

Land use/land cover mapping for conservation of UNESCO Global Geopark using object and pixel-based approaches

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Abstract. Land Use/Land Cover (LULC) is essential in planning and management activities especially for conserving eco-environment, soil and vegetation research as well as urban planning. Higher resolution imagery and accuracy of LULC for monitoring ecosystem survival are preferred especially when it takes into account environmental issues. Langkawi had faced problems related to environmental issues after it has been designated as a geopark. Therefore, this study aims to map and evaluate digital classification methods of mapping of LULC using Very High Resolution (VHR) Quickbird satellite imagery in one of the Langkawi UNESCO Global Geopark, that is Kilim Karst Geoforest Park (KKGP) which is located at northeast of Langkawi, Kedah, Malaysia. Object-based and pixel-based classification methods were explored and compared. Object-based method involved multi-resolution segmentation part where scale parameter, shape and compactness should be assigned as accurate as possible, so that the image is segmented to homogenous area. Both segmentation and classification processes were conducted in e-Cognition software. While, a supervised classification, Maximum Likelihood Classification (MLC) involved selection of training areas was used for pixel-based method using ERDAS Imagine software. Then, classification accuracies were assessed by comparing both techniques using error matrix and Kappa coefficient. The results from the classified image shows that the object-based approach provides more accurate results with an overall accuracy of approximately 87.91% and Kappa coefficient of 0.85 compared to the results achieved by MLC pixel-based classification with 72.21 % accuracy and Kappa coefficient of 0.66. As a conclusion, the results indicated that object-based technique has more advantages to be applied with VHR imagery for better environmental management and conservation actions.

1. Introduction

Accurate and high resolution of Land Use/Land Cover (LULC) map is required for environmental monitoring as well as natural resources management purpose. Nowadays, the use of remotely sensed data in order to produce LULC map is rapidly increasing since it would give advantages in terms of cost effectiveness and accuracy [1]. Normally, to extract information for LULC from remote sensing imagery, digital image classification is used. Most of the techniques used to produce LULC map of an



area utilize either pixel-based or object-based classification. The most common method used for this purpose is Pixel-Based Image Analysis (PBIA) method. PBIA method has been the mainstream and most common classification technique used in remote sensing imagery [2]. Traditional PBIA analysed spectral properties of every pixel within region of interest apart from [3], where authors did not examine the spatial or contextual information related to the pixel of interest. Some drawbacks or unfavourable effects are identified by the application of per-pixel classification on high-resolution satellite images such as salt and pepper noise effect which leads to the inaccuracy of the classification result [4,5] as well as topographic effect which is caused by solar illumination angle that indirectly contributes to the inaccurate classification results [6].

Recently, apart from the availability of the Very High Resolution (VHR) satellite imagery like IKONOS, Quickbird, Worldview, Pleiades and so on, the use of object-based method for extracting LULC combined with VHR imagery to produce better results by worldwide researchers has increased. In recent years, the classification using object-based approach has become popular and more accurate classification results could be produced by the usage of higher resolution satellite data [7,8]. In addition, Object-Based Image Analysis (OBIA) technique used different ways to extract features from satellite imagery compared to PBIA. In OBIA method, objects become the basic unit where they are generally defined as a group of pixels sharing similar spectral and/or textural properties. Features like texture, pattern, shape, size, tone/colour, site, shadow and association of the objects are generally used for classification. The OBIA method is not only suitable for medium to high resolution satellite imagery but it has also evolved as an alternative to PBIA technique [9,10]. Evaluation of the performance of these two different methods has been conducted in some comparative studies [11,12].

Langkawi is known as one of the famous island in Malaysia notably for tourism activities. The development of coastal zone and the tourism industry increased rapidly in this island since it obtained geopark status from The United Nations Educational, Scientific and Cultural Organization (UNESCO) in July 2007. Kilim Karst Geoforest Park (KKGP) is situated in the northeast part of Langkawi island and it has also received positive impacts from tourism activities all this while. Kilim has turned into a famous tourist destination in Langkawi from a rural region after designated as geopark. However, a number of problems have occurred related to environmental issues as reported by [13-17] in this area. The increase of tourist boat traffic along Kilim River had the potential to increase the risk of environmental emergencies, notably riverbank erosion. This problem does not only cause the riverbank erosion but also has a negative impact on the mangrove ecosystem. The erosion of Kilim riverbank occurs because of the tourist boat activities which directly cause the disrupting for mangrove ecosystem and marine life. The speed of tourist boat would cause the huge wave to crash down the riverbank and leads to mangrove trees collapse [18]. Furthermore, research done by [17] in this area also revealed that there is contamination of chemical elements such as Cadmium, Cd which are originated from the oil combustion of boating activities and this will give adverse effects to mangrove ecosystem for long term period. Figure 1 shows the problems that had occurred in Kilim recently.



