VOL. 14, NO. 10, MAY 2019 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

IMPLEMENTATION OF LAND COVER CHANGE DETECTION BASED ON SUPERVISED CLASSIFICATIONS OF MULTISPECTRAL SATELLITE DATA FOR LEVERAGING INTERNET OF THINGS

A. Ahmad, U. K. M. Hashim[1], R. Abd Wahid[2], H. Sakidin[3], S. F. Sufahani[4], A. R. M. Amin[5], M. M. Abdullah[1] and S. Quegan[6]
[1]OptiMAS Research Group, Centre for Advanced Computing Technology (C-ACT), Faculty of Information and Communication Technology, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, DurianTunggal, Melaka, Malaysia
[2]TropicalMap Research Group, Faculty of Geoinformation and Real Estate, Universiti Teknologi Malaysia, Johor, Malaysia
[3]Department of Fundamental and Applied Sciences, Universiti Teknologi PETRONAS, Bandar Seri Iskandar, Perak, Malaysia
[4]Fakulti Sains Gunaan dan Teknologi, Universiti Tun Hussein Onn Malaysia, Parit Raja, Batu Pahat Johor, Malaysia
[5]Fakulti Sains Gunaan, Universiti Teknologi MARA Cawangan Terengganu, Kuala Terengganu, Terengganu Darul Iman
[6]Department of Applied Mathematics, School of Mathematics and Statistics University of Sheffield, Sheffield, United Kingdom
E-Mail: asmala@utem.edu.my

ABSTRACT

The study reported in this paper aims to detect land cover changes using multispectral and multitemporal remote sensing data. The data came from Landsat TM satellite covering the area of Klang, located in Selangor, Malaysia. Initially, pre-processing was carried out to identify the stability of three supervised methods namely maximum likelihood (ML), neural network (NN) and support vector machines (SVM) as the size of training pixels changed For this purpose, Landsat bands 1, 2, 3, 4, 5 and 7 for the year 1998 were used as the input for each of these methods to classify land covers within the study area. The generated land cover classifications were evaluated by statistically comparing each land cover with a reference data set using a confusion matrix. Subsequently, these methods were used to classify land covers of the same area using Landsat data acquired in the year 2000 and 2005. The 2005 classification was then statistically compared with the 2000 classification using a confusion matrix for each of the methods. This produced land cover changes that occurred between 2000 and 2005 which were generated using SVM, ML and NN. Results showed that land cover change detection using SVM was quantitatively and qualitatively more accurate compared to ML and NN mainly due to the least affected by the size of training pixels. The findings of the study are relevant and beneficial in leveraging the internet of things practices.

Keywords: land cover; change detection; remote sensing; multispectral; classification.

INTRODUCTION

The internet of things or IoT can be defined as a system that is able to interact and communicate with other system, objects, environments and infrastructures, resulting in volumes of data to be processed and translated into useful actions that make life much easier for human beings. In other words, the IoT system requires information for decision and action to be taken. One of the most important types of information needed by regional and national governments concerns the condition and use of land within its territory, and how these are changing. To infer land use, land cover information has been long collected, processed and interpreted using various approaches. Traditionally, land cover information was obtained by means of manual monitoring and observation such as surveying on foot or land vehicles. Nevertheless, such approach was time consuming, logistically expensive and not practical particularly for large and remote areas. A more modern approach was then introduced, popularly known as aerial photography, where camera is mounted on an aeroplane or helicopter enabling a wider filed of view of photographs. Although capable of capturing picture of larger areas in a much shorter time, such approach was found very expensive, weather-dependent besides exposing the operators to air accidents. To overcome such situations, with advancement of technology, satellite remote sensing is introduced where land cover information are able tobe 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].

