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Satellite Data Classification Accuracy Assessment Based from Reference Dataset

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***Abstract*—**In order to develop forest management strategies in tropical forest in Malaysia, surveying the forest resources and monitoring the forest area affected by logging activities is essential. There are tremendous effort has been done in classification of land cover related to forest resource management in this country as it is a priority in all aspects of forest mapping using remote sensing and related technology such as GIS. In fact classification process is a compulsory step in any remote sensing research. Therefore, the main objective of this paper is to assess classification accuracy of classified forest map on Landsat TM data from difference number of reference data (200 and 388 reference data). This comparison was made through observation (200 reference data), and interpretation and observation approaches (388 reference data). Five land cover classes namely primary forest, logged over forest, water bodies, bare land and agricultural crop/mixed horticultural can be identified by the differences in spectral wavelength. Result showed that an overall accuracy from 200 reference data was 83.5 % (kappa value 0.7502459; kappa variance 0.002871), which was considered acceptable or good for optical data. However, when 200 reference data was increased to 388 in the confusion matrix, the accuracy slightly improved from 83.5% to 89.17%, with Kappa statistic increased from 0.7502459 to 0.8026135, respectively. The accuracy in this classification suggested that this strategy for the selection of training area, interpretation approaches and number of reference data used were importance to perform better classification result.

***Keywords*—**Image Classification, Reference Data, Accuracy Assessment, Kappa Statistic, Forest Land Cover

I. INTRODUCTION

THE potential benefits of classifying and updating the status of forest resources through remotely sensed data is widely recognised. Through the use of successive satellite imagery, ongoing forest resources information for a particular forest can be obtained at a lower cost per unit area and in less time than conventional methods of forest classification and mapping using aerial photographs. [20] claimed that synoptic remote sensors such as Landsat and radar provide information to aid first-order stratification and classification of humid tropical forest. Such first order surveys can delimit forested area from most non-forest areas and help in stratifying forest class according to land form and tree density. Other users of remote sensing [4] and [1] asserted that despite the geographical difference, a common set of forest classes had been identified in most optical satellite imagery. Thus, the continuous classifying of the country's forest cover becomes economically feasible with optical data or other earth resource satellite observations to evaluate forest resources.

The collection of reliable data to survey and map logging activities in the hill forest is difficult due to terrain characteristics, the complexity of the forest and accessibility. Remote sensing has been a valuable source of information over the past few decades in mapping and monitoring forest activities [5]. Forest cover mapping/classification is one of the most widely used applications of remote sensing. In many countries the approach has been accepted that facilitates fast and up-to-date classification of the forest. Classification of land cover related to forest resource management in Malaysia is a priority in all aspects of forest mapping using remote sensing and related technology such as GIS [11], [15] and [12]. Additionally, information about forest cover from satellite remote sensing has been used as the main source for further analysis in aspects of forest planning and management including forest rehabilitation [10], inventory [24], and catchment monitoring [16]. Remote sensing data of the Earth's surface are readily available in digital format. These data can be used to identify features of interest in the image with the assistance of computers. The mapping of forest cover type/land use has been one type of study using satellite imagery. Several models have been developed by researchers in forest management planning.

Tropical rain forests vary considerably in term of species composition, size of stems, basal area, crown cover and stratum level from place to place, even within the same natural forest type. Furthermore, transition from one type to another does not often have a clear-cut boundary. These variations make classification complicated. In this regard, an assessment of classification accuracy should take into consideration the effect of variability. This accord with [14] who suggested the generation of forest maps in which not all boundaries are definite and fixed, but where some are just transition zones. [3] however reported that tropical forest type classes can be easily classified from Landsat TM data and widely used for land use planning, land cover and forest classification

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purposes. Therefore the main objective of this paper is to assess classification accuracy of classified forest map from difference number of reference data. This comparison was carried out through observed and interpreted data of satellite imagery.

