Comparison of pixel-based and object-based image classification techniques in extracting information from UAV imagery data

H I Sibaruddin[1], H Z M Shafri[1], B Pradhan[2] and N A Haron[1]

[1]Department of Civil Engineering, Faculty of Engineering, Universiti Putra Malaysia, 43400 Serdang, Selangor, Malaysia
[2]School of Systems, Management and Leadership, Faculty of Engineering and Information Technology, University of Technology (UTS), Broadway NSW 2007, Australia

hilkham86@gmail.com, helmi@upm.edu.my

Abstract. As the rapid development is being focused in the urban area, there is a need for the utilisation of a rapid system for updating this profile immediately. One of the current technologies being applied in recent years is the use of unmanned aerial vehicle (UAV) for mapping purposes. The use of UAV is widespread in various fields because it is low cost, has high resolution and is able to fly at low altitude without the constraints of cloudy weather. Typically, the method of data extraction for UAV in Malaysia is still very limited and the traditional methods are still being implemented by some industries. The features from aerial photo orthomosaic are manually detected and digitised from visual interpretation for the mapping purposes. Unfortunately, these methods are tedious, expensive, consume much time, and may involve much fieldwork, to acquire only a limited information. Pixel-based technique is often used to extract low level features where the image is classified according to the spectral information where the pixels in the overlapping region will be misclassified due to the confusion among the classes. The supervised object-based image analysis (OBIA) classification technique is widely used nowadays for automatic data extraction. Therefore, the general objective of this study is to assess the capability of UAV with high resolution data for image classifications. The pixel-based and OBIA classifications were compared using the Support Vector Machine (SVM) classifier. The classifications were assessed using different numbers of sample size. The result shows that OBIA gives a better result of Overall Accuracy (OA) than pixel-based. The consequences of this study accommodate further understanding and additional insight of utilising OBIA technique with different classifiers for the extended study.

1. Introduction

Generally, remotely sensed data is available and can be acquired from ground-base, aerial platform and satellite platform [1]. It is not always easily found within the public domain. This is because most of these data are acquired by using the equipment that is too expensive to build and maintain. Simultaneously, the deployment of unmanned aerial vehicle (UAV) system that is equipped with a capability to operate without human within public coverage [2] is an advent technology in recent years. A huge quantity of data points can be captured in a short time covering large area, added with

the tendering major cost efficiency to user needs [3]. It is far exceeded compared to the traditional methods, which are limited for certain areas of interest (inaccessible) as well as the tediousness and the long dependency of time required to acquire the data in the site areas [4].

The UAV becomes prominent in various disciplines due to its availability of high spatial resolution data, lightweight of sensors and platforms, incorporated with the flexibility of flight planning or deployment, and removal of the long dependency that have led to a growing interest for a variety of this technology [5,6,7]. UAV could also obtain a timely imagery of areas that are difficult or dangerous to access by traditional means. In addition, it can predict the acquisition points and possibly perform a direct geo-referencing [4]. Nowadays, the classification using pixel-based technique is very limited. In general, it has some considerable difficulties dealing with the rich information content of high-resolution data [8,9] for example from high resolution satellite data, and UAV imagery. It produces inconsistent classification results and it is far beyond the expectations in extracting the objects of interest.

Presently, the object-based image analysis (OBIA) technique is quite significant with the environment of image classifications. The OBIA technique takes the forms, textures and spectral information into consideration. The initial phase of classification starts with grouping the neighbouring pixels into meaningful areas [10,11]. The segmentation and topology generation should be set corresponding to the resolution and the scale of the expected objects. In this classification, the single pixels are not classified. However, it will extract the homogenous image objects during a previous segmentation step [12]. OBIA technique gives a better classification result than pixel-based technique for high and very high resolutions [8,13,14]. Therefore, this research had been conducted to assess the high-resolution data for classification using pixel-based and object-based techniques.

2. Dataset and Methodology

Dataset and methodology are the most important element in this research because it affects the success of the research.