Remote sensing technology has long been used to record the image of the Earth by means of identifying, observing, and measuring an object without coming into direct contact with it. This process involves the detection and measurement of radiation of different wavelengths reflected or emitted from distant objects or materials, by which they may be identified and categorized by type, substance, and spatial distribution. Remote sensors collect data by detecting the energy that is reflected from the Earth. These sensors can be on satellites. Remote sensors can be either passive or active. Passive sensors respond to external stimuli. They record radiation that is reflected from Earth's surface, usually from the sun. Because of this, passive sensors can only be used to collect data during daylight hours. Nevertheless passive remote sensing systems, such as Landsat Thematic Mapper (TM), have been used for a wide range of applications in many different fields such as land cover classification, hazard assessment, natural resource management and urban planning. Among the Landsat satellites, Landsat 5 TM is the fifth satellite of the Landsat program. It has a maximum transmission bandwidth of 85 Mbit/s. It is deployed at an altitude of 705.3 km and takes 16 days to scan the entire Earth. The Thematic Mapper (TM) is an advanced, multispectral scanning, Earth resources sensor designed to achieve higher image resolution, sharper spectral separation, improved geometric fidelity and greater radiometric accuracy and resolution than its predecessor, the multispectral scanner (MSS) sensor. TM data are sensed in seven spectral bands simultaneously. Band 6 senses thermal (heat) infrared radiation. Landsat can only acquire night scenes in band 6. A TM scene has an Instantaneous Field Of View (IFOV) of 30m x 30m in bands 1-5 and 7 while band 6 has an IFOV of 120m x 120m on the ground.

Remote sensing 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 due to lack of proper evaluation and testing procedures used [2]. In supervised classification methods, maximum likelihood (ML), support vector machines (SVM) and neural network (NN) have been widely used by researchers due to their practicality and accuracy. SVM classification is performed by making use of an efficient hyperplane searching technique that uses minimal training area and therefore consumes less processing time [3]. 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). In ML classification, the distribution for each class in each band is assumed to be normal and the probability a given pixel belongs to a specific classis calculated based on this assumption. Each pixel is then assigned to the class that has the highest probability. Classification is performed by calculating the discriminant functions for each pixel in the image. In NN classification, classification can be done even in the conditions where land covers are not linearly separable in the original spectral space. Classification is performed by making use of multiple nonlinear activation functions at different layers. The training pixels help in identifying the threshold and weight vector connected in the network.

A number of studies have attempted to carry out land cover change detection at some parts of the world. [4-6] made use of maximum likelihood (ML) classification to detect land cover changes in several countries. However the true performance of the proposed technique could not be known since no comparison with other classification techniques was made. [7-8] attempted to use several vegetation indices for land cover change detection but the robustness of the methods were not compared with more promising methods such as supervised classification. [9] Carried out hybrid classification by making use of ISODATA clustering followed by an unnamed supervised technique and then performed an analysis by means of cross tabulation technique to see the conversion from 2000 to 2004; nevertheless the results were not comparatively analysed with other advanced techniques such as support vector machiness (SVM) and neural network (NN). Following these issues, this study attempts to carry out change detection by means of three supervised classification techniques, i.e. ML, SVM and NN and then analyses the results quatitatively and qualitatively.

METHODOLOGY

The study area was Klang, located in Selangor, Malaysia. It covers approximately 540 km^2 within longitude 101° 10’ E to 101°30’ E and latitude 2°99’ N to 3°15’ N. The area has 11 primary land covers i.e. coastal swamp forest, dryland forest, oil palm, rubber, industry, cleared land, urban, coconut, bare land, sediment plumes and water [10]. This study involves three main phases i.e. data pre-processing, data processing and land cover change detection analysis. Landsat satellite data were obtained from Agensi Remote Sensing Negara (ARSM) and United States Geological Survey (USGS) involving data from 1998, 2000 and 2005 [11]. In data preparation, the data were initially calibrated where pixel raw digital number was converted into radiance [2]. Geometric correction was performed to correct 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.

In data pre-processing, we performed a preliminary assessment to understand the performance of ML, SVM and NN when the size of the training pixels was varied. Such situation may occur when carrying out land cover change detection later due to cloud and cloud shadow issues. For this purpose, the 1998 Landsat data were used. 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 training 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 neighbouring 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. Sampling was carried out by means of stratified random sampling technique. This was done by dividing the population (the entire classification

VOL. 14, NO. 10, MAY 2019 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

image) into homogeneous subgroups (the ROI for individual classes) and then taking a simple random sample in each subgroup. 11 training sets were extracted based on percentage of pixels within the ROIs, viz. 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80% and 90%. Each of training sets was fed into each of the classifiers i.e. ML, NN and SVM where the accuracy of the classification was assessed by means of percentage classification accuracy.

In data processing, we applied the ML, SVM and NN classification to the 2000 and 2005 data to determine land cover changes within these dates. Similarly, 11 land covers were considered i.e. coastal swamp forest, dry land forest, oil palm, rubber, industry, cleared land, urban, coconut, bare land, sediment plumes and water.

In land cover change detection analysis, further analyses were carried out to determine which classification scheme is the most reliable to be used to detect land cover changes between 2000 to 20005.