Figure 1. Riverbank erosion (A,B) and mangrove collapsed (C,D) at Kilim River.

Therefore, to ensure the sustainability of mangrove ecosystem and its survival, it is vitally crucial to monitor this area by producing LULC map with higher resolution and higher accuracy. This

area should be monitored wisely so that these problems do not affect the geopark status as well as the existing fragile environment. Monitoring of riverbank erosion and degradation of mangrove ecosystem requires higher resolution imageries and maps. This is why higher resolution of LULC for this area should be produced as a preventive and conservation actions. There were some studies regarding LULC of Langkawi island explained in [19,20]. However, no one has used OBIA method for mapping LULC especially for Kilim Geopark area. Meanwhile, study conducted in [18] focused on Kilim area involving mapping of LULC and mangrove species distribution using moderate resolution satellite image, SPOT with pixel-based Maximum Likelihood Classification (MLC) technique. Therefore, this study is the first research that has been conducted using very high resolution (VHR) imagery, Quickbird with the OBIA method for KKGP area. The main aim for this study is to map the LULC of Kilim with high resolution and high accuracy for environmental management purposes to cope up with the problems stated above. The aim of this research will be completed by two objectives as follows: 1) to map LULC of KKGP from VHR Quickbird imagery using object and pixel-based approaches, 2) to evaluate the performance of both methods used in producing LULC map of Kilim.

2. Materials and Methods

2.1. Study area

This study has been conducted exactly in Kilim, a traditional village which is located on the northeast of the Langkawi Island. The terrain here is dominated by limestone (karst). Other land covers such as mangrove, pinnacles, caves, forest and urban area makes this area very interesting especially for tourism benefits. Approximately 47,800 hectares of total land area is designated as Kilim Karst Geoforest Park, Langkawi, Kedah [21]. The temperature in Kilim ranges from 22.50 to 34.50 degree Celsius and the monthly rainfall varies from 69.0mm to 870.0 mm. Figure 2 (A) shows the selected study area.

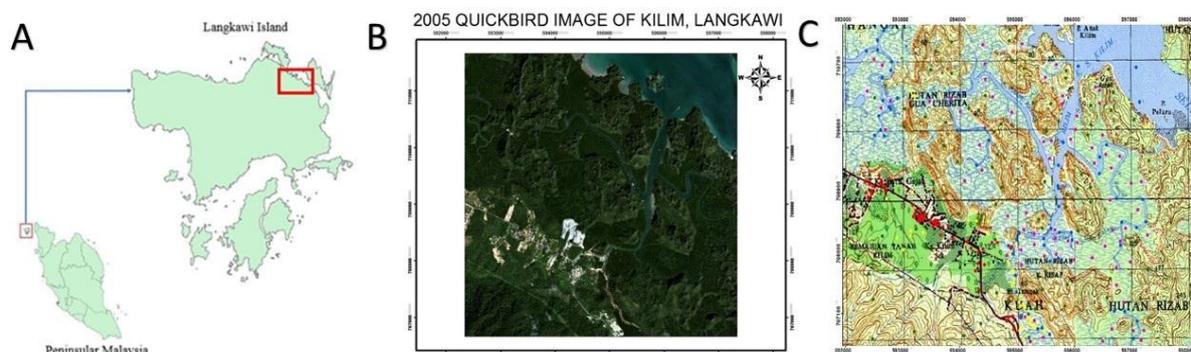


Figure 2. A) Study area, B) Quickbird image, and C) Topographic map with validation points.