II. Methodology

A. *Data acquisition, geometric and radiometric correction*

Landsat TM data for path 126 row 57 was acquired from the Malaysian Center for Remote Sensing (MACRES) in Kuala Lumpur dated 8 May 2001. The image processing techniques employed in this study were conducted using PCI ImageWorks version 7.0 and all final hardcopy maps were produced in ArcView software version 3.4. The ancillary data used for supporting satellite data were obtained from Jerantut Forestry Department and Department of Survey and Mapping Malaysia. Topographical map (1995)-L 7030 series; sheet number 4161, forest resource map (2002) and forest operation map (2002) (all at of 1:50000 scale) were used to perform the image processing and classification. These maps were also used in conducting a ground observation to verify the classification results from satellite imagery. The imagery was geometrically corrected using 1:50000 scale topographical map and resampled to a local Malaysia Rectified Skew Orthomorphic (MRSO) projection type (Spheroid name:Modified Everest and Datum name:Kertau 1948) with 30m pixels using a cubic convolution resampling method. Ground control points (GCP's) on the satellite image and on the topographic maps were identified and the linear geometric correction function was applied. The final projected imagery was geometrically accurate to RMSE of 0.645 pixel or about 16m.

B. *Development of classification schemes*

Image classification is defined as the extraction of differentiated classes or theme categories from raw remotely sensed digital data. The image classification in this study is used to provide a base map of the forest resources in Sungai Tekai Forest Reserve (Figure 1). A primary component of mapping land cover is developing a land cover classification system. Many current land cover classification systems are designed specifically for use with remotely sensed data. These systems often resemble each others in order to maintain cohesiveness and allow for data integration. A hierarchical framework is often implemented within a classification system. This type of framework allows the level of detail to vary for different project scopes and for the creation of land use and land cover categories that are compatible with other classification systems. The purpose of the classification scheme used in this study is to provide primary information about forest land cover and other non forest features such as rivers, logyard and the existing forest road system. On the other hand, the classification scheme complies with the local classification for forestry purposes. The classification scheme and descriptions is as follows: (1) Primary Forest- Medium to large crown. High-density canopy cover >50%. This class remaining of the natural forest formation (*virgin forest*) and had no intervention, (2) Logged Over Forest- Sparse /medium crown. Low-density canopy cover (<10-50%). This class refers to the area in which harvesting operation have taken place under the Malaysian selective management system (SMS), (3) Agricultural Crop/Mixed Horticulture- Sparse fragmented (forest fraction 10-70%). This class is includes the area with a self-plantation of small trees by villagers and *orang asli* (aborigines). This includes fruit trees for self-consumption, (4) Water Bodies- This class covers the area by the main river which crosses the study area and also the reservoir, and (5) Bare Land- Refers to area of exposed soil with very little or without vegetation coverage including the forest road network, forest camp and logyard areas.

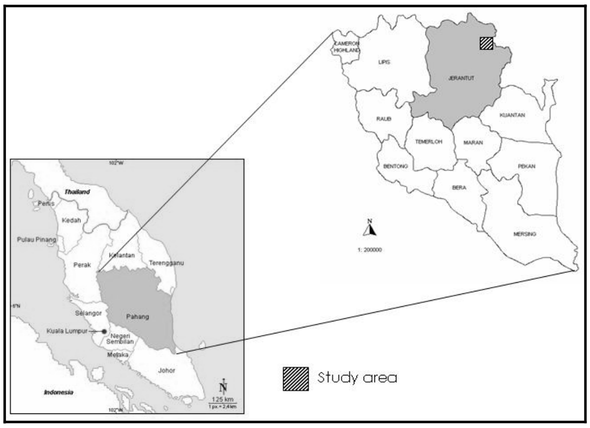

Fig. 1 The location of Sungai Tekai Forest Reserve in Peninsular Malaysia

C. *Processing and analysis of satellite imagery*

Enhancement technique of the satellite data was performed before further processes were carried out. Enhancement using linear enhancer and some resetting of the brightness and contrast were enough to improve the visual contrast of the image to an appreciable degree. Visual analysis of the enhanced image (Landsat TM Bands 4, 5, 3) clearly showed separability between forest cover, forest road, and other types of land cover. For the purpose of study, several filters (3 X 3) were tested and then used, such as median and edge sharpening. Median filter was chosen for this study due to its clear and smooth results. The median filter computes the median value of the grey level value within the rectangle filter window surrounding each pixel, resulting in smooth image data and preserving sharp edges.

