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Comparison of pixel –based and artificial neural networks classification methods for detecting forest cover changes in Malaysia

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Abstract. According to the FAO (Food and Agriculture Organization), Malaysia lost 8.6% of its forest cover between 1990 and 2005. In forest cover change detection, remote sensing plays an important role. A lot of change detection methods have been developed, and most of them are semi-automated. These methods are time consuming and difficult to apply. One of the new and robust methods for change detection is artificial neural network (ANN). In this study, (ANN) classification scheme is used to detect the forest cover changes in the Johor state in Malaysia. Landsat Thematic Mapper images covering a period of 9 years (2000 and 2009) are used. Results obtained with ANN technique was compared with Maximum likelihood classification (MLC) to investigate whether ANN can perform better in the tropical environment. Overall accuracy of the ANN and MLC techniques are 75%, 68 % (2000) and 80%, 75 % (2009) respectively. Using the ANN method, it was found that forest area in Johor decreased as much as 1298 km2 between 2000 and 2009. The results also showed the potential and advantages of neural network in classification and change detection analysis.

1. Introduction

Land use and land cover (LULC) change detection is important for many decisions making and management activities related to the earth surface like hydrological modeling and environmental management [1]. LULC provides key environmental information for many scientific purposes, and also to a range of human activities such as urban planning [2]. The growth of population associated with the climate change is found to be the main reason for the loss of forest cover over time [3]. Deforestation in particular has a large impact on the catchment process and biochemical cycles like carbon and nitrogen, soil erosion and flood [1]. Remote sensing is a valuable tool to get quick information about various LULC types and to monitor their changes over time [4]. In this paper, we have employed two Landsat Thematic Mapper images covering years 2000 and 2009 to (i) classify different LULC types in the state of Johor using traditional pixel based and Artificial Neural Network image classification techniques and (ii) to detect the LULC changes using a post classification method. Pixel based classification is implemented based on statistical probability method [5]. Neural network is a supporting tool for image processing and remotely sensed change detection. It is based on back propagation training algorithm [6]. Many researches [7, 8, 9, 10, and 11] showed that the classification accuracy is improved by neural network in comparison to the pixel based method mainly because the data distributions are strongly non-Gaussian in ANN whereas; the MLC uses Gaussian distribution parameter [12].

2. Data and methodology

2.1. Study area

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The study area considered in this study is the entire state of Johor. Johor is one of the developed states in Peninsular Malaysia (Figure 1). In term of the area and population, Johor is the fifth largest and second populous state in Malaysia, with a total area of 19,210 km^2 and population of 3,233,434 in 2010 [13]. The largest land uses in Johor are oil palm and forest; however, most of the forested areas had been changed to oil palm plantations in recent years [14].

Figure 1. Study area showing the state of Johor [15].

2.2. Data used

Enhanced Thematic Mapper (ETM+) (2000) and Landsat Thematic Mapper (2009) data were used to perform the LULC classification. These data (level 1T) were downloaded from the Earth Explorer website [16], and they are corrected for geometric and topographic errors. We used 6 spectral bands (visible, near infra-red and shortwave infra-red) except for the thermal band to perform the classification. These data with 30 m spatial resolution enable the generation of moderate resolution LULC classes covering the entire state of Johor.

2.3. Methods

In order to obtain more accurate results, before performing the change detection both images were atmospherically corrected (because of the difference in months and sun angle) using Atcor2 program available in the Erdas Imagine software. Subsequently mosaicking and finally co-registration of ETM+ and TM data were performed. Before classification, the land cover types in the study area were defined with the help of a land use map produced by the department of Agriculture Malaysia (year 2008). The main land cover types are forest, oil palm, urban area, rubber and water bodies. After that, each mosaicked images were classified using maximum likelihood (ML) and neural network classification techniques. ML algorithm was performed as supervised classification, and it is based on user defined spectral signature (training area). Training areas were selected according to the land use maps of years 2000 and 2008. Finally, the ML supervised classification was performed. This classification is a standard pixel based technique which is based on a multivariate probability density function of classes [6]. Whilst, Artificial Neural Network (ANN) is a technique that can simulate functions and it is synonymic to human brain [9]. Three types of networks are commonly used in remote sensing namely: Hopefield networks, Kohonen networks, and the multi-layered feed forward networks [5]. Unsupervised and semi-supervised classifications commonly use Kohonen networks, whilst Hopfield network is used in stereo matching [4].

