Hayder Abd Al-Razzaq Abd / International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622 www.ijera.com
Vol. 3, Issue 3, May-Jun 2013, pp.686-693

Feature Extraction and Based Pixel Classification for Estimation the Land Cover thematic map using Hyperspectral data

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ABSTRACT

There are a few studies have been used the hyperspectral remotely sensed imageries to identify the Land use and land cover into UPM University campus. UPM is one of the oldest Malaysian Universities located in the west Malaysia, Selangor state, Serdang it chosen for this research. High resolution images from hyperspectral satellite and Google earth have been used to conduct this research. The study area divided into nine classes (Clear water, Lake, Soil, Roads, Building R- roof, Building C- roof, Building B- roof, Grass, Tree) to estimate the thematic map of land cover of the UPM campus, using two algorithms the classification performed with Support Vector Machine under feature extraction classification and Maximum likelihood under based pixel classification, then did the comparison between the two techniques. Through the whole study duration. The results demonstrated that the accuracy of SVM is better than of Maximum likelihood and the overall accuracy for SVM and Maximum likelihood were 98.23%, 90.48% respectively.

Keywords – *hyper spectral image, support vector machine, Maximum likelihood, feature extraction, based pixel classification. land cover.*

1. INTRODUCTION

Land cover and land use is the discernible to the Vegetation, Geologic, Anthropogenic or Hydrologic features on the earth's land surface. Land cover describes the physical state of the earth’s surface and immediate surface in terms of the natural environment and the manmade structures (such as water bodies, vegetation, urban area, soils, earth’s surfaces and ground water). These land cover features can be classified using the remotely sensed satellite imagery of different spectral, temporal and spatial resolutions. Land cover mapping using high spectral resolution has many advantages, since it helps in different kind of mapping applications such as species identifications, soil types, mineral classifications etc. The hyperspectral data has a large number of contiguous bands that have high level of spectral resolution. The hyperspectral data processing possesses both challenges and opportunities for land cover classification. Land cover classification can be conducted using various algorithms by processing the remotely sensed data into different themes. The present research examines and compares the results obtained from various classification algorithms using hyperspectral data for land cover mapping to find out which algorithm and technique better for such a land cover mapping.

2. BACKGROUND

Hyperspectral remote sensing (HRS) images can be acquired from different kind of hyperspectral sensors, such as AVIRIS, EO-1 Hyperion, ASIA and HyMap, have revealed very wide usefulness in many applications (environment, agriculture and geosciences). Generally, the hyperspectral remotely sensing image has massive information and the fine spectral resolution which can capture the subtle differences between the spectral reflectance of different vegetation species [1], that will make the hyperspectral remote sensing data processing is very complex in the terms of data uncertainty [2], curse of dimensionality [1] and small samples [3,4], as a result of that it is very difficult to employ traditional or normal type of classification with hyperspectral data with getting as output high performance. The Huge of any phenomenon that detected with hayperspectral imagery leads to serious problem related to decrease the accuracy of the classification for this phenomenon to extract the information [5]. Support vector machine (SVM) has been shown to outperform classical supervised classification algorithms, therefore it has been recently used for classification of hyperspectral data. In comparison with approaches based on empirical risk, which minimize the misclassification error on the training set, structural risk minimization seeks the smallest probability of misclassifying a previously unseen data point drawn randomly from a fixed but unknown probability distribution. Furthermore, an SVM tries to find an optimal hyperplane that maximizes the margin between classes by using a small number of training cases. The basis of the SVM and the results of some studies suggest that SVM classification may be unaffected by the dimensionality of the data set, however, some studies have shown that the accuracy of SVM classification could still be increased by reducing the dimensionality of the data set. The SVM has been widely used and promoted for land-cover classification studies, including multispectral and hyperspectral data with some studies suggesting that the method is not affected by the Hughes phenomena. However, a recent research shows that the accuracy of SVM classification is influenced by the number of features used, therefore, is affected by the Hughes phenomenon with the impact most evident when a small training set is used. It is possible that the Hughes effect had not been observed in some other studies because the opportunity for it to become manifested in the results was limited through experimental design, notably through the use of a large training set. Two broad categories of feature-reduction techniques: they are feature extraction and feature selection, with feature extraction, the original remotely sensed data set is typically transformed in some way that allows the definition of a small set of new features which contain the vast majority of the original data set's information. More popular, are feature-selection methods. The latter aim to define a subset of the original features which allows the classes to be discriminated accurately. Feature selection typically aims to identify a subset of the original features that maintains the useful information to separate the classes with highly correlated and redundant features excluded from the classification analysis. The results of the same research have shown that the accuracy of classification by an SVM can be significantly reduced by the addition of features and that the effect is most apparent with small training sets. With the AVIRIS data set, a significant reduction in accuracy with the addition of features was observed at all training set sizes evaluated. With the DAIS data set, a statistically significant decline in accuracy was also observed for small training sets (≤ 25 cases per class). However, even with a large training sample using the DAIS data set, feature selection may have a positive role, providing a reduced data set that may be used to yield a classification of similar accuracy to that derived from use of much larger feature set. As the accuracy of SVM classification was dependent on the dimensionality of the data set and the size of the training set, it may be beneficial to undertake a feature-selection analysis prior to a classification analysis. Another study compared the results of SVM and maximum likelihood classifier (MLC) in classification to provide a land use/cover map in an urban area. A broadband image was simulated and derived a band reduced image from the AVIRIS image. The simulated broadband image provides the identical spectral coverage of the six TM bands (excluding the thermal band). The band reduced image was created by using data dimensionality reduction technique to select 85 AVIRIS bands, which allow performing some classification types (e.g., maximum likelihood classifier) to be effectively performed without having to substantially increase the amount of training data. The hyperspectral imageries contain a huge amount of redundant spectral information in the adjacent bands, and the principal component analysis (PCA) method was used to reduce the data dimension, and the output image consists of six PCA bands that contain 99.9% of the information from the 85 AVIRIS bands. A land use-cover classification scheme based on the Anderson scheme [21] was designed, which includes 7 major categories: low-density urban, medium-density urban, high-density urban, forest, grassland, barren land and water. The three urban land classes vary by their built-up densities. Training and reference samples were selected through the use of high-resolution images from Google Earth and National Land Cover Data.