2.1. Study Area

The study area was located at the National Land and Survey Institute (INSTUN) in Behrang, Perak, Malaysia. The area of research interest was subset and limited to 0.3628 km^2 between the latitudes 3° 45' 58.3'' N to 3° 46' 2.16'' N and the longitudes 101° 30' 34.94' E to 101° 31' 26.01' E.
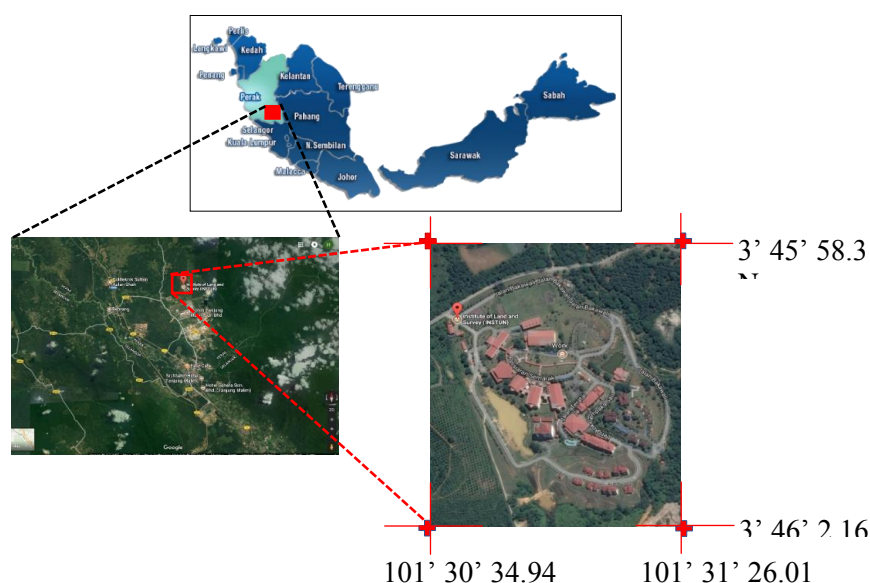

Figure 1. Study area in INSTUN, Perak, Malaysia

The study area was surrounded by man-made infrastructures, such as buildings, roads, drainage systems, courts for sports, concrete benches, pavements and parking lots. Among the natural features in the study area were bare soil, dead grass, grass lands, sand, crops, shrubs and trees. Other features include water bodies, such as swimming pools, lakes, septic tanks and shadows from tall buildings and trees.

2.2. Data & Software Used

The imagery was obtained using the UAV eBee SenseFly as depicted in Figure 2. This well-established equipment operated as a fully autonomous drone to capture high-resolution aerial data. It was safe, ultra-light and easy to operate with highly-automated data collection tools [15]. The optical sensor attached to this model during the flight time was a non-metric camera, Canon IXUS / ELPH 16.1 MP with a visible colour band (red, green, and blue).

Figure 2. UAV ebee SenseFly for data capturing

The orthomosaic images with the digital surface model (DSM), digital terrain model (DTM) and contour line were generated using Pix4D. The e-cognition version 9.0 was used for OBIA classification and ENVI version 5.1 was used for pixel-based classification.

Figure 3. Orthomosaic

2.3. Flow of Study

The flow of research was split into two phases, namely the classification of pixel-based technique and the classification of object-based technique. The results of the classifications are very important to determine the dominant method for image classification for high-resolution data.
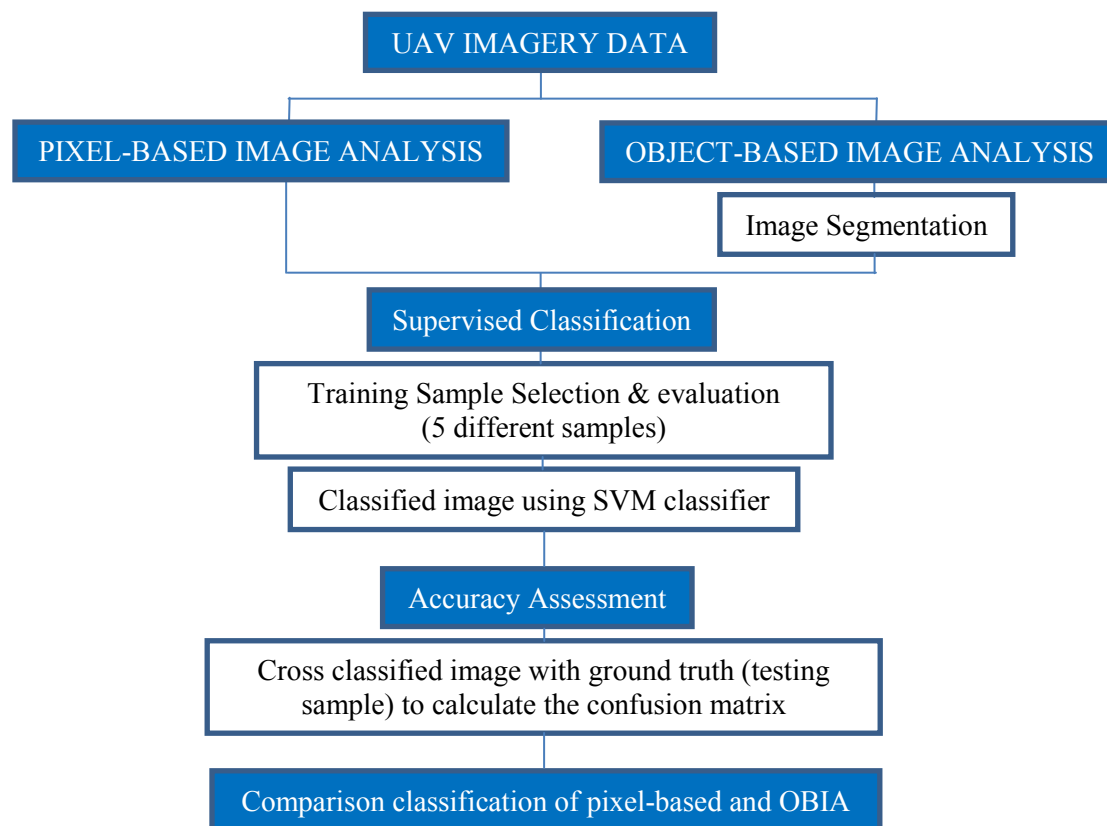
UAV IMAGERY DATA