RESULTS

The results can be categorised into three phases, i.e. data pre-processing, data processing and land cover change detection analysis, as follows.

Data pre-processing

The classification results for 10% through 90% training set size were evaluated by using confusion matrices [12-13] to assess the capability of SVM, ML and NN in classifying the 11 predefined land covers. In order to better see these classes, suitable colours were assigned to the land covers: coastal swamp forest (green), dryland forest (blue), oil palm (yellow), rubber (cyan), industry (thistle), cleared land (purple), urban (red), coconut (maroon), bare land (orange), sediment plumes (dark green) and water (white). Classification and reference (ground truth) data set were compared among all cases. Figure-1 shows the classification result by applying ML, NN and SVM method for two extreme cases 10% (the smallest) and 90% (biggest) training set sizes. Visually, based on qualitative visual analysis of the land cover colour distribution, it is obvious that ML and SVM are capable to classify the more land covers compared to NN for both cases. For 10% training set size, NN recognizes most land covers as oil palm in which is not the case. Similarly, for 90% training set size, NN recognizes most land covers as rubber. For ML, it is noticeable for both cases, coconut is found far too abundant along the sea side areas and encroaches markedly towards the inland areas in which likely to be an ambiguous case. In other words, it is likely that misclassification occurs between oil palm and coconut in ML classification. It is likely that these results are due to the similarities of spectral properties between oil palm and coconut. It is also found that there is a discrepancy between the far abundant coconut near the dry land forest for the 10% compared to the 90% training pixel. For SVM, it can be seen that the distribution of classes is rather consistent for the 10% and 90% training pixels indicating that the performance of SVM is not much influenced by the training set size.

In terms of quantitative analysis, for both (10%, 90%) training set sizes, SVM (92.67%, 93.16%) has the highest overall accuracy, followed by ML (89.98%, 90.61%) and NN gives the lowest accuracy (60.64%, 21.78%). SVM and ML have a similar performance trend where the classification accuracy for 90% is higher than the 10% training set size. However, the performance is vice versa for NN. The accuracy differences of the extreme cases for SVM, ML and NN are found to be 0.49%, 0.62% and 38.87% respectively. This shows that SVM has higher stability when making use of relatively small numbers of training data points compared to ML and NN. ML can be signified as the method that depends much on the accuracy and sufficiency of the training pixels. NN has been known as a method that not only depending on training pixels or learning the rules but its process is also affluence by the network topology that encompasses the hidden layer and interconnections.

VOL. 14, NO. 10, MAY 2019 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

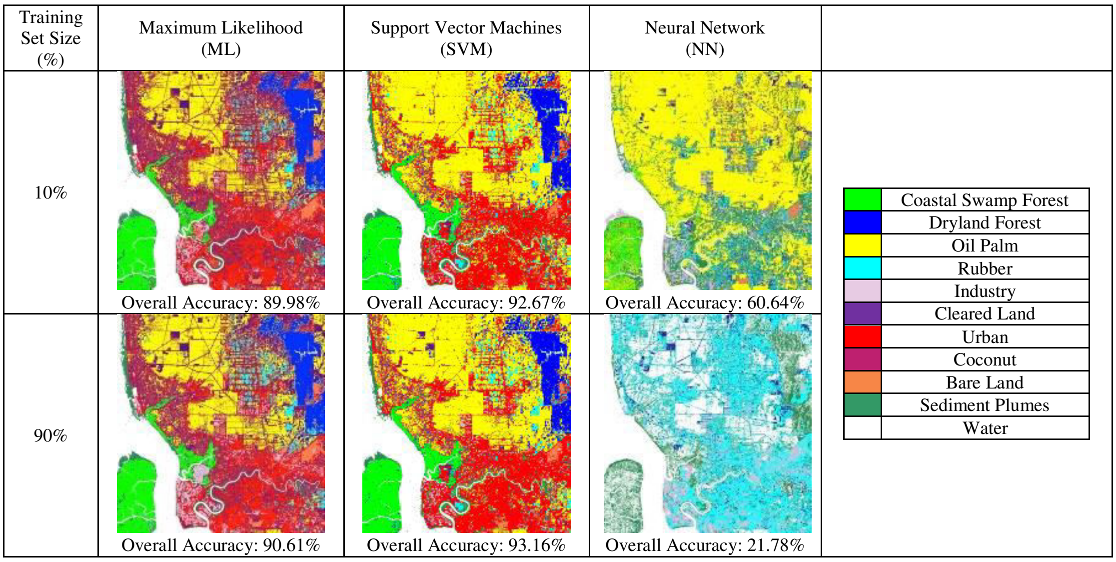

Figure-1. ML, SVM and NN classification for Landsat 5 TM data acquired in 1998 for 10% and 90% training set size.

