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Mangrove Forest Classification Using Decision Tree-Learning Method

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Abstract: The potential of recent advances of remote sensing technique which is decision-tree learning method was applied for classifying and detecting the rapid changes in Mengkabong mangrove forest area. The multi-temporal of Landsat series (TM, ETM+ and OLI_TIRS) from the year 1990, 2000, 2005, 2010, and 2013 were used in this study. The result of this study showed the use of decision-tree learning method combining with the data set of multi-temporal Landsat series and GIS data can be effective in delineating spatial and temporal change of the mangrove forest. Seven land cover classes were classified in the Mengkabong area. Integrated tasseled cap transformation (TCT) index in Landsat data has improved the classification accuracy of mangrove due to the similarity of the spectra mangrove, forest and water-vegetation mixed pixels. The selection of good attributes from spectral features of Landsat data, topographic data and GIS database have promoted the high accuracy of mangrove classification result with 90.8%. In conclusion, the decision-tree learning method was successfully classified and detects the mangrove forest in the Mengkabong area.

Key words: Mengkabong area・Multi-temporal・LANDSAT series・TCT index・GIS

INTRODUCTION

The machine learning techniques have been increasingly used in remote sensing applications related to wetlands research. Recent research has demonstrated that the decision-tree learning, one of the most popular machine learning approaches, can be accurate and efficient in land cover classification based on remotely sensed data [1-3]. The decision-tree learning algorithm can create classification rules directly from the training data without human intervention. In addition, unlike many other statistical analysis approaches, such as maximum likelihood classification, the decision tree does not depend on assumptions about value distribution or the independence of the variables from one another [4].

This is important for incorporating ancillary GIS data, because they usually have various value distributions and may be highly correlated [5]. Rule sets can be applied to classify of multi-temporal images after they have been acquired from decision-tree learning. Using the same rule sets can ensure the classification results are comparable between different temporal images, which should be more advantageous than traditional methods for monitoring mangrove forest change from time series of remote sensing data [6, 7]. Application remote sensing technology in mangrove studies promotes many advantages such as a very cost-effective technique, time-saving and can provide a long-term data access [8].

Therefore, the objectives of this study is to investigate the capability of the decision tree-learning method to classify and detecting the changes of mangrove forest land cover in Mengkabong area integrating of multi-temporal Landsat data series (TM, ETM+ & OLI_TIRS). The rule set derived from the data of 2013 to the date of 1990, 1995, 2000 and 2005 in order to detect changes of the mangrove forests over the period. We anticipated that the decision-tree method would be able to improve the performance mangrove forest monitoring with multi- temporal Landsat data and GIS ancillary data.

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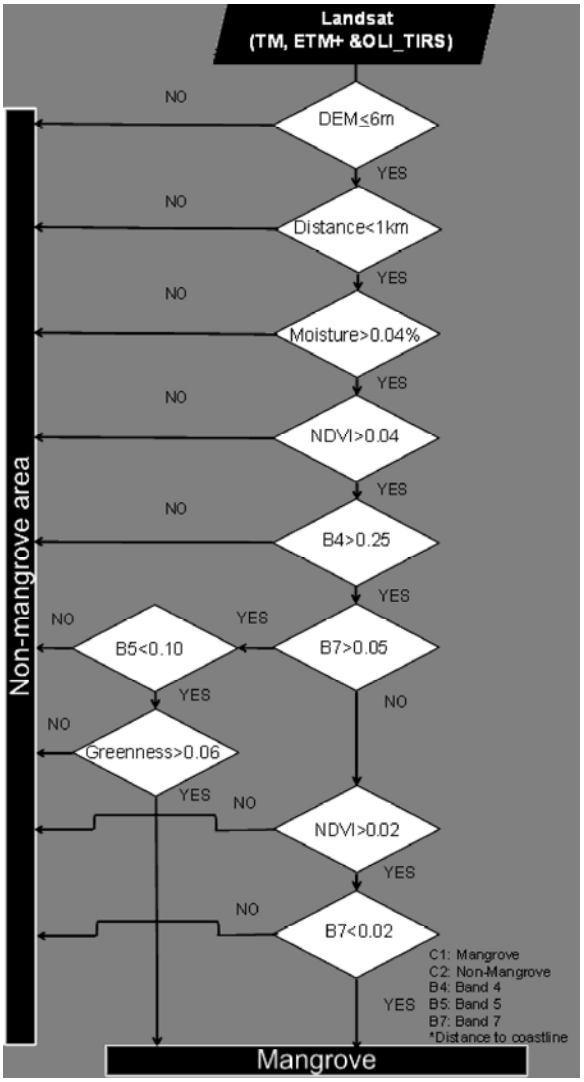

Fig. 1: Decision-tree learning classification method.