D. *Digital Image classification*

The satellite imagery was interpreted using both digital and visual methods. The composite image was tested in order to choose the best band combination. The false colour composite image (FCC) of 5-4-3 (RGB) was used for the further after performing linear enhancement. Supervised classification was performed instead of the unsupervised classification method since this method is showed better extraction of information. In supervised classification, pixel categorisation is carried out by establishing numerical descriptors of one or more land cover types. In this process, the represented patterns area recognized with the help of topographical and knowledge by forest resource manager. However, the knowledge of the data and recognition of the feature types in the study area is not too difficult because most of the study areas were covered by forest. In order to obtain a satisfactory result, 30 points per class were marked as a training data, which would have been 150 in this case. The emphasis was to identify good example of features related to primary forest cover and logged over forest. Parametric Maximum Likelihood Classifier (MLC) was used as a decision rule. The MLC rule is based on the probability that a pixel belongs to a particular class and the input bands have normal distributions. The MLC is considered to give more accurate result than parallelepiped classification but it is much slower due to extra computation.

In the classification, the signature separability functions were used to examine the quality of training site and class signature, before performing the classification. Signature separability contains all the available information about signature and class information for each class. The importance of using this panel is to determine how well each class is separated from each of the other classes. This function allows the operator to use statistical analysis to increase the accuracy of the very subjective process of classification. For this purpose, Battacharrya Distance was used to measure the signature separability. Battacharrya Distance is a value between 0 and 2, where 0 indicates complete overlap between the signature of two classes and 2 indicates a complete separation between two classes (PCI, 1997b). The larger the separability values achieved, the better the final classification result. The following rules are followed for the ranges of separability values; 0.0 to 1.0 (very poor separability), 1.0 to 1.9(poor separability), and 1.9 to 2.0 (good separability), respectively.

The signature separability was arranged in matrix form. The average of the signature separability is 1.876657, minimum separability is 1.587674 and maximum separability is 1.972366. Spectral separability between classes was weaker in the case of primary forest and logged over forest classes, whose signatures were closer together in the measurement space. There was some spectral mixing of signatures within bare land and within agricultural/mixed horticulture classes. However, this mixing was not deemed to be a major problem in view of the study's broad classification scope. Texture identification for the land cover types were assessed visually and statistically. Training sets were created manually to identifying certain features that belong to a specific class, such as forest, logged over forest, agricultural crop, water bodies, and bare land. The signature observations were used to discriminate surfaces for each pixel to assign it a probability measure of being a different land cover type. Certain properties of the imagery such as their contrast and the greyness are useful as parameters to identify the different land cover types in order to perform the classification process. This approach is effective in determining the training set on the remotely sensed data. Then, the final output (post classification) of the classified image was filtered using low pass median filter to produce a better, smooth view by aggregate and avoiding the isolated individual pixels.

E. Accuracy assessment

Accuracy assessment is an important step in the classification process. The goal is to quantitatively determine how effectively pixels were grouped into the correct feature classes in the area under investigation. The forest land cover types derived from digital image interpretation and analysis requires validation with data obtained from ground verification. The confusion matrix, derived from image map and field data, as described by [21], [9] and [21] was generated for the accuracy assessment. Additionally, a coefficient of agreement between classified image data and ground reference data were calculated using Kappa and its variance [19], [7] and [8]. The accuracy of thematic map was determined by the constructed matrices along with kappa statistics in order to test whether any difference exists in the interpretation work. Briefly, Kappa statistic considers a measure of overall accuracy of image classification and individual category accuracy as a means of actual agreement between classification and observation. The value of Kappa lies between 0 and 1, where 0 represents agreement due to chance only. Meanwhile 1 represents complete agreement between the two data sets. Negative values can occur but they are spurious. It is usually expressed as a percentage (%). [2] claimed that the Kappa statistic has been shown to be a statistically more sophisticated measure of classifier agreement and thus gives better interclass discrimination than overall accuracy. Kappa statistic value and variance for each matrix is significantly different from random and if two error matrices are significantly different from each other [23].