To understand the trend further, linear regression analysis was applied to all classifications. Figure-2(a) shows plot of classification accuracy versus training set size for ML. Although fluctuating, there is somewhat an increasing trend when classification accuracy is plotted against training set size. The linear regression analysis gives R^2 of 0.1681 indicating weak positive correlation between the classification accuracy and training set size. Figure-2(b) shows plot of classification accuracy versus training set size for NN. It can be seen there is a decreasing trend between classification accuracy and training set size. The regression analysis gives R^2 of 0.7516 indicating a somewhat strong negative trend between the classification accuracy and training set size. Figure-2(c) shows plot of classification accuracy versus training set size for SVM. There is a noticeable increasing trend between classification accuracy and training set size. The regression analysis gives R^2 of 0.7117 indicating a rather strong positive correlation between the classification accuracy and training set size. Figure-2(d) shows plot of classification accuracy versus training set size for ML, NN and SVM. Clearly, SVM and ML have the higher stability compared to NN in which the accuracy drops drastically as training size increases. However, SVM noticeably outperforms ML due to much higher R^2 besides having the least difference in classification accuracy as training set size increases.

Data processing

Table-1 shows land cover area in km^2 classified using SVM, ML and NN for the year 2000 and 2005 while Table-2 shows land cover changes in km^2 from 2000 to 2005 based on SVM, ML and NN classification. The land covers are classified into 11 classes; coastal swamp forest, coconut, urban, industry, dryland forest, oil palm, bare land, rubber, cleared land, water and sediment plumes. For SVM classification, the major conversions are the bare land area and urban area. During the 5-year period, the bare land has decreased by 118 km^2. Urban area experienced the highest increase, i.e. 107 km^2. This is followed by the coastal land forest 15 km^2, oil palm 29.3 km^2 increase, cleared land 13.5 km^2 increase and industry 6.5 km^2 increase. Other significant changes have been declines in the sediment plumes 3.9 km^2, water 3.4 km^2, rubber 0.93 km^2 and coconut 0.8 km^2.

VOL. 14, NO. 10, MAY 2019 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

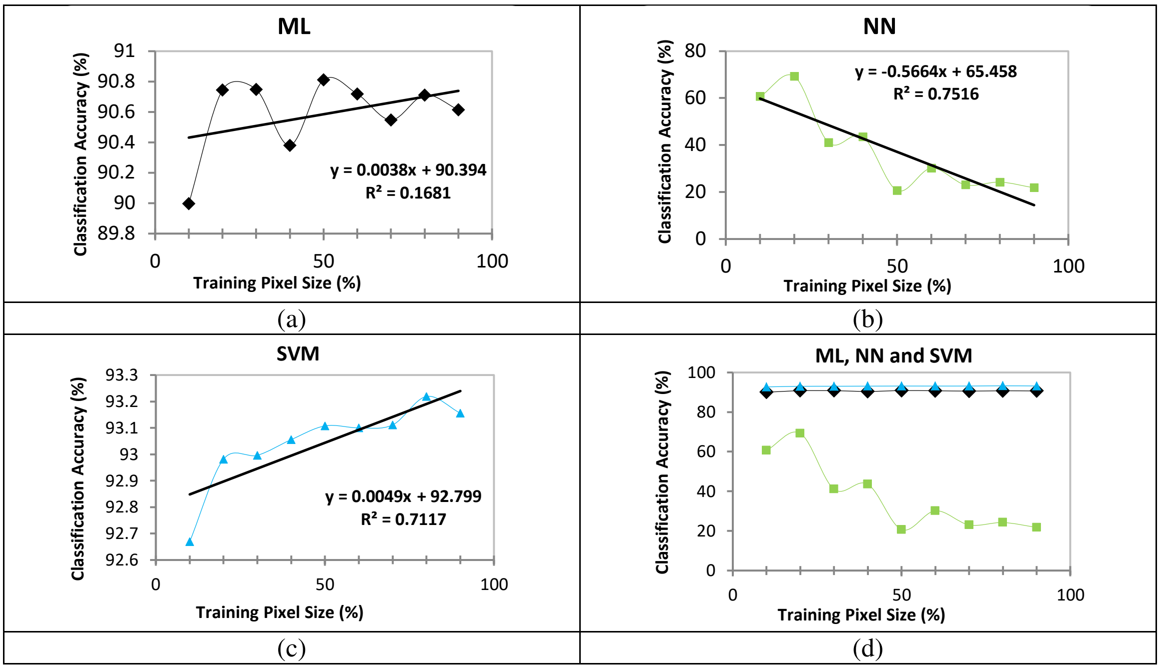

Figure-2. Classification accuracy versus training set size for ML, SVM and NN classification for 10% through 90% training set size. Trendline with $R^2$to indicate the correlation between classification accuracy and training set size.