In land cover classification feed forward networks are most commonly used and they are usually trained by back propagation algorithm. There are three layers included in the network namely (i) the input layer (i.e. spectral bands used for classification) (ii) the output layer is the number of land-cover categories to be generated and (iii) the hidden layer that connects components of the input layer and the output layer by a weighted channel [12]. In this study, the input layer is the 12 input nodes representing the spectral bands (two multispectral images) and the output layer has 6 nodes, which are the 6 land cover classes, (including clouds). The rate of training was kept to 0.2 and the training momentum rate of 0.9 was used. The training root mean square error (RMSE) was set to 0.1, and then the classification was performed. After classification, the accuracy of the classified images was assessed using reference data (land use maps of year 2000 and 2009). A total of 250 random points were selected from the images generated via a stratified random sampling method. The accuracy was assessed using error matrices (overall, user's and producer's accuracies and Kappa statistics). Finally,

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a post classification change detection technique was adopted to detect the LULC changes in Johor between 2000 and 2009 [6].

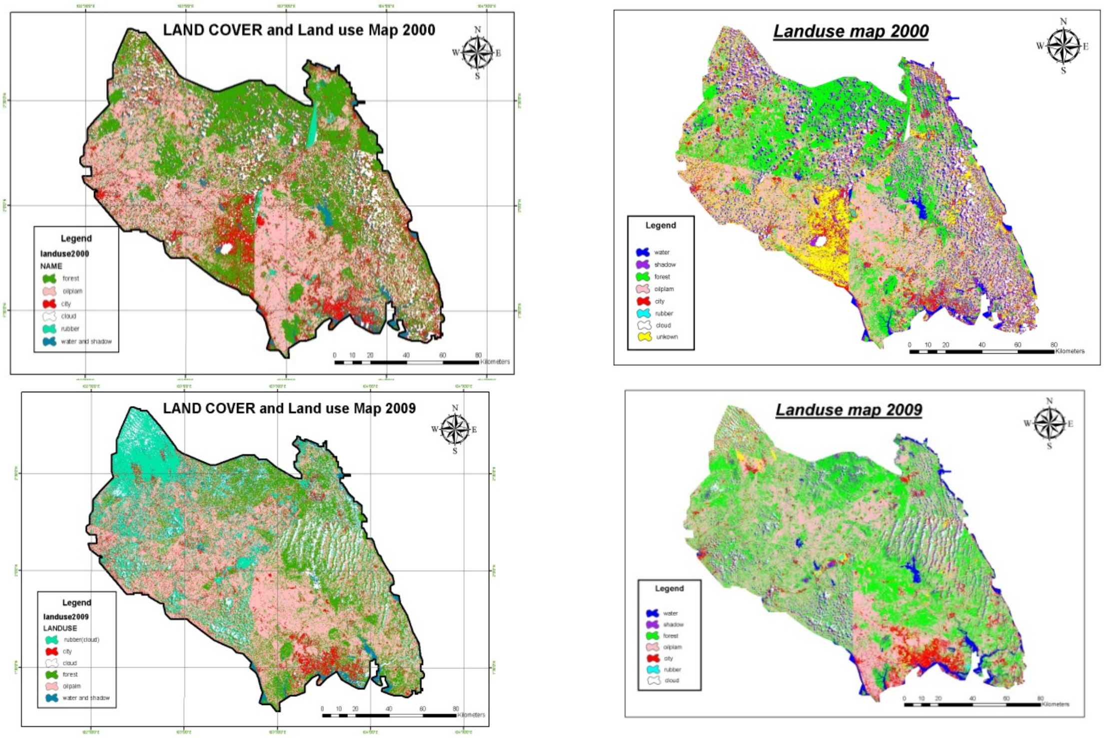
3. Results and discussions

3.3. Landuse/landcover classification

The final LULC (Land use and land cover) maps presented in figure 2 and figure 3 show that the major classes are forest, oil palm, rubber, city and water. An evaluation of accuracy of the classified images (table 1) shows that the overall accuracy for Artificial Neural Network (ANN) classification is 75% (year 2000) and 80% (year 2009), and it is higher than the pixel based classification result of 68% (2000 image), and 75% (2009 image).

3.2. Change detection

Since the ANN technique provided higher accuracy compared to the MLC classifier, we used the classified images with ANN technique to detect the forest cover changes between 2000 and 2009. The total forested area as estimated using ANN technique in year 2000 is 6191 $km^{2,}$ and this number decreased to 4461 km^{2} in year 2009 (table 2). The reason for the changes is mostly due to the development of oil palm plantation that plays a major role in the country's economy. Moreover, development of the Iskandar Malaysia region in Johor could have claimed some forested areas for the development of urban areas.