The result summarizes the accuracy assessment for each image classified with SVM and maximum likelihood methods. The AVIRIS image with 85 bands has the higher overall classification accuracy when classifying with the SVM method. Note that the researcher failed in classifying the same image with the maximum likelihood (MLC) method, largely due to the inability of this conventional method in dealing with the substantial data dimensionality increase with relatively limited training sample size. Support vector machines (SVM) substantially outperformed the maximum likelihood classifier in each image. In terms of specific land cover classes, the AVIRIS data which classified using the SVM method shown a better accuracy, particularly for the three urban classes, when comparing with the outcomes from other images, the SVMs generally outperformed the MLC method. Overall, the improved capability of hyperspectral imagery helped better resolve spectrally complex classes, particularly when classified with the support vector machine method. Support Vector Machine is one of the best classifiers that adopted to perform the classification of hyperspectral remotely sensed imageries classification successfully. The result or the output of the Support Vector Machine show that this classifier is better than another classifiers such as Minimum Distance Classification (MDC), Maximum likelihood Classifications (MLC) Artificial Neural Network (ANN), and Spectral Angle Mapper Classification (SAM) [6, 7, 11].

Recently SVM became the most popular and effective statistical learning algorithm that use in pattern recognition and machine learning fields, SVM has such advantages as less requirement to prior knowledge, more suitability to small size of samples [8], more robustness to noises [9], and higher learning efficiency and more powerful generalization capacity [10]. So it can be used to spatial data processing and analysis including hyperspectral RS image classification [11], spatial fitting and regression [12], data mining [13], and object detection [14]. SVM, as one of the most effective statistical algorithms, it is considered the structural risk minimization (SRM) criterion more than considered empirical risk minimization (ERM) in other methods. Because SVM is advantageous to reduce difficulties that will face the hyperspectral data when classifying a small-size samples, high dimensionality, poor generalization and uncertainty impacts, it has been applied to hyperspectral Remote Sensing image classification in recent years [15, 16]. The SVM is perfect classifier algorithm than other traditional classifiers and it is perfect for high dimensional features such as the direction use for hyperspectral image's bands but the wasting time and the computation capacity are still big challenges, therefor, feature extraction and dimensionality decreasing still meaningful on many case.