Table-1. Land cover area in km^2 classified using SVM, ML and NN for the year 2000 and 2005.

Land cover Type	Total of Area (km) for 2000			Total of Area (km) for 2005		
	SVM	ML	NN	SVM	ML	NN
Coastal swamp forest	45.80	37.60	0.00	61.55	48.20	331.25
Sediment plumes	17.93	34.89	0.00	14.00	18.19	0.00
Urban	52.81	79.25	5.66	160.32	161.36	0.00
Industry	2.80	29.57	0.00	9.27	45.96	9.83
Water	54.65	41.72	52.21	51.26	46.74	0.11
Dryland forest	72.43	44.70	122.57	27.90	18.30	143.19
Bare land	131.85	84.76	2.39	12.87	20.37	15.82
Cleared land	3.90	9.40	0.00	17.39	14.62	39.97
Oil palm	150.99	100.51	145.98	180.29	164.76	0.00
Rubber	3.02	10.21	32.97	2.09	1.11	0.00
Coconut	4.12	67.70	178.53	3.37	0.68	0.14

The decrease of the bare land areas and the increase of the urban areas are due to the fact that Klang was experiencing rapid urbanization process due to the increase in residential areas as well as industrial areas. The increase in the oil palm area was due to the enlargement of oil palm plantation areas, especially Felda, to meet local and global demands. The cleared land area also gave the significant increase due to the process of urbanization and deforestation. For ML classification, the major conversions are the urban area and coconut area. During the 5-year period, the urban has increased by 82 km^2, while coconut has decreased by 67 km^2. Bare land experienced 64 km^2 decrease, oil palm increased 64 km^2, dryland forest decreased 26 km^2, sediment plumes decreased 17 km^2, industry has increased 16 km^2 pixel and rubber has decreased 9 km^2. Other significant change was experienced by coastal swamp forest with 11 km^2 increase, cleared land 5 km^2 increase and water 5 km^2 increase. For NN classification, the major conversions were the coastal swamp forest and coconut area. During the 5-year period, the coastal swamp forest has increased by 331 km^2, while coconut has decreased by 178 km^2. This was followed by oil palm with 146 km^2 decrease, water 52 km^2 decrease, cleared land 40 km^2 increase, rubber 33 km^2 decrease, dry land forest 21 km^2 increase, bare land 13 km^2 increase, industry 10 km^2 increase and urban 6 km^2 decease. Sediment plumes gave the unexpected result of no changes, 0 pixel during this period.

Table-2. Land cover changes in km^2 classified using SVM, ML and NN for the year 2000 to 2005.

Land cover Type	Land Cover Change (pixel) 2000-2005			Land Cover Change (km^2) 2000-2005			Land Cover Change (%) 2000-2005		
	SVM	ML	NN	SVM	ML	NN	SVM	ML	NN
Coastal swamp forest	17493	11779	368053	15.74	10.60	331.25	34.37	28.19	-
Sediment plumes	-4355	-18556	0	-3.92	-16.70	0.00	-21.87	-47.86	-
Urban	119460	91230	-6286	107.51	82.11	-5.66	203.59	103.61	-100.00
Industry	7189	18219	10918	6.47	16.40	9.83	231.01	55.46	-
Water	-3773	5584	-57889	-3.39	5.03	-52.10	-6.21	12.05	-99.78
Dry land forest	-49486	-29329	22915	-44.53	-26.40	20.62	-61.48	-59.06	16.83
Bare land	-132205	-71538	14921	-118.98	-64.38	13.43	-90.24	-75.96	562.42
Cleared land	14993	5801	44407	13.49	5.22	39.97	345.75	55.57	-
Oil palm	32456	71392	-162205	29.30	64.25	-145.98	19.41	63.93	-100.00
Rubber	-948	-10110	-36628	-0.93	-9.10	-32.97	-30.85	-89.09	-100.00
Coconut	-824	-74472	-198206	-0.76	-67.02	-178.39	-17.96	-1.09	-0.41