2.2. Data

The primary data used in this study is a standard VHR Quickbird satellite panchromatic-multispectral (0.6m – 2.4m spatial resolution) bundled image. This data has been acquired for year 2005, before Langkawi was designated as geopark. This data would become as a control data in order to assess the LULC changes before and after it was designated as geopark since the LULC in this island was influenced by tourism activities significantly [20]. Figure 2 (B) shows the natural colour of Quickbird imagery used in this study. Reference data also known as ground truth data in producing classified LULC from remote sensing imagery is very essential in finding the features in the real world [22]. The collection of in situ data, the use of aerial photograph and so on are parts of the various types of data collection for accuracy assessment stage [23]. In this study, Langkawi topographic map as shown in Figure 2 (C), year 2002 from Department of Survey and Mapping Malaysia (JUPEM) has been used as the primary ancillary data for visual reference in selecting training and testing samples together with panchromatic band of Quickbird. Handheld GPS receiver was used to obtain the ground coordinate of

points within the study area and were used to facilitate classification and carry out accuracy assessment. Figure 2 (C) also shows the distribution of points used as validation for classified image.

2.3. Pre-processing and classification

Pre-processing of Quickbird image has been done using ERDAS Imagine 2014. In pre-processing steps, radiometric and geometric corrections have been applied on satellite image. The classification of satellite image using PBIA method has been done in ERDAS software after converting the Digital Number (DN) of satellite pixel to reflectance values. e-Cognition 8.7 software was used to perform OBIA classification after the multispectral and panchromatic bands of the satellite data were pansharpened. Next, ERDAS Imagine 2014 software has been used in this study to perform pixel-based MLC classification. MLC algorithm is a statistical decision criterion to aid in the classification of overlapping signatures. It works by assigning pixels to the class of highest probability. We used MLC algorithm because it is the established standard statistical method for digital image classification although, it is based only on spectral information of remote sensing data but it is advantageous from the probability theory point of view [24]. This technique involves the selection of training areas to represent land cover classes. The signature of the training area is then used to determine to which class the pixels should be assigned.

Object-based classification in this study has been performed using e-Cognition 8.7 software which was developed by DEFINIENS. Both spectral and spatial contextual properties of pixels are examined through this method [25]. There are two main steps involved in OBIA approach. The first and most crucial phase in object-based classification is Multiresolution Segmentation (MRS). In this step, the image is divided into the homogeneous objects and the aim of this step is to create meaningful objects where these objects would be classified based on contextual, textural, spatial and relational information. Scale parameter, colour/shape and smoothness/ compactness are the main parameters in this stage that should be assigned as accurate as possible to suit the reality. Next, the second step involved in OBIA is the classification phase. In this study, we used standard Nearest Neighbour (NN) classifier. The classification of objects is carried out by this classifier with a given feature space and given samples for the concerned classes. The algorithm searches for the closest sample object in the feature space for each image object after the sample objects has been selected for each class. If an image object is the closest sample object belonging to class A, the object will be assigned to class A. The formula used here is as follows:

$$d = \sqrt{\sum_f \left[\frac{v_f(s) - v_f(o)}{\sigma_f} \right]^2}$$

Where d : distance between sample object s and image object o ; $v_f(s)$: feature value of sample object for feature f ; $v_f(o)$: feature value of image object for feature f ; σ_f :standard deviation of the feature values for feature f .

2.4. Accuracy assessment

Classified images need to be evaluated in order to know the accuracy of the results. Hence, accuracy assessments of both classification methods are carried out using confusion matrix [26]. Overall accuracy, Kappa statistics, Producer and user accuracies, omission and commission error for each class are calculated.

3. Results and Discussions

The results of LULC classification for both object and pixel-based methods obtained through the analysis of satellite imagery are diagrammatically illustrated in Figure 3. The optimal spatial scale parameters for the LULC classification for OBIA approach in this study are selected as follows: scale parameter (30), colour/shape (0.3), smoothness/compactness (0.3). This parameter is set up in the

multi-resolution segmentation by object-based nearest neighbour classification step. While, for MLC pixel-based classification parameters, default setting are selected.