PIXEL-BASED IMAGE ANALYSIS

OBJECT-BASED IMAGE ANALYSIS

Image Segmentation

Supervised Classification

Training Sample Selection & evaluation
(5 different samples)

Classified image using SVM classifier

Accuracy Assessment

Cross classified image with ground truth (testing
sample) to calculate the confusion matrix

Comparison classification of pixel-based and OBIA

Figure 4. Flow of study

2.3.1. Pixel-based Classification. The pixel-based classification technique was performed by assigning a pixel to a class fundamentally by referring to the spectral similarities [12]. In this pixel-based classification stage, the supervised classification using Support Vector Machine (SVM) classifier had been applied to UAV imagery data. The classification parameter was set as default in the SVM classifier embedded in the ENVI software.

2.3.2. *Object-Based Classification.* The OBIA technique encompasses the segmentation of image data into objects on scale levels. The segmentation of the images object primitive is handled by the factor of scale, shape and compactness. Multi-resolution segmentation is a powerful region-based segmentation algorithm [16]. It is a bottom up region merging approach that groups the areas of neighbouring pixels into meaningful segments or objects according to the homogeneity criteria.

The trial and error method of segmentation was utilised. Using the trial and error method, the parameter for image classification used was at the scale of 125, 0.1 for shape and 0.3 for compactness.

2.3.3. Image Classification. The classification was made using the non-parametric SVM classifier. The two-hyperplane were selected in the SVM classifier. In SVM, it was not merely maximising the distance between the two given classes. However, it also important to not include any points between them. The aim was to find out in which class the new data points fall into [17]. Overall, SVM was reported to produce results of higher accuracies compared to the traditional approaches but the outcome depended on the kernel used, choice of parameters for the chosen image classification, and the method used to generate SVM [18].

The parameters set during this study were the combination of default parameters of C as 2 and Gamma as 0. These values were used for the initialisation of the accuracy comparison between these

two methods without any optimisation of parameters. The training and testing samples were selected for this validation process by random selection. Five different samples of 100, 200, 300, 400, and 500 were selected for training samples. Five samples of 43, 86, 129, 171, and 214 were used for the testing. The ground truth data validation was acquired to verify the actual classes on the classification.

2.3.4. Accuracy Assessment. The accuracy assessment was made using the confusion matrix table for the error assessment. Seven classes of natural and man-made features were selected for this assessment. The accuracy assessment of both classifications was taken using the confusion matrix and kappa statistics [19]. The confusion matrix was generated and the indicator of the Overall Accuracy (OA) and kappa statistics were used as validation of the classification results.

3. Result and Discussions

There are two major results produced in this study which comprise result of pixel-based and OBIA classification with different of sample size.