MATERIALS AND METHOD

Study Area: Mengkabong mangrove forest is located in Tuaran district which is placed in west coast of Sabah. The Mengkabong mangrove forest is a major of the mangrove forest in this district and dominated by *Rhizophora apiculata* species, which is a healthy and dense mangrove. Conversions to the aquaculture area and land reclamation for house settlement have been a major factor that effects on degradation of Mengkabong mangrove forest area [9].

Acquisitions Satellite Images and References Data: The Landsat data series (TM, ETM+ & OLI/TRS) were selected and were downloaded freely from Earth Explorer US Geological Survey (USGS) website (http://earthexplorer.usgs.gov/).The multi-temporal of Landsat data series (TM, ETM+ & OLI_TIRS) that were used in this study were covering from year 1990, 1995, 2000, 2005, 2010 & 2013. The references data mainly include field data, topography data and vegetation map.

Satellite Image Analysis: The Landsat data that were selected for this study were analyzed for pre-processing analyses. The pre-processing analyses were analyzed in the *Environment for Visualizing Images (ENVI) 5.1* software and *MS-Excel-2010.*

Applying a Decision Tree-Learning Method: All the multi-temporal Landsat data that were used in this study were processed for the features extractions using tasseled cap transformation (TCT) index [10-12], normalize vegetation index (NDVI) and band ratio [13, 14]. Then, all the satellite data were processed of decision tree-learning method, which knowledge rule exhibited. The extracted classification rules that contain two types of data: 1) remote sensing data, including: reflectance value of Landsat data of each band and the NDVI value 2) GIS data, including elevation and distance to the coastline. The classification results were overlaid to detect the mangrove change. Figure 1 show the decision tree-learning procedure applied in this study.

RESULTS AND DISCUSSION

Decision-Tree Learning Classification of Mengkabong Mangrove Land Cover: Seven land cover classes of Mengkabong area were classified by decision tree-learning method. The land covers types in these areas were included mangrove, open water, built-up, water-vegetation, secondary forest, grassland and bare soil area. Spectral profile of each land covers were produced significant differences in spectral profile characteristics and the result presented in Figure 2. According to previous studies [15, 16] spectral profile of remote sensing data could be useful to identify the specific features of the land covers types.

Result of NDVI attributes analysis presented in Figure 3 was useful to differentiate the different classes of vegetation and non-vegetation classes. The negatives of NDVI values were represented the water, built-up and bare soil areas. The mangrove and secondary forest in this study shows a high of NDVI values which are 0.08 and 0.06, respectively. Previous study suggested that

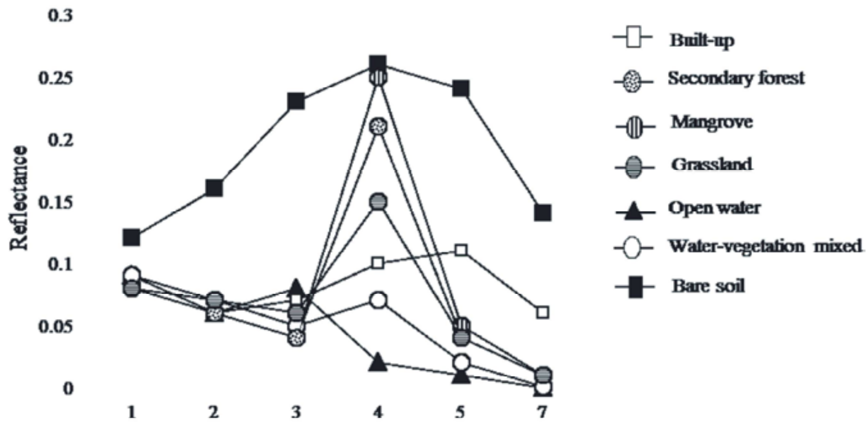

Fig. 2: Spectral characteristics of mangrove and non-mangrove land cover types using Landsat data series.

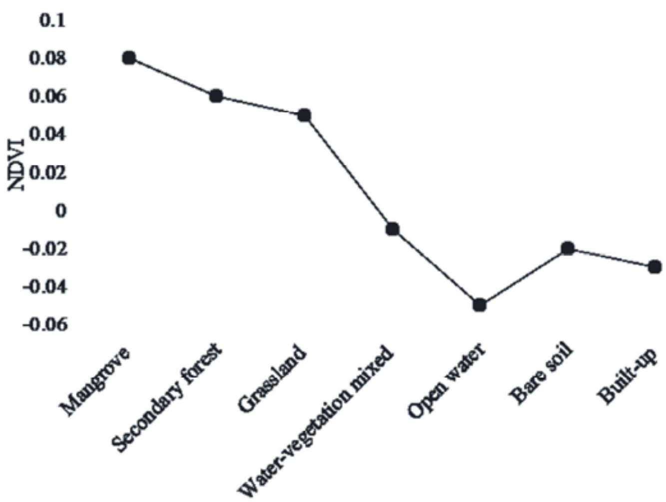

Fig. 3: Spectral characteristics of mangrove and non-mangrove land cover types using NDVI value.

the standard of high NDVI values from 0.4 to 1 were corresponded to the density of vegetated area [17]. This can be supported that the Mengkabong mangrove forest was dominated by *Rhizophora apiculata* species, which is a healthy and dense mangrove.Thus, the thresholds of NDVI values used in this study were useful to identify the different vegetation classes.