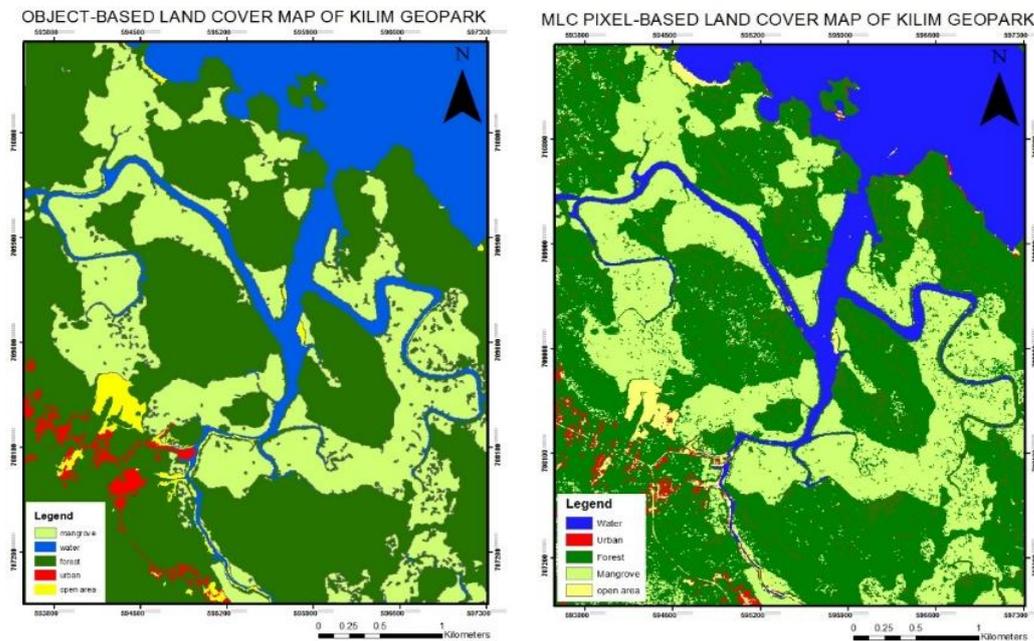


Figure 3. LULC map of KKGPP produced using OBIA (left) and PBIA method (right).

The spatial distribution of LULC for KKGPP map depicted five general classes like mangrove area, urban, open area, water body and forest. Referring to the LULC map produced by MLC-PBIA method, it can be observed that there are mixed classes at the mountainous area such as at lower-left of the map where forest class is mixed with mangrove class whereas, this problem does not occurred in LULC map produced by OBIA. This is because the topographic effect which is caused by solar illumination angle is identified as the main factor that causes this problem. Furthermore, the effect of topographic shadow, illumination variations and elevation differences also leads to the unsatisfactory result in PBIA approach [27]. In order to overcome this problem, the use of expert knowledge and digital elevation data especially for the area with high topographic variation is required in order to improve the classification result. Since fifty percent of this study area is covered by mountainous and karst area, many shadows in the image are assigned as forest, mangrove and water classes using expert knowledge and the interpretation of topographic map.

Besides, although this study used VHR Quickbird imagery which may provide the ability for mapping in details, the automatic information extraction of VHR data could become complicated notably when PBIA classification is used because of the problem from images with off-nadir view angles and shadows as well as false signals problem. PBIA cannot solve these types of problems since in traditional PBIA classification; spectral responses from all training pixels for a given class are integrated. This would cause the resulting signature consisting of responses from a group of other land covers in the training samples. Figure 4 shows the example of the mixing classes between mangrove and forest area in MLC pixel-based classification method. This problem occurred due to the use of only spectral information of pixels in satellite data, hence the results looks like pepper-and-salt picture. Mixed class could be reduced in OBIA since it works by taking into account not only spectral elements but also shape, texture, size and geometry of objects during classification process. In addition, most of study proved that OBIA method has a greater potential for classifying higher resolution imagery where the overall classification accuracy results exceeds the performance depicted using PBIA algorithm.



Figure 4. Misclassification of forest and mangrove classes due to mixing pixel problem.

In OBIA classification, it is crucial to analyse the optimal selection of segmentation scale parameter since it mainly controls the quality of the segmentation results of remote sensing images. Image segmentation is a critical step in this type of classification where multi-scale segmentation at different levels is used in this study to extract different LULC classes. Table 1 shows the results of segmentation obtained using different scale, smoothness/shape and compactness.

Table 1. Level of segmentation and classification used in the OBIA classification.