3.1. Image Classification

The image classifications using SVM classifier for pixel-based technique and OBIA technique had been tested. The results in Table 1 to 5 showed that OBIA technique produced better image classification than those produced using pixel-based technique. This result was due to the consideration of the factors of spectral, shape, and texture in OBIA technique. Sample 3 indicated the highest OA for pixel-based classification. On the other hand, with the increment in the sample size, the OA was becoming constant with more than 70% OA was achieved using the pixel-based technique. However, OBIA results were very consistent with all the samples achieved above 70% with Sample 5 provided the highest OA with the total of 75.23%. The validation used the default value to clarify the potential of the best classification and it was very important to show that the OA of OBIA gave better results than the OA of pixel-based image classification.

Table 1. Comparison of pixel-based and OBIA for sample 1

CLASS NAME	PIXEL-BASED				OBIA			
	PRODUCER ACCURACY	USER ACCURACY	OVERALL KAPPA STATISTIC	OVERALL ACCURACY	PRODUCER ACCURACY	USER ACCURACY	OVERALL KAPPA STATISTIC	OVERALL ACCURACY
SOIL/SAND (SS)	91.67%	55.00%			57.14%	40.00%		
URBAN TREE (UT)	80.00%	61.54%			0.00%	0.00%		
BUILDING/ROOF (BR)	14.29%	16.67%			66.67%	80.00%		
GRASSLAND (GR)	0.00%	0.00%	0.3343	**48.84%**	100.00%	100.00%	0.6231	**69.77%**
IMPERV. SURFACE (IS)	0.00%	0.00%			90.00%	75.00%		
WATER (WA)	0.00%	0.00%			75.00%	81.82%		
SHADOW (SH)	0.00%	0.00%			100.00%	100.00%		

Table 2. Comparison of pixel-based and OBIA for sample 2

| CLASS NAME	PIXEL-BASED				OBIA			
	PRODUCER ACCURACY	USER ACCURACY	OVERALL KAPPA STATISTIC	OVERALL ACCURACY	PRODUCER ACCURACY	USER ACCURACY	OVERALL KAPPA STATISTIC	OVERALL ACCURACY
SOIL/SAND (SS)	91.30%	80.77%			64.29%	60.00%		
URBAN TREE (UT)	65.00%	72.22%			88.89%	100.00%		
BUILDING/ROOF (BR)	85.71%	52.17%			72.73%	44.44%		
GRASSLAND (GR)	45.45%	35.71%	0.5513	**63.95%**	100.00%	100.00%	0.6736	**73.26%**
IMPERV. SURFACE (IS)	11.11%	100.00%			80.00%	84.21%		
WATER (WA)	0.00%	0.00%			65.22%	78.95%		
SHADOW (SH)	100.00%	75.00%			33.33%	100.00%		

Table 3. Comparison of pixel-based and OBIA for sample 3

| CLASS NAME	PIXEL-BASED				OBIA			
	PRODUCER ACCURACY	USER ACCURACY	OVERALL KAPPA STATISTIC	OVERALL ACCURACY	PRODUCER ACCURACY	USER ACCURACY	OVERALL KAPPA STATISTIC	OVERALL ACCURACY
SOIL/SAND (SS)	88.89%	84.21%			66.67%	70.00%		
URBAN TREE (UT)	70.00%	75.00%			76.92%	76.92%		
BUILDING/ROOF (BR)	90.48%	70.37%			70.59%	60.00%		
GRASSLAND (GR)	58.82%	52.63%	0.6656	**73.08%**	88.89%	88.89%	0.6764	**73.64%**
IMPERV. SURFACE (IS)	61.54%	66.67%			83.33%	86.21%		
WATER (WA)	22.22%	66.67%			62.86%	64.71%		
SHADOW (SH)	75.00%	100.00%			100.00%	100.00%		

Table 4. Comparison of pixel-based and OBIA for sample 4

CLASS NAME	PIXEL-BASED				OBIA			
	PRODUCER ACCURACY	USER ACCURACY	OVERALL KAPPA STATISTIC	OVERALL ACCURACY	PRODUCER ACCURACY	USER ACCURACY	OVERALL KAPPA STATISTIC	OVERALL ACCURACY
SOIL/SAND (SS)	91.49%	82.69%			72.41%	72.41%		
URBAN TREE (UT)	64.10%	71.43%			61.11%	78.57%		
BUILDING/ROOF (BR)	93.10%	79.41%			65.22%	50.00%		
GRASSLAND (GR)	52.17%	44.44%	0.6466	**71.52%**	81.82%	75.00%	0.6657	**72.67%**
IMPERV. SURFACE (IS)	52.94%	69.23%			84.62%	84.62%		
WATER (WA)	18.18%	33.33%			65.22%	71.43%		
SHADOW (SH)	83.33%	100.00%			100.00%	100.00%		