F. Ground verification

Observations and verifications for the ground features were collected for most part of the study area where the location could be reached. The information was collected in February 2003 with assistance from the Jerantut Forestry Department at 200 training sites. Several earth covers were selected as training area. The salient landmarks on the ground were recorded, as were the GPS coordinates. Ground observations were also made for the main logyards and rivers. Ground verification were carried out using area frame sampling-unaligned systematic random sampling with the aid of topographic map and printed satellite imagery showing the observed site and surrounding area. Once the sample site was reached, landmarks were identified in order to confirm its exact position. Each observation site was given a number and its land cover annotated on the survey form together with the coordinate location. Every site was checked in order to avoid assumptions and possible mistakes.

A total of 97 sample segments were adopted instead of 100 due to cloud problems in three of them. The 97 sample segments were distributed unaligned systematically random over the 100 square km frame area using the MRSO coordinate system grid, which representing a sampling frequency of 5.59 percent of the 100 square km area. A total of four observation sites (sub-sample) were made in the every sample segment. Observation was made in the 60m by 60m area in the four corners of the sample segment. This size was chosen because it was adequate to carry out field survey and appropriate to enclose a land cover variation in the test site using Landsat TM. Despite the extensive field work, it was not possible to check all the areas due to difficulties in access to the sample units in remote area and terrain conditions in the area. Limited time for the study also affected the field work. Only 50 of 97 sample units were observed. Other restrictions included; the topographical map which contained limited information; secondary road in poor condition due to improper maintenance; imagery acquisition which was nearly two years behind the ground verification work. The remaining 47 sample segments were only used as interpreted data (Figure 2). However, a representative sample was checked for each scene

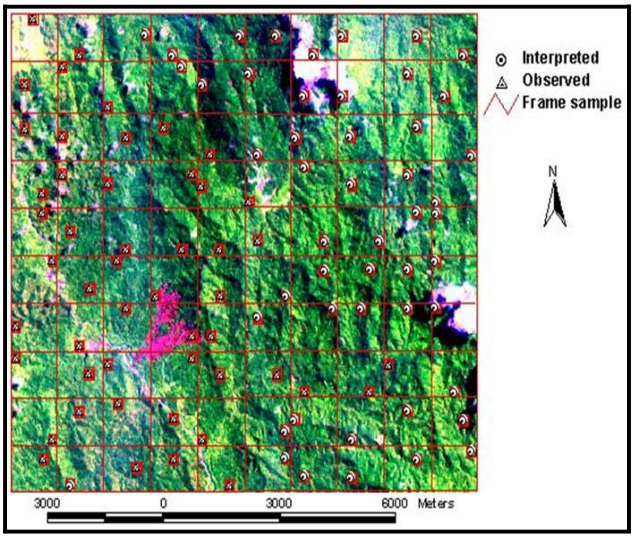

Fig. 2 Location of sample segments of the satellite imagery showing observed and interpreted locations

III. RESULTS AND DISCUSSION

Based on the digital image processing and visual interpretation of the imagery, five classes can be identified by the difference in spectral wavelength. One of the main problems during the classification of this area is related to the spatial configuration of mixed agriculture and the different stages of secondary succession of forest stand. Relatively, both of them only exist as scattered small size features but the mixed spectral responses of pixels representing their class are responsible for data misclassification. Other problems to differentiate land cover are the road networks, logyards and forest campsites. These cover types were included in the class of bare land based on the classification schemes that have been developed, and considering that the main objective of this project was estimation of the forest cover areas. Other factors that can be considered are the topography pattern and the amount of distribution of bare land intensity. The statistical results of land cover classification of Landsat TM image are shown in Table 1**,** which contains per class pixel count and their relative proportions.