Level	Scale	Shape	Compactness	Extracted classes
1	100	0.5	0.5	Vegetation, water, urban
2	60	0.5	0.3	Forest, mangrove, water, urban
3	30	0.3	0.3	Forest, mangrove, limestone, agriculture, shadow, karst, water, urban, open area

The optimal selection of segmentation scale parameter for this study is 30 which is at level 3. This is because the segmentation result for all classes has shown that there are approximately no mixed-areas for different classes on the image used and they could be differentiated from each other successfully. For instance, by using this scale, we could separate the forest with mangrove area and urban with open area wisely. However, by using the scale of 60 (level 2) and 100 (level 1), the segmented area for forest and mangrove as well as the urban and open area are still mixed. This would cause a degradation in the accuracy for produced LULC map. Water body, urban and vegetation are extracted at level 1.

Next, in order to evaluate the performance of the classification accuracy results, confusion matrix has been used in this study. This step is very important because it would determine how good is the map produced through the image processing like classification. A map with unknown accuracy may lead to unnecessary or inappropriate actions. Hence, the known pixels from ground truthing are identified on the topographic map and the panchromatic bands are used as reference data. Confusion matrix in Table 2 and 3 are generated by linking the corresponding classes to the sample points. Producer's accuracy, user's accuracy, omission and commission errors, overall accuracy, and Kappa index of agreement are derived for each class. Accuracy assessments of both methods are compared as shown in Table 2 and Table 3:

Table 2. Confusion matrix for OBIA classification.

Object-based Classification								
Classified Data	Reference Data							
		Mangrove	Forest	Open Area	Urban	Water	Total	Commission Error (%)
	Mangrove	63	5	0	0	0	68	7.4
	Forest	11	76	0	0	0	87	12.6
	Open Area	0	0	44	10	0	54	18.5
	Urban	0	0	11	53	4	68	22.1
	Water	0	0	0	0	62	62	0
	Total	74	81	55	63	66	339	
	Omission Error (%)	14.9	6.2	20.0	15.9	6.1		

Table 3. Confusion matrix for PBIA classification.

Pixel-based Classification								
Classified Data	Reference Data							
		Mangrove	Forest	Open Area	Urban	Water	Total	Commission Error (%)
	Mangrove	71	6	3	1	2	83	14.5
	Forest	3	75	7	13	20	118	36.4
	Open Area	0	0	30	14	6	50	40.0
	Urban	0	0	15	35	2	52	32.7
	Water	0	0	0	0	36	36	0
	Total	74	81	55	63	66	339	
	Omission Error (%)	4.1	7.4	45.5	44.5	45.5		

The confusion matrix statistic to evaluate the performance of both OBIA and PBIA classification methods in this study are displayed in Table 2 and 3. A total of 339 ground truth points for five classes are extracted from topographic map of Langkawi combined with field data used to assess the accuracy of LULC map produced in this study, where the classified data (prediction) was compared to the reference data (ground truth) in confusion matrix tables. According to Table 2 for OBIA classification, from a total of 63 points of urban's reference data, 10 points are wrongly classified as open area and other remaining points are correctly classified as urban while statistics for urban class in Table 3 (PBIA) indicate that 28 points are wrongly classified as open area (14 points), forest (13 points) and mangrove (1 point).

Besides, general comparison of all classes revealed that there are many points which are wrongly classified as other classes especially for water, urban and open area for PBIA method. These facts could be proved by omission and commission errors for PBIA method from Table 3 where all these errors were higher than omission and commission errors of OBIA method in Table 2. Omission error refers to the percentage of incorrect pixel classification for ground truth data. For example, it can be observed from Table 2 and 3 that there are 20 and 45.5 percent of the open area class identified as something else. Meanwhile, commission error refers to the percentage of incorrect classification of classified data. According to Table 2 and 3, 18.5% and 40% of the classified open areas are not actually open areas. Generally, both omission and commission errors for all classes in OBIA approach has low values compared to PBIA except for omission's mangrove class. Overall statistics showing that the classification of LULC using OBIA method has produce good results.