The Maximum Likelihood classifier assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. Unless a probability threshold is selected, all pixels are classified, each pixel is assigned to the class that has the highest probability. If the highest probability is smaller than a threshold, the pixel remains unclassified. [17] In the study which was done in 2007, different classifications such as Artificial Neural Network (ANN) classifier, Spectral Angle Mapper (SAM), Decision Tree (DT) classifier, Spectral Angle Mapper (SAM) and Maximum Likelihood Classifier (MLC) were implemented in a hyperspectral image in Malaysia. The higher accuracy of results as shown by the MLC classifier, this study suggests that the hyperspectral data which was derived from the optimal band configuration of the airborne sensor has a sufficiently Gaussian distribution that is able to give a full and representative description of the respective classes (spectrally separable tree species classes) and fulfills the requirement (biased towards) for such a parametric algorithm [17]. The problem of not having enough training samples with hyperspectral imagery for reliable training of a maximum likelihood classifier is well known.

Another research shows that the provided candidate neighbors which are assessed for suitability spectrally can be used to expand the training set and generate class statistics for high dimensionality data giving improvements in classifier performance comparable to that observed with randomly selected unlabeled samples, along with a more complex evaluation process [18]. The study which was done in 2009 it found the main difficulty of texture recognition is the lack of effective tools to characterize different scales of textures and then to improve the problem, the wavelet co-occurrence parameters, mean, homogeneity, and standard deviation of different level discrete wavelet transform images were used as texture features, then the texture features combined with PCA band of image were adopted as the characteristic vector of training samples for SVM, and Decision Tree and Maximum likelihood classification. The experimental results showed that SVM method gave the highest correct classification rate within all of these three methodologies while Maximum Likelihood gave the lowest rate and also adding texture feature information by the proposed approach to images improved classification accuracy for all of SVM, Decision Tree, and Maximum Likelihood classification [19].

3. METHODS AND MATERIALS

3.1. Study Area

The study area was in campus of University Putra Malaysia (UPM) that located in Serdang, Selangor state, Malaysia. UPM university one of the biggest and oldest universities in Malaysia, it has been established in 1931, UPM is a research university in central Peninsular Malaysia, near to the biggest and the capital city, Kuala Lumpur. It was formerly known as University Pertanian Malaysia or Agricultural University of Malaysia or University Putra Malaysia. UPM is a very good research university providing undergraduate and postgraduate courses with a research focus on different sciences. The Fig. 1 below describes the study area.

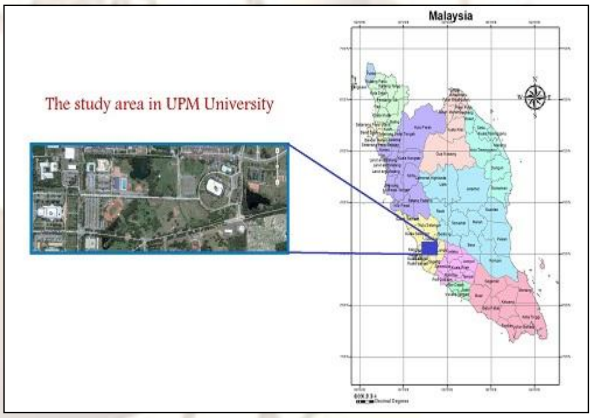


Fig. 1: The study area in UPM University Campus.

3.2. Data

The data has been used to conduct this study was hyperspectral remotely sensed imagery has 20 bands this imagery is represented the study area in UPM campus .The Area Of study area was (729,828) m^2 .The hyperspectral imagery has been geo-referenced to coordinate system {UTM, Zone 47N, with spatial resolution 1 meter and Fig. 2 reveals the hyperspectral image

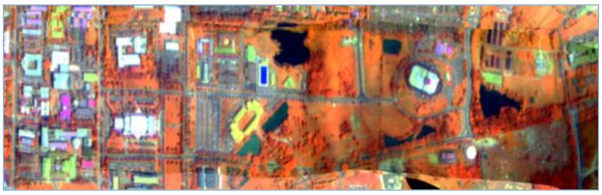


Fig. 2: Hyperspectral imagery of study area

The datum was (WGS-84) .The wavelength of the 20 bands between Wavelength between {443.7250, 889.1100} in other words is include the visible and near infrared of electromagnetic spectrum and the Table below describes the location of study area with using WGS 84 as a Datum. The date of capturing this imagery was in May, 2004. The method that used to perform this study reveals in the flow chart in Fig. 3.

Table 1: The coordinate system of the study area boundaries with WGS-84 Datum.

