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CHANGE DETECTION FROM LANDSAT-5 TM SATELLITE DATA

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ABSTRACT

In this study, we carried out land cover change detection using satellite remote sensing data. The data came from Landsat-5 TM satellite covering the area of Klang, located in Selangor, Malaysia. Initially, region of interests (ROI) were drawn on each of the land cover classes identified in order to extract the training sets. Landsat bands 1, 2, 3, 4, 5 and 7 were then used as the input for the Support Vector Machine classification. The accuracy of the classifications was then assessed by comparing the classifications with a reference data set using a confusion matrix. The classification results were used to identify the conversion of land cover from year 2000 to 2005, using statistical change detection techniques. The outcomes of change detection analysis are reported in terms of pixel counts, percentages and areas.

Keywords: support vector machine, change detection statistics, change detection analysis, landsat-5 TM.

INTRODUCTION

Remote sensing data recorded from a satellite platform has become a vital tool for mapping land covers. Remote sensing technology enables data acquisition of land covers to be carried out faster and at a cheaper cost compared to conventional methods. Change detection is one of the important tasks required for remote sensing applications such as town planning, disaster management, ecological forecasting, habitat fragmentation, deforestation management, coastal change and urban sprawl. Change detection can be defined as the process of identifying differences in the state of an object or phenomenon by observing it at different times [15]. Generally, change detection can be carried out using remote sensing techniques by comparing imagery collected over the same area at different times to highlight features that have changed. There are two basic of change detection methods; pre-classification and post-classification. The pre-classification techniques use multi-temporal satellite imagery directly to identify the changes or non-changes of land cover [2]. The post-classification techniques involve classifying each of the images independently, then generating the thematic maps. Comparison of the corresponding labels is eventually performed to detect land cover changes [2].

Lian Classification can be performed using unsupervised and supervised approaches; the latter is more preferred due to its accuracy and practicality [3], [4]. The main difference is that supervised classification needs a priori information of the land covers but unsupervised classification does not.

A number of supervised classification methods exist to classify land cover in remote sensing data [5]. SVM is a non-parametric method which is based on efficient hyperplane searching technique. It uses minimal training pixels and therefore needs less processing time.

SATELLITE IMAGERY

Landsat 5 was launched on March 1, 1984 and decommissioned in June 5, 2013. The satellite has provided the global science community with over 900,000 individual scenes and is the longest running satellite of the series (Figure-1). Table-1 shows the specification of landsat 5.

Figure-1. Landsat 5 satellite [16].

Table-1. Landsat 5 satellite specification [16].

Spectral bands	**Band**	**Spectral wavelength range**(μm)	**Wavelength region**
	1	0.452 - 0.518	Visible blue
	2	0.528 - 0.609	Visible green
	3	0.626 - 0.693	Visible red
	4	0.776 - 0.904	Near infrared
	5	1.567 - 1.784	Mid infrared
	6	10.45 - 12.42	Thermal infrared
	7	2.097 - 2.223	Mid infrared
Spatial Resolution (IFOV)	30 m - Visible, near and mid infrared bands 120 m - thermal bands		
Sampling	1 samples/IFOV along scan		
Cross Track Coverage	185 km		
Radiometric Resolution	8 bits		
Radiometric Calibration	Internal lamps, shutter and black body		
Scanning Mechanism	Bidirectional Scanning with Scan Line Corrector		
Period of operation	Landsat 5: 1984 - 2013		
Main sensor	TM		
Altitude	705 km		
Repeat Cycle	16 days		
Equatorial Crossing	9:45 AM +/- 15 minutes		
Type	Sun synchronous, near polar		
Inclination	98.2°		

IMAGE PRE-PROCESSING

Non-idealities in sensors, the curvature of the earth and variations in the position, velocity and attitude of the remote sensing platform can all lead to geometric errors that need to be corrected [8]. Initially, georeferencing based on image-to-image registration was carried out to correct for these geometrical errors. Registration process was applied on the 2005 image by making use the 2000 image as the reference image. The process was started by selecting Ground Control Points (GCP) as the reference coordinates for both images. Spatial interpolation was finally performed based on coordinate transformation which made use the selected GCP.