Other accuracy metrics such as producers and users accuracy are also evaluated in this study. Producer accuracy refers to the percentage of real land cover types on the ground that is displayed on the classified map correctly. It can be seen from Figure 5 that the range of producer accuracy for OBIA is from 80% to 93.9% while for PBIA method, the range is from 54.5% to 95.9%. Both methods have lowest percentage for open area class followed by urban class. This is because open area and urban area are composed of mixed pixel and OBIA has proven to be more effective compared to PBIA by possessing higher values of producer accuracy with more than 80% for both open and urban area classes [28]. Meanwhile, the percentages of user's accuracy for all classes of OBIA method are higher as compared to percentage for all classes of PBIA classifier, except water class. Water class for both classifier demonstrated highest percentage in this study. User accuracy refers to the reliability of

the class on which map would actually be presented on the ground. For instance, the producer's accuracy for the forest class is 93.8% while the user's accuracy is 87.4%. This means that even though 94% of the reference forest areas have been correctly identified as "forest", only 87% of the areas identified as "forest" in the classification are actually forest.

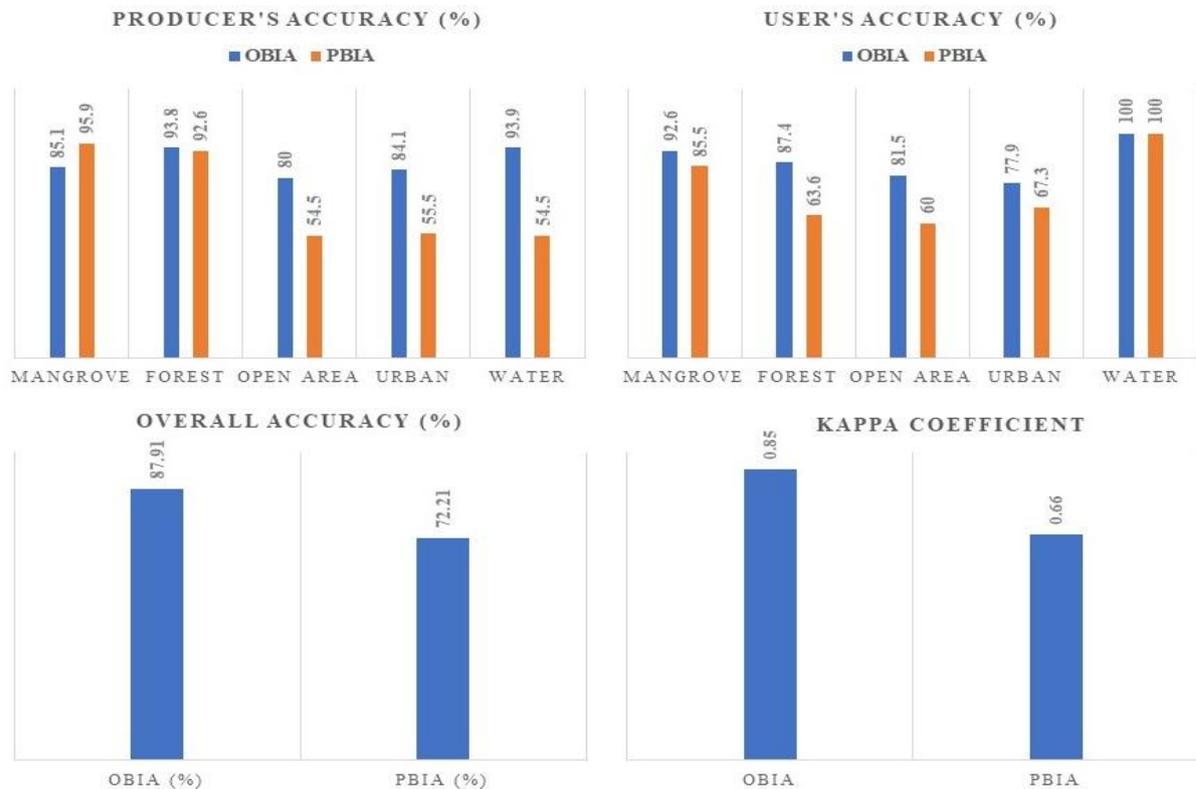


Figure 5. Comparison between OBIA and PBIA for producer's and user's accuracy.