Land cover change detection analysis

Figure-3 shows area versus land cover (left) and changes versus land cover for SVM, ML and NN (right) for coastal swamp forest (CSF), dry land 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). For SVM, for the year 2000, oil palm and bare land the largest area while industry, rubber and coconut have the smallest area (left plot). The most notable increase from the year 2000 to 2005 is experienced by urban while bare land experiences the most noticeable decrease. This is due to the conversion from bare land to urban due to rapid economic development. This involved particularly development of residential and shop premises. Not much changes are experienced by rubber and coconut compared to oil palm due to the priority status in market. As expected, not much changes are experienced by water. For the right plot, the points above x-axis indicate an increase in area while the points below the x-axis indicate a decrease in area. Urban increases the most while bare land decreases the most from 2000 to 2005. The decrease in bare land area is slightly more than the increase Om urban area. This is due to the fact that not all bare land areas are converted to urban since some of them are also converted to priority agriculture particularly oil palm.

For ML, for the year 2000, oil palm and bare land the largest area while cleared land and rubber have the smallest area (left plot). Contradicting to SVM, ML has coconut area for the year 2000 that oris far larger in which less than oil palm for about 30 km^2. This is not likely to be true since in the actual scenario, oil palm is far abundant than coconut. This may due to the fact that ML is very sensitive to the selection of training pixels since oil palm and coconut have somewhat similar physical properties. The most notable increase from the year 2000 to 2005 is experienced by urban and oil palm while bare land and coconut experience the most noticeable decrease. Urban and oil palm increase the most while bare land and coconut decrease the most from 2000 to 2005. The increase in urban area is more that the oil palm area while bare land and coconut decrease at about the same rate. The drastic drop in coconut from the year 2000 to 2005 seems questionable since in the actual scenario, coconut is not planted as much as being captured by ML. This is likely due to the sensitivity of ML to the selection of training pixels in which can lead to ambiguous outcome. For the right plot, urban and oil palm increase the most while bare land and coconut decrease the most from 2000 to 2005. The increase in urban area is more that the oil palm area while bare land and coconut decrease at about the same rate. The drastic drop in coconut from the year 2000 to 2005 seems questionable since in the actual scenario, coconut is not planted as much as being captured by ML. This is likely due to the sensitivity of ML to the selection of training pixels in which can lead to ambiguous outcome.

For NN, for the year 2000, coconut, oil palm and dry land forest are among the largest area while sediment plumes, bare land and urban are among the smallest area. For the year 2005, coastal swamp forest and dry land forest have the largest area while sediment plumes, urban, water, cleared land, oil palm; rubber and coconut have the smallest area. The outcome contradicts that of SVM and ML, as well as opposes the real situation since built-up areas were being developed substantially where forest, agricultural and unoccupied land areas are converted to urban and industrial rapidly in line with Malaysian Vision 2020. For the right plot, at a glance, it can be seen that there is a considerable increase in area change for coastal swamp forest and almost unchanged for urban and industry in which give a clearer picture of the unrealistic land cover change detection when using neural network. This is consistent with the instability of NN classification

ARPN Journal of Engineering and Applied Sciences

accuracy when the training pixels were varied as been revealed in the previous experiment.