The primary forest is the main land cover with an area proportion of about 63 percent. With the close canopy and

TABLEI IMAGE CLASSIFICATION RESULT OF 5 CLASSES

No	Classified classes	Proportion pixel count	Area [ha]	Pixel count	Proportion (%)
1	Primary forest	0.683505	6743.42	74800	63.02
2	Logged over forest	0.284536	2775.16	31611	26.63
3	Agric. crop/mixed Horticulture	0.011340	133.46	3544	2.99
4	Water bodies	0.006185	61.77	689	0.58
5	Bare land	0.015464	155.89	2289	1.93

dark tone colour primary forest can be distinguished clearly. However, Landsat TM cannot identify secondary forest roads and skid trails well because of the mixing spectral reflectance with other features and the resolution limitation of the Landsat TM data. Detection of logged over forest was mainly done through visual and digital interpretation. The boundary between primary forest and logged over forest cannot easily be identified from the imagery. The selective management system (SMS) adopted for the harvesting operation is one of the reasons why the boundary separation is confusing. The other reason is due to the fact that most of the logged over forest from the SMS has already recovered and the gap area is dominated by the emergent trees. However, based on the forest resource map issued by the Jerantut Forestry Department, the information of logged over forest was derived. Different forest blocks have been logged in different years, ranging from 1990-2002 and are categorized as one class.

The proportion of the logged over forest in the study area is about 27 percent. The classified pixel in the primary and logged over forest is affected by the presence of clouds in the imagery. Major agricultural crop/mix horticulture was identified in the North West and a small patch in the north east of the imagery. The agricultural crop/mix horticulture class is easy to identify and differentiate due to its high reflectance and contrast in colour. This class represented about 3.0 percent of the entire study area. The bare land class is an associated feature of logyard areas, forest camps and forest roads. This bare land represented about 2.0 percent, respectively. The main of water bodies are segments of main rivers such as River Kerum and Lake Bangak. Water bodies only cover an area of about 0.58 percent. From the total of six land cover classes, cloud is excluded from the analysis. The cloud only represented a small proportion, about 4.85 percent of the area.

An error matrix was generated for the supervised image map prior to the median filtering by creating a maximum likelihood report. This report calculates the area and percentages of each land class incorporated in a maximum likelihood classification. The ground verification data were utilized in the maximum likelihood report as the independent data set from which the classification accuracy was compared. Accuracy assessment was generated from both 200 reference data (observed) and 388 reference data (inclusive of observed and interpreted data). Visual interpretation of land cover in satellite imagery was performed in those areas which were inaccessible during the field verification. The accuracy assessment report of land cover classification map from 200 and 388 reference data is shown in Table 2 and 3.

TABLE II THE ERROR MATRIX FOR LAND COVER CLASSIFICATION FROM 200 REFERENCE DATA

	Reference data						
Classified data	Water bodies	Logged over for	Primary for.	Bare land	Agric. crop	Total	User's accuracy
Water Bodies	8	1	1	0	0	10	80.00%
Logged over for.	1	32	12	1	2	48	66.66%
Primary for	0	10	90	0	0	100	90.00%
land	0	1	0	15	0	16	93.75%
c. /mixe t.	0	4	0	0	22	26	84.61%
	9	48	103	16	24	200	
ucer's racy	88.88	66.66	87.37	93.75	91.66	Overall accuracy 83.5	

all Kappa Statistic :)2459
all Kappa Variance : 2871

TABLE III THE ERROR MATRIX FOR LAND COVER CLASSIFICATION FROM 388 REFERENCE DATA (OBSERVED AND INTERPRETED)

	Reference data						
ssified lata	Water bodies	Logged over for	Primary for.	Bare land	Agric. crop	Total	User's accuracy
r s	8	2	1	0	0	11	72.73%
;ed for.	3	74	14	1	2	94	78.72%
ary for	0	13	227	1	0	241	94.19%
Bare land	0	1	0	15	0	16	93.75%
Agric. Crop/mixed hort.	0	4	0	0	22	26	84.61%
Total	11	94	242	17	24	388	
Producer's accuracy (%)	72.73	78.72	93.80	88.24	91.66	Overall accuracy 89.17	