Figure 5 also shows the overall accuracy and kappa statistic for LULC mapping in this study. OBIA method has achieved higher overall accuracy and kappa statistic, as compared to PBIA, which are approximately 87.91% and 0.85% respectively. The higher values for both elements indicated that there is strong agreement between classified image and validation points for this classification method. In addition, it also shows that the dynamics of the LULC in this area can be captured by this classification method efficiently. The usual accuracy which is acceptable is 85%. For PBIA method, the overall accuracy and kappa statistics are lower as compared to OBIA's values. The lower overall accuracy and kappa values for this method are caused by the effect of mixing pixel problem which leads to the misclassification as discussed earlier in this section. Similar findings have been observed in other studies [29, 30] in terms of overall accuracy and kappa statistic.

4. Conclusion

This work is devoted to map the LULC of one of the Langkawi UNESCO global geopark, with higher resolution and accuracy for environmental management purpose, due to some of the environmental issues that occurred recently in this area. The mapping was successfully performed by assessing the performance of OBIA and PBIA approaches on VHR Quickbird imagery. The results of OBIA method indicated that this classifier method can produce LULC map more accurately than PBIA and classifies all LULC types with satisfactory performance indices by producing better producer accuracy for each class. Furthermore, overall accuracy and Kappa statistics values for OBIA are higher than PBIA. Overall, the presented results show that OBIA method has great potential and advantages for extracting LULC information with very high resolution satellite imagery.

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References

- [1] Amit K B, Carsten O, Jurgen S, Murodjon S and Olena D 2017 Towards improved land use mapping of irrigated croplands: performance assessment of different image classification algorithms and approaches, *European Journal of Remote Sensing*, 50:1, 187-201.
- [2] Whiteside T G, Boggs G S and Maier S W 2011 Comparing object-based and pixel-based classifications for mapping savannas. *International Journal of Applied Earth Observation and Geoinformation*, 13, 884–893. doi: 10.1016/j.jag.2011.06.008
- [3] Makinde E O, Salami A T, Olaleye J B and Okewusi O C 2016 Object-based and pixel-based classification using Rapideye satellite imagery of Eti-Osa, Lagos, Nigeria. *Geoinformatics FCE CTU* 15(2), 2016, doi:10.14311/gi.15.2.5. pp 59-70.
- [4] Manuel L C and Jorge O C 2006 Contextual classification of remotely sensed images with integer linear programming. *CompIMAGE*. pp. 123–128.
- [5] Weih R C and Riggan N D 2013 Object-based classification vs. Pixel-based classification comparative importance of multi-resolution imagery. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XXXVIII-4/C7*.
- [6] Gholoobi M, Tayyebi A, Taleyi M and Tayyebi A H 2010 Comparing pixel based and object based approaches in land use classification in mountainous areas. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Science*, Volume XXXVIII, Part 8, Kyoto Japan. pp 789-794.
- [7] Steven M d J, Tom H and Hans G M 2001 An integrated spatial and spectral approach to the classification of Mediterranean land cover types: the SSC method. *International Journal of Applied Earth Observation and Geoinformation* 3.2, pp. 176–183.
- [8] Gao Y, Mas J F, Maathuis B H P, Zhang X, Djik V P M 2006 Comparison of pixel based and object oriented image classification approaches—a case study in a coal fire area, Wuda, Inner Mongolia, China. *International Journal of Remote Sensing*, vol. 27, pp. 4039-4055.
- [9] Baatz M, Benz U, Dehghani S, Heynen M, Höltje A, Hofmann P, Lingenfelder I, Mimler M, Sohlbach M, Weber M, and Willhauck G 2004 eCognition Professional: User guide 4.; Munich: Definiens-Imaging.
- [10] Benz U, Hofmann P, Willhauck G, Lingenfelder I and Heynen M 2004 Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry and Remote Sensing*, 58, 239-258.
- [11] Niemeyer I and Canty M J 2003 Pixel-based and object-oriented change detection analysis using high resolution imagery. Proceedings of 25th Symposium on Safeguards and Nuclear Material Management, 13-15 May, Stockholm.
- [12] Manakos I, Schneider T and Ammer U 2000 A comparison between the ISODATA and the eCognition classification on basis of field data. Proceedings of XIX ISPRS Congress, 16-22 July, Amsterdam.
- [13] Free Malaysia Today. Website : <http://www.freemalaysiatoday.com/category/opinion/2016/05/27/mangrove-forest-in-kilim-geo-park-under-threat/>
- [14] Post Magazine. Website: <http://www.scmp.com/magazines/postmagazine/article/1577608/langkawi-victim-its-own-success>
- [15] R. AGE. Website : <http://rage.com.my/langkawi-getting-trashed/>
- [16] Badaruddin M 2012 Effects of tourism activities and development on the physical environment of Kilim river, Langkawi, Malaysia. *The Malaysian Forester* 75(1): p. 81-86.
- [17] Tajam J and Kamal M L 2013 Marine environmental risk assessment of Sungai Kilim, Langkawi, Malaysia: Heavy Metal Enrichment Factors in Sediments as Assessment Indexes. *International Journal of Oceanography*. Article ID 482451, <http://dx.doi.org/10.1155/2013/482451>.