After image registration, the images need to be resized since they covers a very large areas in which some regions fall outside of our area of interest. Therefore, we implemented spatial subset by selecting only the area of interest, i.e. Klang, located in Selangor, Malaysia. The area covers approximately 540 km² within longitude 101° 10' E to 101°30' E and latitude 2°99' N to 3°15' N. This area was represented by 758 rows and 792 columns of pixels amounting 600,336 pixels.

Following the spatial subset, we then need to select suitable spectral bands of the Landsat data that are applicable in the subsequent analyses. This process is called spectral subset where only bands 1, 2, 3, 4, 5 and 7 which consist of visible and reflective infrared we chosen. Band 6 is a thermal band so was not applicable in this study and therefore was omitted. Figure-2 shows Landsat bands 4, 5 and 3 assigned red, green and blue from 2000 and 2005 after underwent georeferencing, spatial subset and spectral subset.

In remote sensing data, clouds are generally characterized by higher reflectance and lower temperature than the background [17]. Thick opaque clouds can block almost all information from the surface or near surface, while thin clouds allow partial surface information to be reflected to satellite sensors. Cloud shadow is another issue in remote sensing data and is formed on the surface due to projection of cloud structure onto local plane of the earth [18]. Cloud and cloud shadow need to be discriminated from others pixels since they tend to cause inaccuracy in subsequent analyses. Therefore, cloud and cloud shadow masking were implemented where cloud and cloud shadow were identified and masked with black colour.

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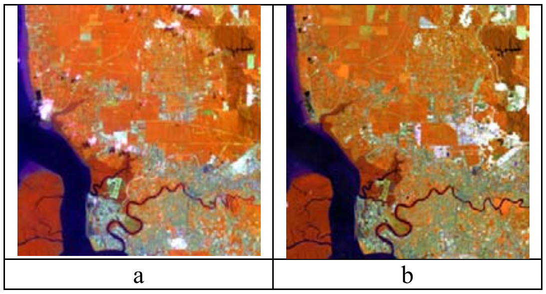

Figure-2. Landsat 5 image of Klang, Selangor from (a) 2000 and (b) 2005 after georeferencing, spatial subset and spectral subset.

IMAGE CLASSIFICATION

SVM classification is performed by making use an efficient hyperplane searching technique that uses minimal training area and therefore consumes less processing time [11], [12]. This method can avoid over fitting problem and requires no assumption on data type. Although it is non-parametric, the method is capable of developing efficient decision boundaries and therefore can minimize misclassification. SVM can be looked as a binary classifier that works by identifying the optimal hyperplane and correctly divides the data points into two classes. There will be an infinite number of hyperplanes and SVM will select the hyperplane with maximum margin. The margin indicates the distance between the classifier and the training points (support vector). Figure-3 illustrates the basic idea of support vector machine.

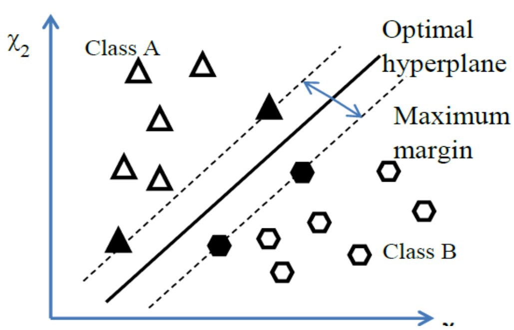

Figure-3. Basic idea of SVM.

In this study, SVM classification was applied to the study area (Klang in Selangor, Malaysia), which covers approximately 540 km² within longitude 101° 10' E to 101°30' E and latitude 2°99' N to 3°15' N. The satellite data were from bands 1, 2, 3, 4, 5 and 7 of Landsat-5 TM dated 15 July 2000 and 22 August 2005.

Visual interpretation of the Landsat data, aided by a land cover map, was carried out and 11 main classes were identified, viz. coastal swamp forest, dryland forest, oil palm, rubber, industry, cleared land, urban, coconut, bare land sediment plumes and water. Regions of interest (ROIs) associated with the ROIs were determined by choosing one or more polygons for each class based on visual interpretation of the land cover map and Landsat data. This was assisted by region growing technique in which pixels within polygons were grown to neighboring pixels based on a threshold, i.e. the number of standard deviations away from the mean of the drawn polygons. Pixels for the 11 classes of land cover were determined based on the land cover map.