LEFT SIDE	101 42 47.74 E	02 59 59.99 N
	101 42 20.70 E	03 00 11.42 N
RIGHT SIDE	101 43 17.03 E	03 00 12.26
	101 43 16.99E	02 59 59.70N

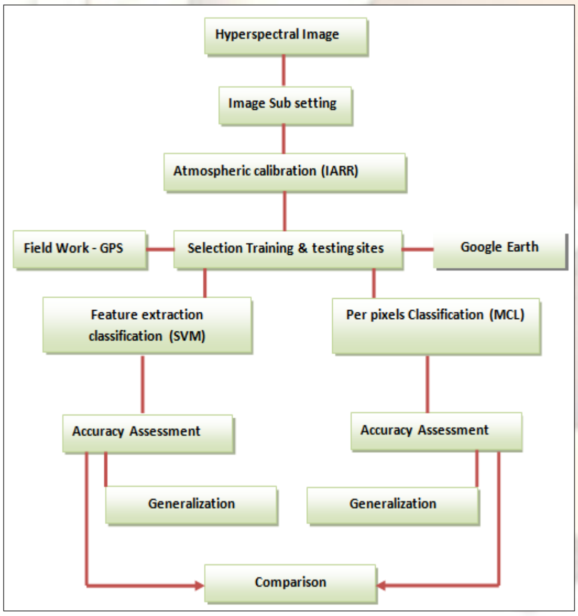


Fig. 3: Flow chart of the methodology.

3.3. Image analysis

3.3.1. Subset the digital imagery

The method that the researcher followed for this study it was after the investigated and interpreted the hyperspectral imagery he found that there was some overlapping with the boundaries of the image, that was important issue should deal with to overcome this problem the researcher sub-setted the image to remove this noise from the imagery by using ENVI software and by selected the area that out of the noise using the spatial subset option then the image has been subsetted. The sub-setting the hyperspectral imagery done before doing any analysis.

3.3.2. Atmospheric correction:

In this stage because the hyperspectral imagery did not correct, and the digital imagery is related to old date, in another words because there is not any field parameters to do the advance atmospheric correction, the internal Average Relative Reflectance (IARR) has been applied to performing the atmospheric correction. This step also did with using the Envi software.

3.3.3. Training and Testing Sites Selection.

The training sites collected from imagery by selecting the region of interest (ROIs) using Envi software, the study area classified into nine categories, therefore, nine ROIs were collected from the hyperspectral imagery and the testing sites collecting using Global Positioning System (GPS) and Google earth from the historical database of Google earth (archive), testing sites selected and it represented the truth samples that represent these classes. Selection testing sites very important to do the assessment of classification result, then study area was classified into (9) classes using two approaches the first one is normal supervised classification (per – pixel classification) it was Maximum likelihood classifier (MLC) to conduct the classification of study area, and also applied the Support Vector Machine (SVM) based on the spatial and the spectral aspect (object oriented classification) both of them have been used to generate the thematic map of land cover for UPM campus and then performed the generalization to both of outputs classification to isolate the unclassified pixel and to make the map has a good visualization . By using the testing sites that collected from Google earth the accuracy assessment of classification result for both classifiers done then the final step it was make a comparison between the results of both classifiers to demonstrates the better technique that can be used to extract better result for land cover mapping.

4. RESULT AND DISCUSSION

4.1 Image Analysis Processing

4.1.1 Subset the digital imagery

First step in this Study was subsetted the hyperspectral imagery to remove and overcome the noise that appeared on the boundaries and the subsetted was conducted with using ENVI software. The result of this subsetted was demonstrates in Fig. 4.

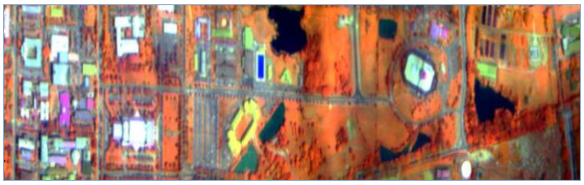


Fig.4: The sub-setted of hyperspectral imagery.

4.1.2 Atmospheric correction:

After the sub-setting the hyperspectral imagery the next step was performed the atmospheric correction, the technique that has been used was internal Average Relative Reflectance (IARR) and that because the hyperspectral image related to 2004 and it is old and there is no any filed measurements to use as variable input parameters to do high atmospheric correction (field spectral measurements and other observations) related to study area in time of over flight the researcher selected this IARR technique for performing the Atmospheric correction and the Fig. 5 below shows the spectral reflectance before and after conducted the atmospheric correction.