Overall Kappa Statistic : 0.8026135
Overall Kappa Variance : 0.0026036

Overall accuracy of 83.5 percent was achieved from 200 reference data, where the highest producer and user accuracy are similar with 93.75 percent respectively. Primary forest has an accuracy of 90 percent, which was confused with logged over forest. Logged over forest have only 66.66 percent accuracy since it was confused with the primary forest class, bare land and agricultural crops. The most probable reason for lower classification accuracy of logged over forest is due to the harvesting system adopted by the Malaysian Forestry Department. In 'selective management system' only the selected trees are felled and the entire felled trees must be more than 45 cm dbh (diameter at breast height) of cutting limit. Some areas (for example in the poor forest stock/volume) look alike primary forest in the image despite having been harvested. Among others, cover types such as agriculture crop/mixed horticulture and bare land area indicates the highest classification accuracy with 84.61 percent and 93.75 percent.

The error matrix generated from 388 reference data shows an increased in overall accuracy compared to 200 reference data, as increase from 83.5 percent to 89.71 percent, respectively. Again, the Kappa calculation shows an improved value with good agreement measure with Kappa value of 0.8026135 and its variance of 0.0026036. The accuracy in this classification suggested that this strategy for the selection of training area, interpretation approaches and number of reference data used were importance to perform better classification result. From Table 7 and 8, observations can be made for classification accuracies for each class. It can be noted that:(i) User's accuracy increased for Primary Forest class from 90% to 94.19%, but decreased producer's accuracy from 88.88% to 72.73%, (ii) User's accuracy and producer's accuracy increased in similar percentage for Logged Over Forest class from 66.66% to 78.72%, (iii) User's accuracy and producer's accuracy decreased for Water Bodies class from 80% to 72.73%, and 88.88% to 72.73%, (iv) User's accuracy and producer's accuracy were similar for Agric. Crop./Mixed Hort. class with 84.61% and 91.66%, and (v) User's accuracy decreased for Water Body class from 80.00% to 72.73%, and also decreased producer's accuracy from 88.88% to 72.73%. By analysing the off-diagonal element, major spectral confusion was found between primary forest and logged over forest. This is followed by agric. crop/mixed hort., logged over forest and water bodies, respectively. [18] recommended that a standard of 85% accuracy is acceptable level of digital image classification, however [22] advocated the inclusion of error matrices to enable users to compute and interpret the value on their own.

The Kappa statistic was calculated from the result of the land cover classification, with five classes shown at the bottom of the confusion table. This implies that the Kappa value of 0.7502459 (with a variance of 0.002871) represents a probable 75 percent better accuracy than if the classification resulted from a random unsupervised classification, instead of the employed maximum likelihood classification. The agreement criteria for Kappa statistic was defined by [13]. The agreement is poor when K<0.4, good when 0.4<K<0.7 and excellent when K>0.75. Alternatively, [17] suggested the use of subjective Kappa value as <40 percent as poor, 40-55 percent fair, 55-70 percent good, 70-85 percent very good and >85 percent as excellent. Thus, according to these agreement scales, the classification denotes very good to excellent agreement. The overall accuracy is considered acceptable for this study. This is because in remote sensing projects, pixel classification can be an arbitrary measure dependent on the level of classification employed, as well as the spatial resolution of the imagery utilized in the analysis. Landsat TM measures vegetation cover rather than basal area, so in this case during the field verification it was difficult to distinguish the bare land (excluding forest road and logyard) due to re-growth of some vegetation and residual trees after logging. One more reason is that the satellite data used were not recently acquired but had been captured about 11 months before the ground verification was carried out. Hence, the sites selected for ground verification would have provided problematic results in those areas where forest cover had disappeared and the recovery process of some areas of logged over forest had started. Recovery is the process of returning from disturbance to a 'biological steady state' which is characteristic of climax, undisturbed forest [6]. Residual and pioneer trees were observed, while fast growing trees increased in dominance, and shade tolerant tree seedlings established and gradually took over. Most sample sites recorded represented the purest example possible and were predominantly in areas with well-confirmed forest cover.