A B

Figure 3. Land use/land cover maps produced using (A) maximum likelihood and (B) artificial neural network classifiers for year 2000 and 2009.

Table 1. Accuracy assessment of maximum likelihood and artificial neural network classifiers

	Maximum likelihood classification 2000			Neural network classification 2000		
Land use - land cover	Producer's accuracy	User's accuracy	Kappa	Producers accuracy	Users accuracy	Kappa
	(%)	(%)		(%)	(%)	

Forest	74.19	76.67	0.533	78	80	0.85
Oil palm	80	64	0.54	87.18	78	0.82
city	69.57	69.57	0.6	78.72	74	0.72
Water	75	60	0.58	77	68	0.66
Rubber	20	100	1	39.47	90	0.88
	Maximum likelihood classification 2009			Neural network classification2009		
Land use - land cover	Producer's accuracy (%)	User's accuracy (%)	Kappa	Producers accuracy (%)	Users accuracy (%)	Kappa
Forest	71,43	66.64	0.65	78.72	80	0.8
Oil palm	91.3	77.78	0.63	92	70	0.79
City	60	75	0.72	68.18	86	0.87
Water	55.56	83.33	0.81	74.14	86	0.85
Rubber	85	77.22	0.7	68	74	0.67

Table 2. Areas change in Johor for 2000 and 2009

Land cover	Maximum Likelihood classification 2000 (area km^2)	Neural network classification2000 (area km^2)	Maximum Likelihood classification 2009 (area km^2)	Neural network classification 2009 (area km^2)
Water	1037.058	Water with shadow :2681.6	1100.38	Water with shadow 2535.36
Forest	5970.48	6191.5	4311.86	4893.37
Oil palm	6494.59	5811.53	8067.85	8202.67.27
City	3302.1(because of haze)	1517.6	1600.46	1619.12
Rubber	675.56	683.59	3100.65+cloud	694.12
Cloud	1974.5	2855.82+haze	1567.68	1520.35

4. Conclusion

This study used two classification methods, namely Artificial Neural Networks (ANN) and Maximum likelihood (ML) to classify different land use and land cover types in the state of Johor. The highest classification accuracy was obtained by ANN, and the Landsat images classified using this method was used to detect the change notably in forest cover between 2000 and 2009. It was found that during a period of 10 years Johor lost approximately 28% of forested areas. It is suggested that the forested areas must be monitored on a continuous manner to detect any illegal deforestation. Also, the state government should make all forested areas as protected forest in order to prevent further loss of this valuable natural resource in the state.

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