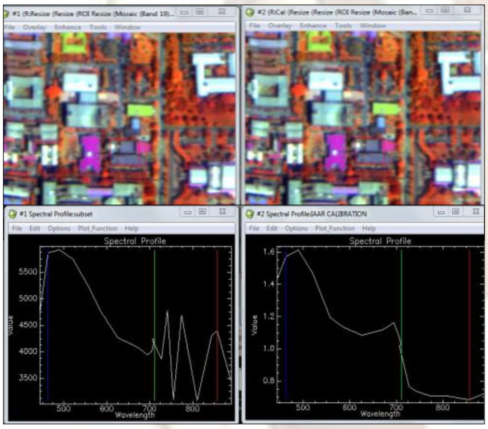


Fig. 5: Spectral reflectance before and after atmospheric correction.

4.1.3. Training Sites Selection

Selecting training is the next step in the analysis, the training sites collect to each type of nine classes of study area by collecting the region of interests (ROIs) for each class to use these training sites to perform the classification then to obtain the thematic map of Land cover, these classes are: (Grass, Trees, Clear water, Lake, Roads, Building R-roof, Building C-roof and Building B-roof) we have three classes of buildings based on their roof's material. The Table 2 reveals the training sites of the study area.

Table 2: Training sites of study area.

No.	ROI Name	Colour	Pixels
1	Grass	Green 1	10.681
2	Trees	Green 3	9.888
3	Clear Water	Blue 1	389
4	Lake	Blue 3	5.573
5	Roads	Black	2.584
6	Building R-roof	Red	5.671
7	Building C-roof	Yellow	11.137
8	Building B-roof	Cyan	1.271
9	Soil	Orange 1	1.246

4.1.4. Testing Sites Selection

The testing sites are very important to conduct the analysis especially to do the accuracy assessment for both of classifications (SVM and Maximum likelihood), with using the high spatial resolution IKONAN from Google Earth the study area was investigated to select testing sites for the features (Soil, buildings roofs and lakes) to use it in accuracy assessment stage, the samples collected by selected some from the historical archive of Google earth and by field work with using the Global Positioning System (GPS) hand held GPS there were some ground truth samples collected for features (soil, swimming pool, Roads, trees and Grass), GPS has the accuracy (-,+5) meters, there were 18 ground samples were collected inside the study area in UPM university campus as indicated in Table 3, these ground truth samples were collected based on the datum WGS84 and Fig. 6 indicates the positions of these samples.

Fig 6: Samples of testing sites in UPM Campus.

Table 3: Demonstrates the Ground truth samples in UPM campus that collected by GPS.

no.	feature class	N	E	Google	GPS
1	Clear Water	03° 00' 08.59"	101° 42' 43.52"		BY GPS
2	Clear Water	03° 00' 07.27"	101° 42' 43.03"		BY GPS
3	Soil	03° 00' 01.79"	101° 43' 07.39"		BY GPS
4	Soil	03° 00' 00.10"	101° 43' 14.67"	BY GOOGLE	
5	Grass	03° 00' 05.32"	101° 43' 02.73"		BY GPS
6	Grass	03° 00' 07.17"	101° 42' 30.73"		BY GPS
7	Roads	03° 00' 03.23"	101° 42' 24.93"		BY GPS
8	Roads	03° 00' 03.96"	101° 43' 05.62"		BY GPS
9	Building R-roof	03° 00' 07.72"	101° 43' 08.83"	BY GOOGLE	
10	Building R-roof	03° 00' 07.74"	101° 42' 24.44"	BY GOOGLE	
11	Building C-roof	03° 00' 07.48"	101° 42' 20.99"	BY GOOGLE	
12	Building C-roof	03° 00' 07.84"	101° 43' 00.24"	BY GOOGLE	
13	Building B-roof	03° 00' 07.38"	101° 43' 01.93"	BY GOOGLE	
14	Lake	03° 00' 10.04"	101° 42' 46.68"	BY GOOGLE	
15	Lake	03° 00' 05.98"	101° 43' 08.14"	BY GOOGLE	
16	Tree	03° 00' 07.80"	101° 42' 26.89"		BY GPS
17	Tree	03° 00' 06.30"	101° 42' 13.09"		BY GPS
18	Building B-roof	03° 00' 05.62"	101° 42' 21.27"	BY GOOGLE	