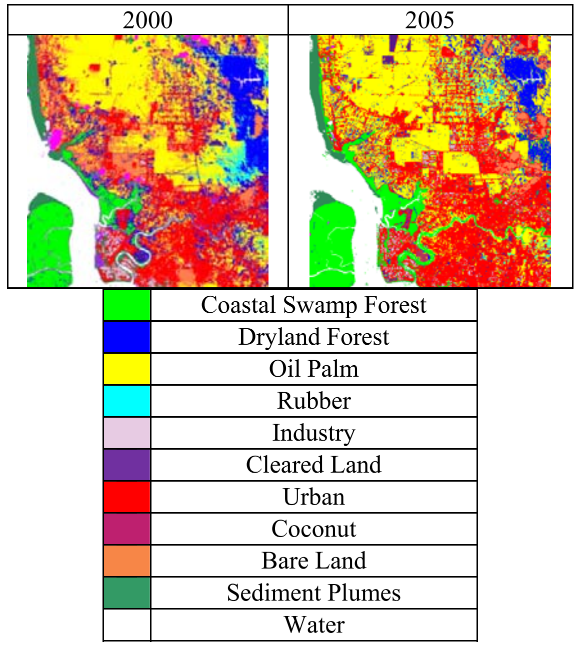

Figure-4. Land cover SVM classification.

CHANGE DETECTION

The classification results were analyzed to obtain the total area of each class. A change detection statistic techniques were used to identify the changes of the classes. The change detection statistics techniques compiled a detailed tabulation of changes between two classification images. The analysis focused primarily on the initial state classification changes; that is, for each initial state class, the analysis identified the classes into which those pixels changed in the final state image. The analysis results are reported in pixel counts, percentages and areas.

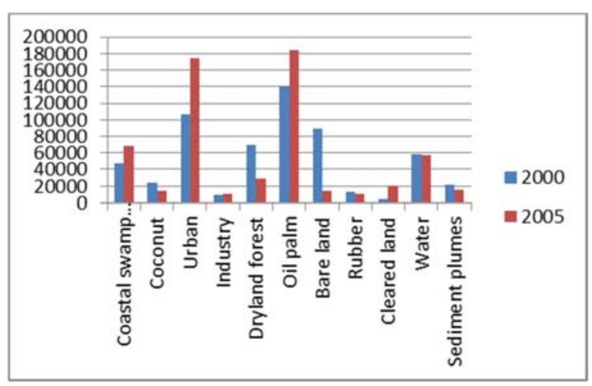

Figure-5. Land cover conversion in 2000 and 2005.

Table-2. Land cover conversion in pixel and percentage.

Area	**Total of conversion** (pixel)	**Total of conversion** (%)
Coastal swamp forest	20570	43.115
Coconut	-9218	-39.236
Urban	68089	63.793
Industry	725	7.83
Dryland forest	-40145	-57.974
Oil palm	44553	31.949
Bare land	-74367	-83.732
Rubber	-1628	-12.893
Cleared land	15927	386.109
Water	-1034	-1.785
Sediment plumes	-6034	-27.667

Figure-4 shows land cover changes between 2000 and 2005 in Klang, Selangor. The land cover has been classified into 11 classes; coastal swamp forest, coconut, urban, industry, dryland forest, oil palm, bare land, rubber, cleared land, water and sediment plumes. Figure-5 illustrates the major conversions were the bare land area and urban area. Table-2 shows during the 5-year period, the bare land has decreased by 83.732%, while urban area has increased by 63.793%. This is followed by the oil palm area (44553 pixel, representing a 31.949% increase), coastal swamp forest (20570 pixel, representing 43.115%), cleared land (15927 pixel, representing 386.109%) and industry (725 pixel, representing 7.83%). Other significant changes have been declines in the dryland forest (-40145 pixel reduction, representing a 57.974% decrease), coconut (-9218 pixel reduction, representing 39.236%), sediment plumes (-6034 pixel, representing 27.667%), rubber (-1628 pixel, representing 12.893%) and water (-1034 pixel, representing 1.785%).