Resource evaluation is not only considered in a statistical sense but also looks at the capability of the data to show trends and to discriminate between groups of classes of interest in forest management. The types of information that can be obtained from the results in the study enable the study of general type discrimination of land cover and forest resource availability, including logged over forest, regeneration and the overall of the forest landscape. The remaining 6743.42 ha of primary forest indicated that the harvest areas are restricted to the resource availability. The logged over forest which covers an area of about 2775.16 ha is important to rehabilitate by the silviculture treatment program including management of natural regeneration, enrichment planting, conversion to forest plantation and so forth. Furthermore, the development program will indicate the future re-growth of the residual tree for the next logging cycle. The forest compartments were overlaid with the forest resource map as depicted in Figure 3. From field verification, the condition of forest structure with respect to canopy closure was evaluated. The canopy closure in the logged over forest is less than 50 % and for the primary forest is ranging from 55 % to 85 %, respectively.

IV. CONCLUSION

The overall accuracy in the ability to separate signatures for both 200 and 388 reference data are very good according to the agreement scale of [16]. The overall accuracy was 83.5 % (kappa value 0.7502459; kappa variance 0.002871). However, when reference data in the confusion matrix included an observed and interpreted approach, the accuracy improved

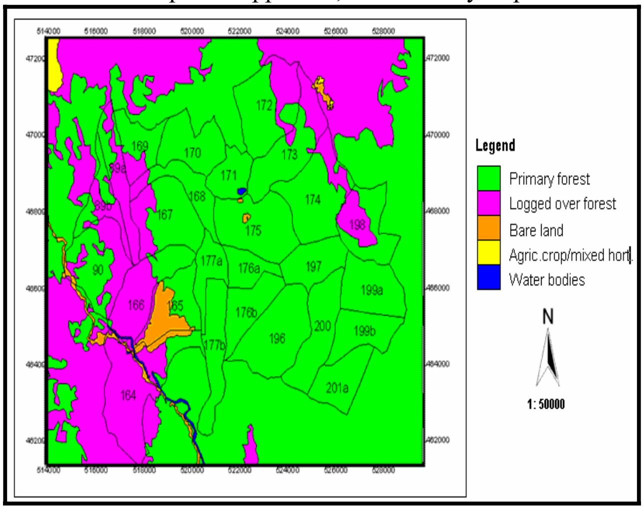

Fig. 3 The boundary of forest compartments overlaid with five classified land cover types

from 83.5% to 89.17%, with Kappa statistic increased from 0.7502459 to 0.8026135, respectively. Despite this, a more detailed identification of the forest strata was not possible because of overlapping spectral in the feature space and the characteristic of the forest area. Although Landsat TM data used in this study has provided an acceptable accuracy from both reference data, further investigation need to be carried out to find out the sufficient reference data to be used in remote sensing studies. In the other hand, the image classification suffered from the cloud images, especially the small portion of clouds and shadow which confused the interpreter during image classification processing. The presence of five percent cover in the image slightly jeopardized the accuracy of land cover classification. Future research into the application of this method with different resolutions, quality image data with varying spectral bands and advanced techniques of image processing and analysis may increase the accuracy of the satellite based prediction and estimation of tropical rainforest resources. Data fusion from optical satellite system and hyperspectral data are needed for the detailed classification of the forest cover types especially to improve the spectral discrimination due to the complexity of the dense tropical forest and again, radar data is requires due to cloud cover problem in many tropical countries. The difficulties in differentiating the boundary line between primary forest and logged over forest by the Malaysian Selective Management System could be possibly done using a spectroradiometer to determine the spectral value and correlate it with the spectral value from satellite images.

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