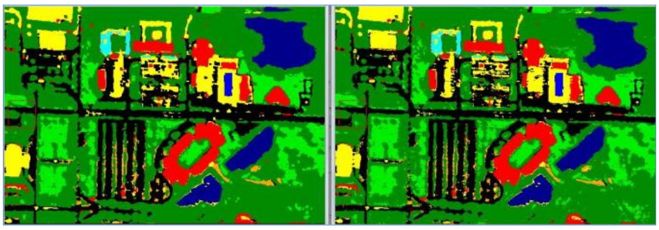
4.1.5. Classification

This research conducting with two types of classification the first one is Maximum likelihood algorithm based per pixel and using the ROIs that collected before to generate the thematic map of Land Cover of UPM Campus for nine classes. The second was SVM based on object oriented classification, the segmentation of image done then by selecting the kernel type that has been used was Radial base function type for conducting the classification.

4.1.5 Post classification (Sieving and Clumping)

The post classification is an important stage to enhance the quality of classifications results. It plays a big role include the recoding of land cover classes, and some modification of the classified remotely sensed imagery by using another information such as ancillary data or expert knowledge. Most of classification that done for land cover have some salt and pepper effects related to the complexity of landscape, that needs to apply some filters to remove that effect, and this procedure can be done by using low pass filter or do some another kind of smoothing like Clumping and Sieving techniques. The parameters had been chosen for SVM and MLC, classifications performed, then the generalization the classified image done using the post classification with

Sieving and clumping to remove the isolated pixels and to give the thematic map better visualization and the result for both classifications were as the Fig. 7,8 below:



After generalization before generalization

Fig. 7: Thematic map of SVM classification.

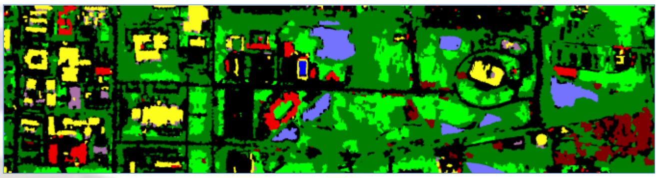


Fig 8: The generalization of Maximum likely hood classification.

And here below Fig. 9 indicates the final thematic map of land use and land cover for UPM Campus using Maximum likelihood algorithm that has been generated by using Envi software.

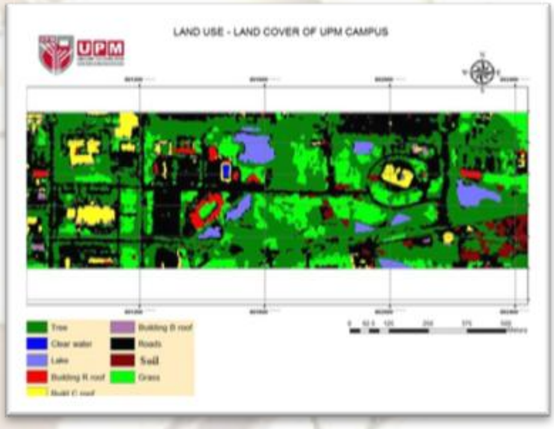


Fig 9: The final thematic map LU_LC for UPM Campus by MCL.

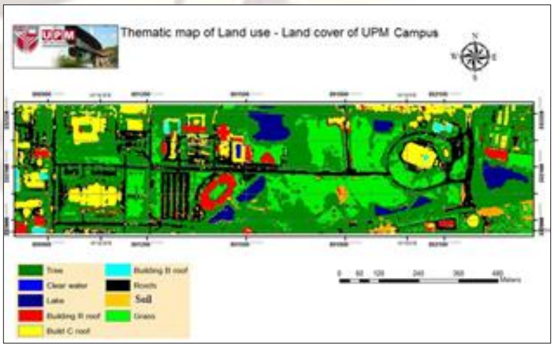


Fig 10: The final thematic map of LU_LC for UPM Campus by SVM.

4.1.6. Accuracy assessment

In this stage the accuracy assessment for two techniques calculated by confusion matrix error and by using the ground truth sites that have been collected from historical archive of Google earth to perform the assessment. The Accuracy assessment use to determine the quality of information generated from remotely sensed data. There are several reasons for conducting the assessment of accuracy to remotely sensed data.

They are:

1) To know how much good the results.
2) To determine and then to correct sources of error.
3) To make comparison between different techniques, algorithms, analysts or interpreters that have been used.
4) Check the quality of the results.