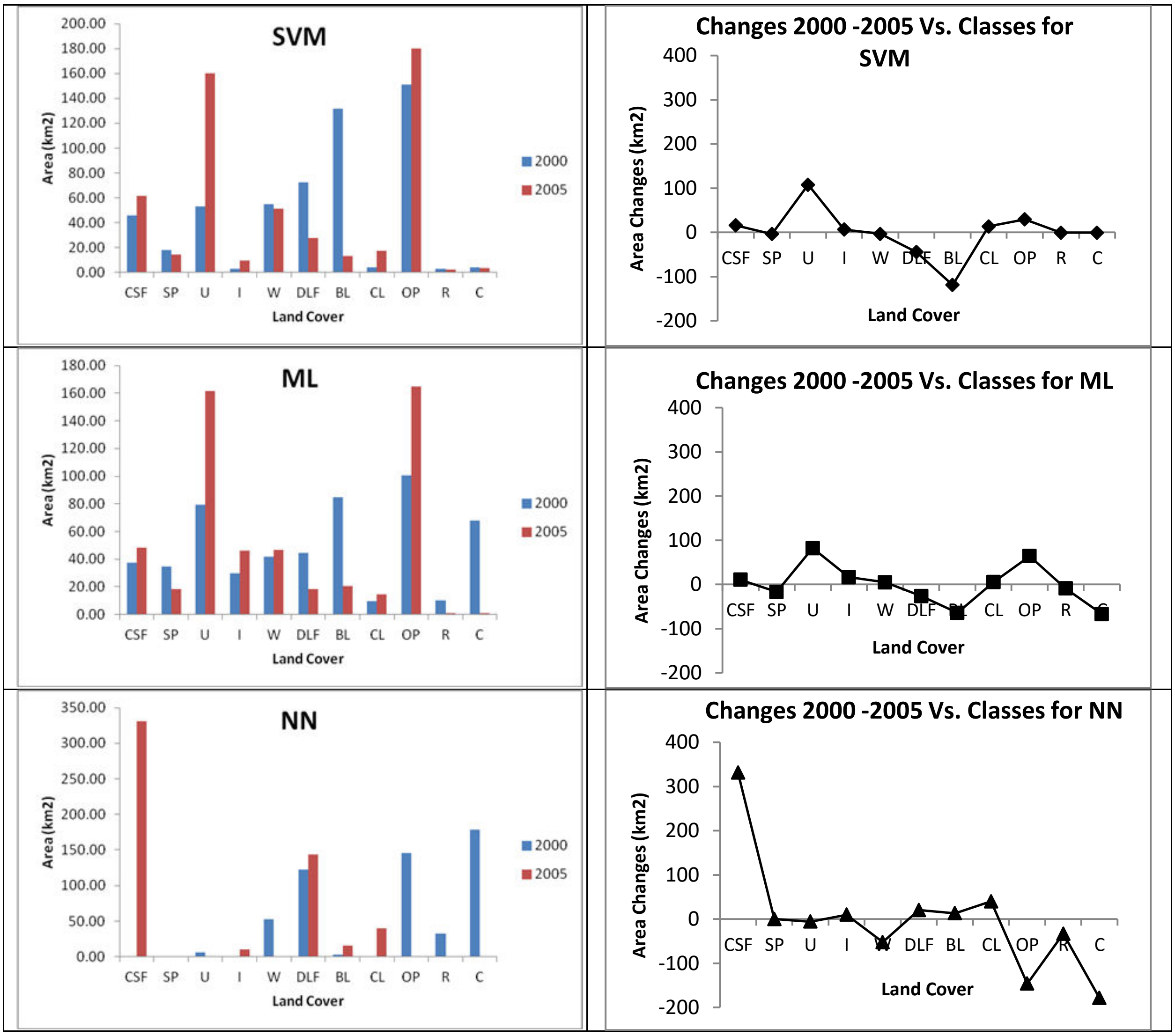

Figure-3. Area versus land cover (left) and area changes versus land cover for ML, SVM and NN (right).

Figure-4 shows land cover changes from 2000 to 2005 using SVM, ML and NN. It can be clearly seen NN is noticeably discriminated from SVM and ML. SVM and ML differs main on coconut where the reduction of coconut from 2000 to 2005 is quite significant in ML compared to SVM. Based on the time series data obtained from Selangor Agricultural Department, the drop of coconut from the year 2000 to 2005 is only about 11 km^2 in which closer to SVM (0.76 km^2) compared to ML (67 km^2). This is realistic since the time series data is meant for the whole Klang district with total area of 630 km^2 whereas for this study the total area considered which is only 490 km^2.

CONCLUSIONS

In this study, changes in land cover have been investigated for 11 land covers i.e. coastal swamp forest, dry land forest, oil palm, rubber, industry, cleared land, urban, coconut, bare land, sediment plumes and water. In detecting changes, land cover classification has been performed using three classification methods, i.e. ML, NN and SVM. The classifications used different training set sizes established from each land cover. The classified images were then evaluated via classification accuracy. The changes were identified by comparing the size of each land cover area. SVM has been identified to be the most appropriate classification scheme in detecting land cover changes particularly due to its stability even when the training set size varies. Overall, change detection based on SVM classification gave the most realistic result compared to ML and NN when compared quantitatively and qualitatively. The information on land cover changes can serve as a vital input for the IoT system that lead to a more accurate decision and action, eventually the betterment of human life.