The attributes of greenness and the moisture of TCT indexes were used to recognize of mangrove classes and if moisture between -0.04 and 0 and greenness was greater than 0.6 at the same time, the pixel belongs to mangrove. Both of these TCT indexes are very useful for mangrove identification [18, 19].

A total of 519 validation samples of mangrove and 4443 validation samples of non-mangrove which included water, secondary forest, water-vegetation, bare soil and built-up area were used for this analysis. The commission of error in mangrove identification was very small (7.5% in 0.90 of kappa coefficients) resulted from adequately considering the particular growth environment of mangrove and extracted moisture and greenness feature. The decision-tree classification in this study was demonstrated that selection of good attributes for mangrove classification was promoted on high accuracies of the result.

Results of Change Detection: Details of detecting change of mangrove forest and other land cover in the study area were summarized in Table 1. Results shows the mangrove forests were extensively distributed in the Mengkabong area. There was a significant decrease from 1995 to 2000 and slightly increased from 2010 to 2013. Generally, the total area of mangrove forest was declining (a reduction of 40 ha from 1990 to 2013) and fragmentation was obvious.

Table 1: Changes in mangrove forest and other land cover types from 1990 to 2013

	1990		1995		2000		2005		2010		2013	
	ha	%	ha	%	ha	%	ha	%	ha	%	ha	%
Open water	1531.26	30.74	1555.20	31.22	1593.81	31.99	1616.67	32.45	1549.80	31.11	1536.84	30.85
Mangroves	1145.16	22.99	1024.20	20.56	945.72	18.98	872.82	17.52	997.20	20.02	1185.12	23.79
Secondary forest	846.90	17.00	826.20	16.58	780.12	15.66	627.21	12.59	518.40	10.41	499.14	10.02
Built-up	921.42	18.50	1037.34	20.82	1142.19	22.93	1186.83	23.82	1309.05	26.28	1048.50	21.05
Bare soil	342.00	6.87	253.17	5.08	198.72	3.99	266.85	5.36	246.33	4.94	270.54	5.43
Grassland	132.75	2.66	238.77	4.79	277.38	5.57	371.52	7.46	324.18	6.51	407.16	8.17
Water-Veg.	62.19	1.25	46.80	0.94	43.74	0.88	39.78	0.80	36.72	0.74	34.38	0.69

Table 2: Error matrices of decision-tree learning classification for 1990, 1995, 2000, 2005, 2010 and 2013.

		Reference Data			
Classified Data		Non-Mangrove	Mangrove	Total Accuracy (%)	Kappa Coefficient
TM1990	Non-Mangrove	234	16	84	0.68
	Mangrove	64	186		
TM1995	Non-Mangrove	221	29	82	0.64
	Mangrove	61	189		
TM2000	Non-Mangrove	226	24	87.2	0.74
	Mangrove	40	210		
ETM+2005	Non-Mangrove	230	18	89.6	0.79
	Mangrove	32	218		
ETM+2010	Non-Mangrove	238	12	90.8	0.82
	Mangrove	34	216		
OLI-TIRS2013	Non-Mangrove	218	24	89.2	0.78
	Mangrove	22	228		

Field investigation has shown that most mangrove forest have been lost in the Mengkabong area. Most of mangrove areas were converted to the shrimp pond and house reclamations. The shrimp pond activity in this area has been started since year 2000 [20].

Thus, the result of this study can be supported the report of the Fisheries Sabah Department. Only certain areas have been well protected. Others land covers area had a similar trend over the study period and changes in these land covers areas were linear. Specifically, built-up areas continually expanded while the secondary forest and water-vegetation mixed areas continually shrank. The open water, bare soils were showing an increasing-decreasing pattern.

Classification Assessment: The error matrices for the six years and their corresponding kappa values are listed in Table 2. The result of the classification assessment of the decision-tree learning method with GIS ancillary data shows that the highest kappa coefficient and the total accuracy of mangrove identification were 0.82 and 90.8%, respectively.

CONCLUSION

In conclusion, this study successfully classified mangrove and non-mangrove areas in the Mengkabong area by integrating the decision-tree learning method with multi-temporal Landsat series and GIS ancillary data. The selection of good attributes, from the spectral features of Landsat data and from topographic data (DEM and distance to coastline) from the GIS database, for the mangrove classification promoted the high accuracy ofresult of 90.8%.

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