After performing the accuracy assessment the results were the Overall Accuracy = 90.48% and Kappa Coefficient = 0.88 for Maximum likely hood classification however, for SVM classification the results were Overall Accuracy = 98.23% and Kappa Coefficient = 0.97, and the commission, omission percentage, producer accuracy and user accuracy demonstrated as the tables (4), (5), (6), (7) below:

Table 4: The percentage of commission and omission errors of MLC.

No.	Class	Commission (Percent)	Omission (Percent)
1	Grass	47.73	26.71
2	Trees	4.44	16.54
3	Clear Water	0.00	0.00
4	Lake	1.28	0.00
5	Roads	12.20	0.51
6	Building R-roof	0.00	5.32
7	Building C-roof	2.42	4.16
8	Building B-roof	0.00	22.22
9	Soil	42.04	0.00

Table 5: The percentage of Prod.Acc. & User Acc. of MLC.

No.	Class	Prod. Acc. (Percent)	User Acc. (Percent)
1	Grass	73.29	52.27
2	Trees	83.43	95.56
3	Clear Water	100.00	100.00
4	Lake	100.00	98.72
5	Roads	99.49	87.80
6	Building R-roof	94.68	100.00
7	Building C-roof	95.84	97.58
8	Building B-roof	77.78	100.00
9	Soil	100.00	57.96

Table 6: The percentage of commission and omission errors of SVM.

No.	Class	Commission (Percent)	Omission (Percent)
1	Grass	9.39	3.34
2	Trees	1.15	1.80
3	Clear Water	0.00	6.06
4	Lake	0.00	0.00
5	Roads	0.00	1.54
6	Building R-roof	0.00	0.00
7	Building C-roof	2.23	0.00
8	Building B-roof	0.00	10.19
9	Soil	0.00	0.00

Table 7: The percentage of Prod.Acc. & User Acc. of SVM.

No.	Class	Prod. Acc. (Percent)	User Acc. (Percent)
1	Grass	96.66	90.61
2	Trees	98.20	98.85
3	Clear Water	93.94	100.00
4	Lake	100.00	100.00
5	Roads	98.46	100.00
6	Building R-roof	100.00	100.00
7	Building C-roof	100.00	97.77
8	Building B-roof	89.81	100.00
9	Soil	100.00	100.00

4.1.7. Comparison

The comparison result was indicated that the SVM classification is better than the MLC and the Table 8 and Fig. 11 below indicate that:

Classification	Overall Accuracy	Kappa Coefficient
SVM	98.23%	0.97
MLC	90.48%	0.88

Table 8: The Comparison results between SVM & MCL.

The different in the accuracy assessment revealed that the object oriented classification is better than the normal classification (per pixel), that related to the classifier with the objected oriented approach will classify the imagery based on the spatial, spectral and the texture characteristics of the features that will support the process of the classification and increase the parameters of classification then the output will be better identification than the per pixel approach, because it considers just the spectral characteristics of feature.

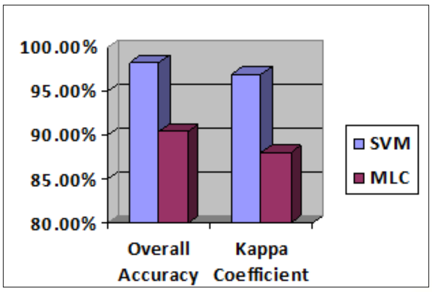


Fig 11: comparison chart between MCL and SVM accuracy results.

5. CONCLUSION

This study covers the processing of hyperspectra data to classify the study area that located in UPM University in Serdang, Selangor, Malaysia with using two methods the first ones with SVM algorithm under feature extraction and the second using MCL under the classification based on pixel to find out the thematic map of land cover and examine which type of classification is better. And the results revealed that the accuracy assessment of SVM is better than of MLC classification and the overall accuracy for both of them, for SVM and Maximum likelihood were 98.23%, 90.48% respectively. The high results that got reflect the ability of these algorithms to deal with the land cover and land use mapping even the area is very small and there is a good variation in the type of features that distributed in study area that will help to get good accuracy and make the identifications for different classy more easier.

6. ACKNOWLEDGEMENTS

The author would like to thank the Assoc. Prof. Dr. Helmi for his support and providing the data, and also the author very grateful from Mr. Eng. Maher Faiq Ismaeel for his supporting.

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