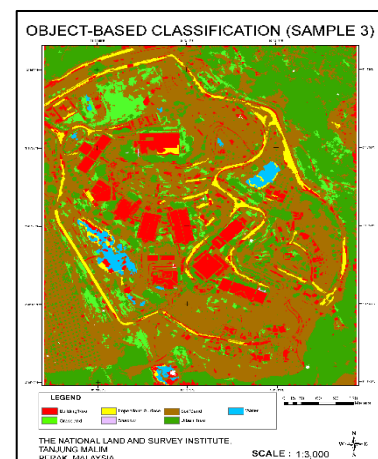**Table 5.** Comparison of pixel-based and OBIA for sample 5

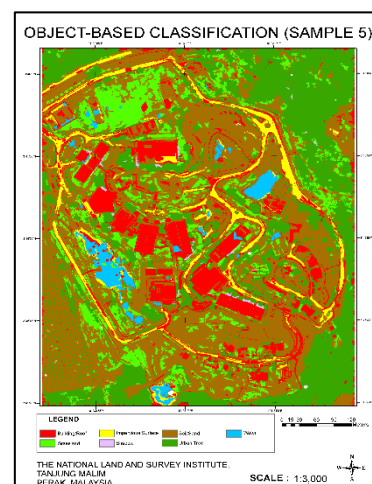| CLASS NAME	PIXEL-BASED				OBIA			
	PRODUCER ACCURACY	USER ACCURACY	OVERALL KAPPA STATISTIC	OVERALL ACCURACY	PRODUCER ACCURACY	USER ACCURACY	OVERALL KAPPA STATISTIC	OVERALL ACCURACY
SOIL/SAND (SS)	89.66%	89.66%			77.78%	82.35%		
URBAN TREE (UT)	72.00%	75.00%			71.43%	78.95%		
BUILDING/ROOF (BR)	88.89%	78.05%			68.97%	57.14%		
GRASSLAND (GR)	37.93%	39.29%	0.6509	**71.63%**	78.57%	73.33%	0.6963	**75.23%**
IMPERV. SURFACE (IS)	42.86%	64.29%			86.00%	81.13%		
WATER (WA)	50.00%	38.89%			64.91%	72.55%		
SHADOW (SH)	100.00%	87.50%			100.00%	100.00%		

Figure 5 to 9 below represent the Pixel-based classification for all sample data.
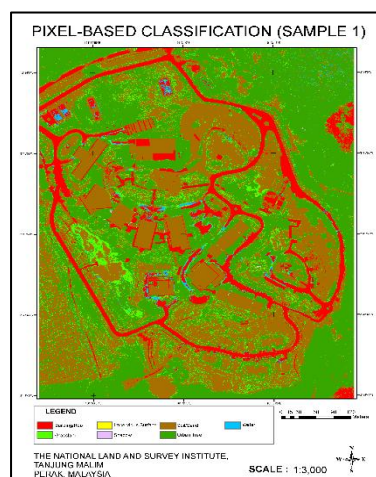
Figure 5. Pixel-Based Sample 1   **Figure 6.** Pixel-Based Sample 2   **Figure 7.** Pixel-Based Sample 3
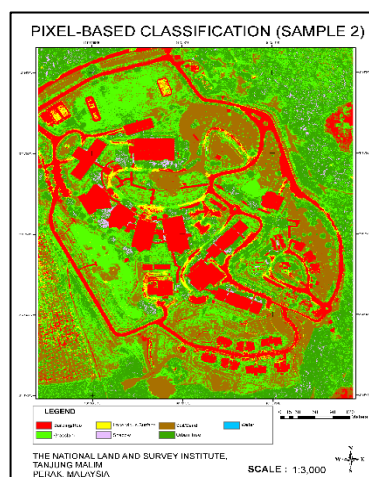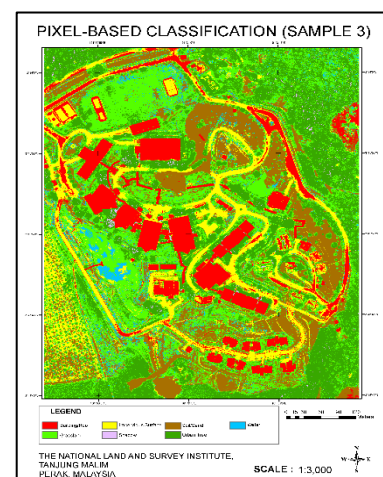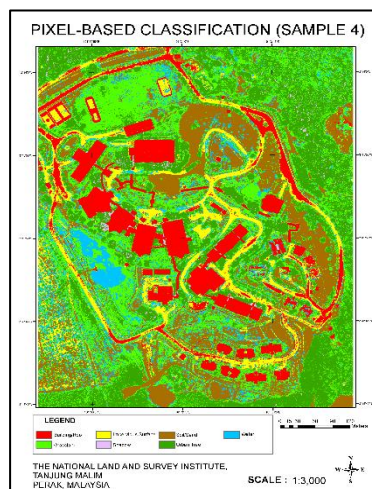
Figure 8. Pixel-Based Sample 4   **Figure 9.** Pixel-Based Sample 5