- [18] Shahbudin S, Zuhairi A, and Kamaruzzaman Y 2012 Impact of coastal development on mangrove cover in Kilim River, Langkawi Island, Malaysia. *Journal of Forestry Research*, 23(2), p.185-190.
- [19] Serwan M J B & Kamaruzaman W Y 2001 Mapping land use/ cover distribution on a mountainous tropical island using remote sensing and GIS. *International Journal of Remote Sensing*, vol. 22, no. 10, 1909–1918.
- [20] Suzana A B, Pradhan B, Usman S L and Abdullahi S 2016 Spatial assessment of land surface temperature and land use/land cover in Langkawi Island. 8th IGRSM International Conference and Exhibition on Remote Sensing & GIS (IGRSM 2016), IOP Publishing, IOP Conf. Series: Earth and Environmental Science 37 (2016) 012064. doi:10.1088/1755-1315/37/1/012064.
- [21] Nabila G F, Faridah H I, Kamziah A K and Nazre M 2012 Assessment of Floristic Composition of Kilim Geoforest Park, Langkawi, Malaysia. *Journal of Agricultural Science*. 4(3): 23-34.
- [22] Kennedy R E, Townsend P A, Gross J E, Cohen W B, Bolstad P, Wang Y Q and Adams P 2009 Remote sensing change detection tools for natural resource managers: understanding concepts and tradeoffs in the design of landscape monitoring projects. *Remote Sens Environ*. 113 (7):1382–1396.
- [23] Biro K, Pradhan B, Buchroithner M and Makeschin F 2010 Use of multi-temporal satellite data for land-use/Land-cover change analyses and its impacts on soil properties in the northern part of Gadarif Region, In: Reuter R, editor. Remote sensing for science, education, and natural and cultural heritage. Paris: EARSel 2010; p. 305–312.
- [24] Chan J C, Chan K and Yeh A G 2001 Detecting the nature of change in an urban environment: A comparison of machine learning algorithms. *Photogrammetric Engineering and Remote Sensing*, 67(2):213-225.
- [25] Blundell J S and Opitz D W 2006 Object recognition and feature extraction from imagery: The Feature Analyst® approach. In: *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences* 36.4, p. C42.
- [26] Congalton R G 1991 A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment*, 37, 35-46.
- [27] Gholoobi M, Tayyebi A, Taleyi M and Tayyebi A H 2010 Comparing pixel based and object based approaches in land use classification in mountainous areas. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Science*, Volume XXXVIII, Part 8, Kyoto Japan. pp 789-794.
- [28] Tehrany M S, Pradhan B and Jebuv M N 2013 A comparative assessment between object and pixel-based classification approaches for land use/land cover mapping using SPOT 5 imagery. *Geocarto International*. Vol. 29, No. 4, 351–369, <http://dx.doi.org/10.1080/10106049.2013.768300>.
- [29] Makinde E O, Salami A T, Olaleye J B and Okewusi O C 2016 Object-based and pixel-based classification using Rapideye satellite imagery of Eti-Osa, Lagos, Nigeria. *Geoinformatics FCE CTU* 15(2), 2016, doi:10.14311/gi.15.2.5. pp 59-70.
- [30] Adam H E, Csaplovics E and Elhaja M E 2016 A comparison of pixel-based and object-based approaches for land use land cover classification in semi-arid areas, Sudan. 8th IGRSM International Conference and Exhibition on Remote Sensing & GIS (IGRSM 2016), IOP Publishing. IOP Conf. Series: Earth and Environmental Science 37 (2016) 012061. doi:10.1088/1755-1315/37/1/012061.