# Land Cover Change Detection Using Multispectral and Multitemporal Remote Sensing Data

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**ABSTRACT** – Land cover classification is an essential process in remote sensing work flow. For this purpose, supervised methods have been preferred by many researchers due to its practicality and accuracy compared to unsupervised methods. Nevertheless there have been very minimal effort to evaluate the performance of different supervised methods particularly for tropical land covers such as those in Malaysia. The study reported in this paper aims to detect land cover changes using multispectral and multitemporal remote sensing data. The data come from Landsat TM satellite covering the area of Klang, located in Selangor, Malaysia. Landsat bands 1, 2, 3, 4, 5 and 7 are used as the input for three supervised classification methods namely maximum likelihood (ML), neural network (NN) and support vector machine (SVM). Region of interests (ROI) are drawn for each of the land cover classes in order to extract the training sets. The accuracy of the generated classifications are then assessed by comparing the classifications with a reference data set using a confusion matrix in which showing SVM gives a more stable and realistic results compared to ML and NN.

## 1. INTRODUCTION

Traditionally, land cover information are obtained by means of manual monitoring and observation such as surveying on foot or land vehicles. Nevertheless, such approach is time consuming, logistically expensive and not practical particularly for large and remote areas. A more modern approach is by aerial photography where camera is mounted on an aeroplane or helicopter. Although capable of capturing picture of larger areas in a much shorter time, such approach is very expensive, whether-dependence besides exposing the operators to air accidents. To overcome such situations, with advancement of technology, satellite remote sensing is later introduced where land cover are captured using sensors mounted on a satellite. This is a far better option to the aerial photographs, where land cover images are able to be captured globally, continuously and with a cheaper cost.

Due to the continuous monitoring capability, satellite remote sensing is seen as a more practical alternative for changes in land cover due to human activities and natural phenomenon compared to conventional approaches [1]. The techniques for land cover change detection include post-classification comparison, difference map and principal component analysis. Post-classification comparison is frequently used, however, in most cases, the comparative performance of various techniques are not evaluated thoroughly. Consequently, optimal results could not be achieved because of lack of proper evaluation and testing procedures used [2]. This study attempts to detect land cover changes from Landsat data where ML, NN and SVM methods are performed and evaluated.

## 2. METHODOLOGY

This study involves five phases i.e. input data, data pre-processing, data processing, analysis and output generation. Landsat satellite data were obtained from Agensi Remote Sensing Negara (ARSM) and United States Geological Survey (USGS) involving data from 2000 and 2005. In data pre-processing, the data were initially calibrated where pixel raw digital number is converted into radiance:

$$L = gain * DN + bias \quad (1)$$

where L is the pixel value in radiance, DN is the cell value digital number, gain is the gain value for a specific band, and bias is the bias value for a specific band. Atmospheric correction is the process of removing the effects of the atmosphere on the reflectance values of images taken by satellite. Atmospheric Effects are caused by scattering and absorption of EM radiation in the atmosphere and have significant effects mainly on visible and infrared bands that tend to affect processing and interpretation of images [2]. Geometric correction is the process of correcting the data for geometric distortion due to non-systematic error occurred. This was done by initially applying geometric correction on a base-data selected from one of the Landsat data and then registering all other data onto the base-data. Subset was carried out for the selected area within the image, since satellite data usually covers a very large area. For classification, supervised classification methods, i.e. Maximum Likelihood (ML), Neural Network (NN) and Support Vector Machine (SVM) were applied to reflective bands 1, 2, 3, 4, 5 and 7 of the Landsat-5 satellite data, while thermal band 6 was omitted, with varying size of training pixels [7]. 11 land covers were considered i.e. coastal swamp forest (CSF), dryland forest (DLF), oil palm (OP), rubber (R), industry (I), cleared land (CL), urban (U), coconut (C), bare land (BL), sediment plumes (SP) and water (W).

## 3. RESULTS AND DISCUSSION

The classified images were compared to identify the changes by using the change detection statistic method. The changes were identified by comparing the pattern and size of each land cover area qualitatively and quantitatively. Figure 1 shows land cover classification using ML, NN and SVM. ML and SVM shows a more realistic classification of land covers compared to NN. On the other hand, SVM was found more stable due to not much being affected by varying training set size compared to ML when the size of the training pixels was varied; its accuracy is not much affected compared to ML [7]. SVM also have shown a more realistic land cover area distribution changes compared to ML (Figure 2) related to the real scenario.

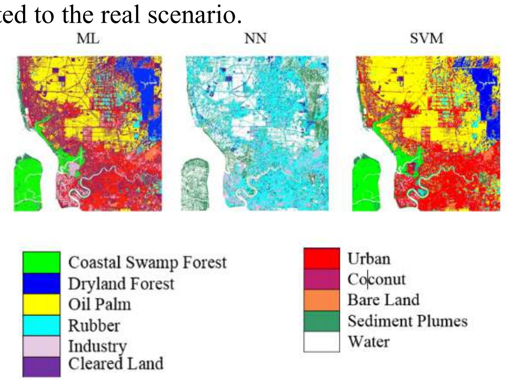
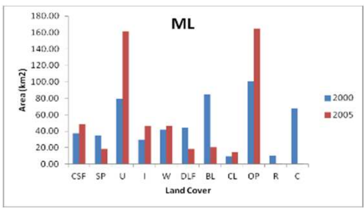
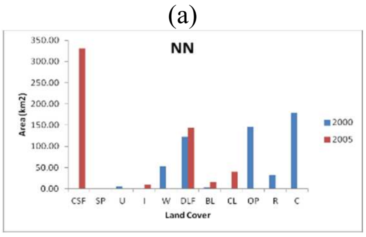


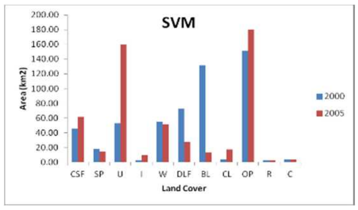

Figure 1 Land cover classification Using ML, NN and SVM




(a)




(b)




(c)

Figure 2 Land cover changes based on area ($km^2$)

## 4. CONCLUSIONS

Change detection based on SVM gives a more stable and realistic results compared to ML and NN due to its stability even when the size of the training pixels varies.

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