The decrease of the bare land areas and the increase of the urban areas are due to the fact that Klang is experiencing rapid urbanization process due to the increase in residential areas as well as industrial areas. The increase in the oil palm area is due to the enlargement of oil palm plantation areas, especially Felda, to meet local and global demands. The cleared land area gives the unexpected result, which is an increase of 386.109%. This increase is due to the process of urbanization and deforestation.

CONCLUSIONS

This study evaluates the conversion of land cover from the year 2000 until 2005. Support Vector Machine classification was used in producing the change detection statistics. The biggest decrease in area is found in cleared land. On the other hand, the biggest increase in area is discovered in urban area. The significant changes were due to the areas which have underwent rapid urbanization.

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REFERENCES

[1] J.S.Deng, K.Wang, Y.H. Deng and G. J.Qi. 2008. PCA-based land-use change detection and analysis using multitemporal and multisensor satellite data. International Journal of Remote Sensing.

[2] Jwan Al-doski, Shattri B. Mansor and Helmi Zulhaidi Mohd Shafri. 2013. Change Detection Process and Techniques. Civil and Environmental Research.

[3] A. Ahmad and S. Quegan. 2013. Comparative Analysis of Supervised and Unsupervised Classification on Multispectral Data. Applied Mathematical Sciences. 7(74): 3681-3694.

[4] A. Ahmad. 2012. Analysis of Landsat 5 TM Data of Malaysian Land Covers Using ISODATA Clustering Technique. Proceedings of the 2012 IEEE Asia-Pacific Conference on Applied Electromagnetics (APACE 2012). pp. 92-97.

[5] G.G. Wilkinson. 2005. Results and implications of a study of fifteen years of satellite image classification experiments. IEEE Transactions on Geoscience and Remote Sensing. 43(3): 433-440.

[6] A. Asmala. 2012. Analysis of Maximum Likelihood Classification on Multispectral Data, Applied Mathematical Sciences. 6(129): 280-285.

[7] D. LU and Q. Weng. 2007. A survey of image classification methods and techniques for improving classification performance. International Journal of Remote Sensing. 28(5): 823-870.

[8] J. A. Richards and X. Jia. 2005. Remote Sensing Digital Image Analysis: An Introduction. 4th Ed., Springer, Berlin, Germany.

[9] A. Ahmad.2012. Analysis of Maximum Likelihood Classification Technique on Landsat 5 TM Satellite Data of Tropical Land Covers. Proceedings of 2012 IEEE International Conference on Control System, Computing and Engineering (ICCSCE2012). pp. 1-6.

ARPN Journal of Engineering and Applied Sciences

[10] Y. Chiang and L. Lin.2013. Mapping overused slopelands from SPOT data using support vector machines and artificial neural networks. Journal of Applied Remote Sensing. 7(1).

[11] N.I.S. Bahari, A. Ahmad and B. M. Aboobaider.2013. Application of support vector machine for classification of multispectral data, 7th IGRSM International Remote Sensing and GIS Conference and Exhibition. IOP Conf. Series: Earth and Environmental Science 20.

[12] S.V. Stehman and R. L. Czaplewski. 1998. Design and Analysis for Thematic Map Accuracy Assessment: Fundamental Principles. Remote Sensing of Environment. 64(3): 331-344.

[13] T.Kavzoglu and I. Colkesen. 2012. The effects of training set size for performance of support vector machines and decision trees. Proceeding of the 10th International Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Sciences Florianopolis-SC, Brazil.

[14] Wiliam J. Blackwell and Frederick W. Chen. 2005. Neural Network Applications in High-Resolution Atmospheric Remote Sensing. Lincoln Laboratory Journal. 15(2): 299-322.

[15] A. Singh. 1989. Review Article Digital change detection techniques using remotely-sensed data, International Journal of Remote Sensing. 10(6): 989-1003.

[16] USGS. 2016. http://landsat.usgs.gov/about_landsat5.

[17] A. Ahmad and S. Quegan. 2012. Cloud masking for remotely sensed data using spectral and principal components analysis. ETASR Eng. Tech. Appl. Sci. Res. 2, 221-225.

[18] J.J. Simpson and J.R. Stitt. 1998. A procedure for the detection and removal of cloud shadow form AVHRR data over land, IEEE Transactions on Geoscience and Remote Sensing. 36(3): 880-897.