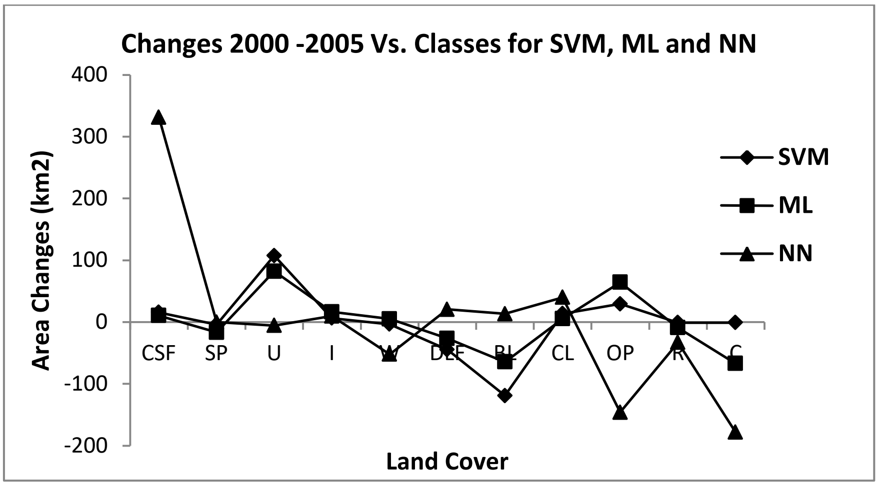

Figure-4. Land cover changes from 2000 to 2005 using SVM, ML and NN.

ACKNOWLEDGEMENTS

The Authors would like to thank Universiti Teknikal Malaysia Melaka for providing student research funding for this study through UTeM Zamalah Scheme.

REFERENCES

[1] S. M. Zaidi, A. Akbari, A. A. Samah, N. S. Kong, J. Isabella and A. Gisen. 2017. Landsat-5 time series analysis for land use/land cover change detection using NDVI and semi-supervised classification techniques. Polish Journal of Environmental Studies. 26(6): 2833-2840.

[2] Q. Liu, L. Liu, and Y. Wang. 2017. Unsupervised change detection for multispectral remote sensing images using random walks. Remote Sensing. 9(5): 1-17.

[3] E. M. Kaur and E. N. Kaur. 2017. Change detection using fuzzy SVM for identifying regions from within remote sensed images. International Journal of Scientific Research and Management. 5(7): 5805-5809.

[4] H. A. A Abd and H. A. Alnajjar. 2013. Maximum likelihood for land-use/land-cover mapping and change detection using Landsat satellite images: a case study south of Johor. International Journal of Computational Engineering Research. 3(6): 1-8.

[5] U. K. M. Hashim, A. Ahmad, B. M. Aboobaider, H. Sakidin, Subatira and M.S.M. Isa. 2016. Change detection from Landsat-5 tm satellite data. ARPN Journal of Engineering and Applied Sciences. 11(17): 10234-10238.

[6] M. Inzamul and H. R. Basak. 2017. Land cover change detection using GIS and remote sensing techniques: A spatio-temporal study on Tanguar Haor, Sunamganj, Bangladesh. The Egyptian Journal of Remote Sensing and Space Science. 20(2): 251-263.

[7] K. Rokni, A. Ahmad, A. Selamat and S. Hazini. 2014. Water feature extraction and change detection using multitemporal Landsat imagery. Remote Sensing. 6(5): 4173-4189.

[8] M. Gandhi G., S. Parthiban, N. Thummalu and A. Christy. 2015. NDVI: Vegetation change detection using remote sensing and GIS - A case study of Vellore District. Procedia Computer Science. 57: 1199-1210.

[9] M. M. El-Hattab. 2016. Applying post classification change detection technique to monitor an Egyptian coastal zone (Abu Qir Bay). The Egyptian Journal of Remote Sensing and Space Science. 19(1): 23-36.

[10] N. I. S. Bahari, A. Ahmad and B. M. Aboobaider. 2014. Application of support vector machines for classification of multispectral data. IOP Conf. Series: Earth and Environmental Science. 20: 1-8.

[11] A. Ahmad. 2012. Classification simulation of RazakSAT Satellite. Procedia Engineering. 53: 472-482.

[12] Ahmad and S. Quegan. 2015. The effects of haze on the accuracy of satellite land cover classification. Applied Mathematical Sciences. 9(49): 2433-2443.

[13] Ahmad and S. Quegan. 2016. The effects of haze on the accuracy of maximum likelihood classification. Applied Mathematical Sciences. 10(39): 1935-1944.