Meanwhile, figure 10 to 14 below show the Object-based classification for different sample size data.
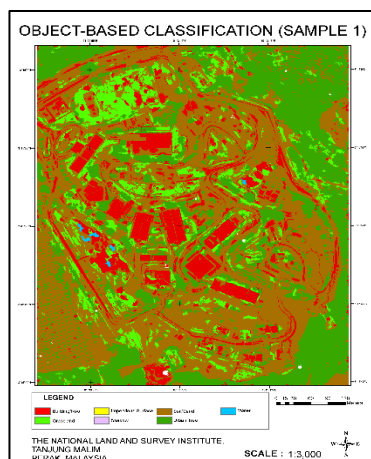
Figure 10. OBIA Sample 1   **Figure 11.** OBIA Sample 2   **Figure 12.** OBIA Sample 3
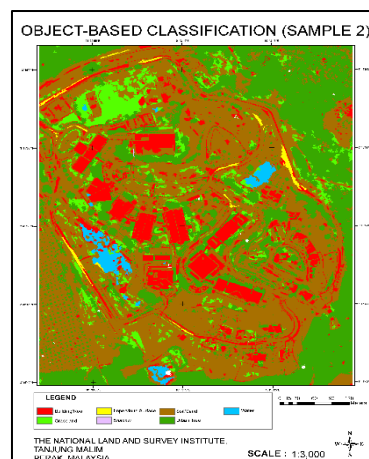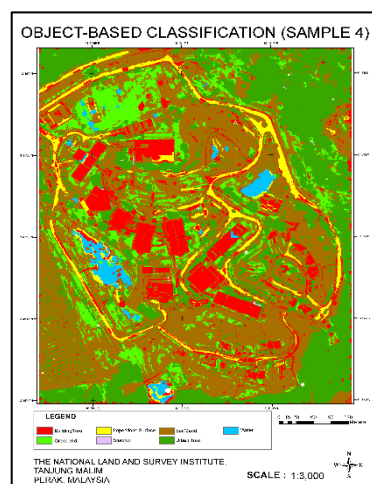
Figure 13. OBIA Sample 4   **Figure 14.** OBIA Sample 5

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Based on the results gained, there was a slight difference between both classifications. By using pixel-based classification, it produced a small group of pixels or individual pixels. Therefore, it generated classes with mixed clusters of pixels representing the heterogeneity nature of the image. Even though Sample 5 in the pixel-based classification gave a better result than Sample 4, the soil or sand classes were quite dominantly misclassified with the water classes.

However, the object-based classification gave a better result and more acceptable accuracy than pixel-based classification for almost all the sample size, with Sample 5 produced the highest result among them. This result suggested that OBIA has a great potential for extracting features information. The visual difference between the classifications for both method was obvious. In the pixel-based classification, the results were highly misclassified particularly in the area that was spectrally heterogenous. However, the object-oriented classification appears to overcome some of the problems encountered when using the pixel-based technique with several classes being classified as the same on the ground.

4. Conclusion

Based on the results, it can be concluded that OBIA technique performs better than pixel-based technique. This is because the pixel-based technique only considers spectral properties, while OBIA technique is more sophisticated, where other than spectral properties, it also considers shape and texture properties. In addition, the high-resolution data gives better classifications using OBIA technique than pixel-based technique and provides satisfied result for features extraction. Therefore, OBIA classification is suitable and has high potential for features extraction. The consequences of this study accommodate an additional insight of utilising OBIA technique with different classifiers for the extended study.

Acknowledgements

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