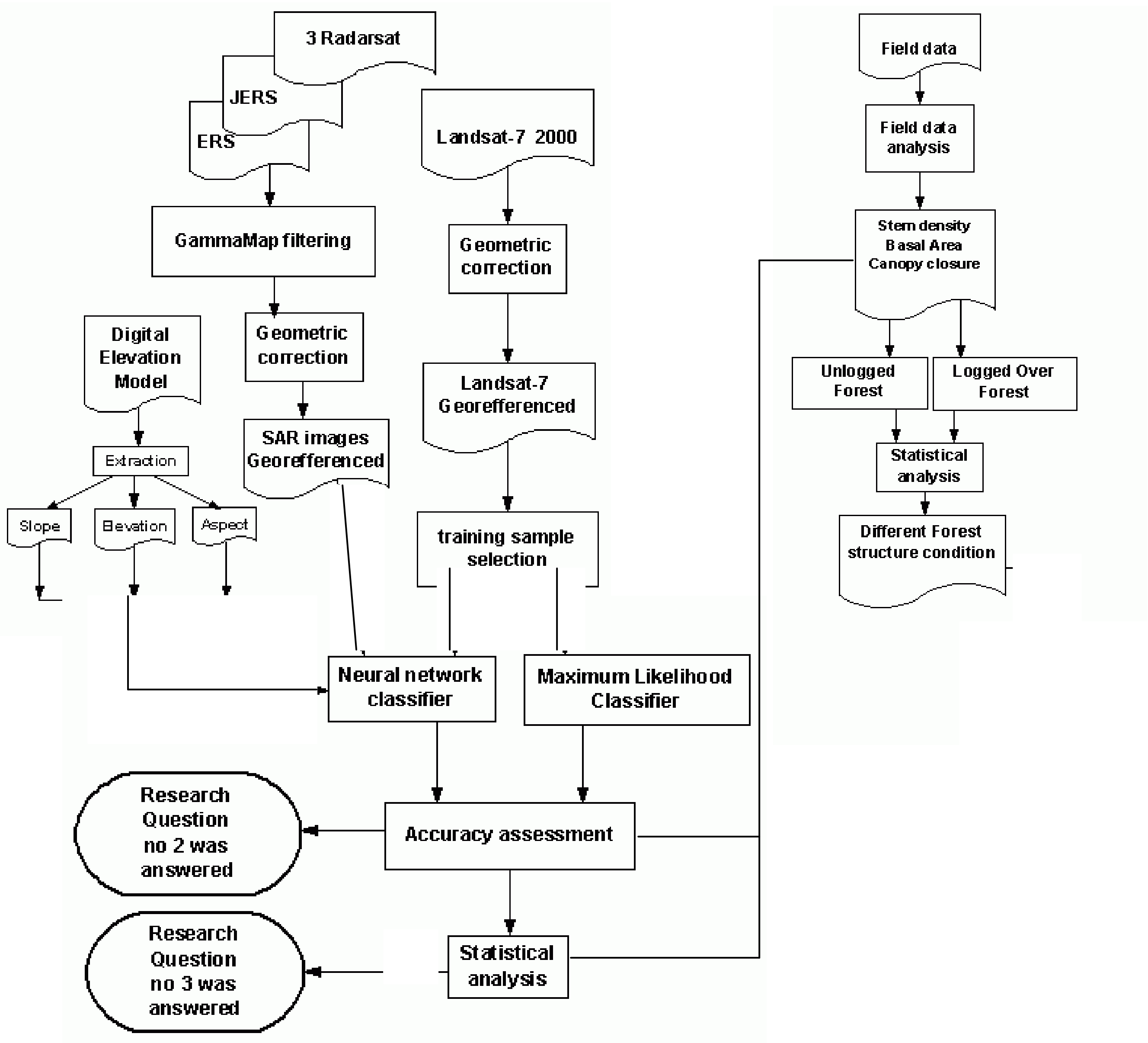

Figure 1. Research Methodology.

The quantitative accuracy assessment was performed in order to get more exact information on how accurate the several image classification methods in detecting logged over and unlogged forest. The quantitative accuracy assessment is performed by calculating the overall accuracy, user accuracy, producer accuracy, and KHAT statistic.

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 (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 looks to the error matrix of 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 is actually unlogged forest. The opposite situation is found in classifying logged over forest. There are only 55% of the logged over forest sample plots are classified correctly. But, there are 97% of the areas called logged over forest are really logged over forest.

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

The adding of ancillary information like digital elevation model (DEM) is proved to increase the classification accuracy. The overall accuracy of 74.1% (Table 2) give an indication that adding DEM in the input layer is significantly improves the accuracy than using input from spectral information alone. This result confirms that digital elevation model is the 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 are not improving 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 detecting logged over with 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 neural networks classifier with input from Landsat-7 ETM+ and digital elevation model (topographic information) was found to improve classification accuracy, thus, giving better results than maximum likelihood classifier in detecting logged over and unlogged tropical rain forest (Z-test, Z = 5.14, P<0.05). The overall accuracies of neural networks and maximum likelihood classifier were 74.1% and 64.2%, respectively.

Neural networks classifier with input from optical sensor (e.g. Landsat-7 ETM+) and digital elevation model can classify two logged over forest classes, which are then called low and highly degraded, with significant difference in stem density and basal area per hectare (t-test, T = -2.46, p = 0.009). 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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