Abstract
This paper assessed the performance of object-based supervised support vector machine (SVM) and rule-based techniques in classifying tropical vegetated floodplain using 0.6m QuickBird image and LIDAR dataset of 1.4 points per square meter (PPSM). This is particularly significant in hydraulic modelling in which vegetation roughness is a big uncertainty and largely relies on land cover classification. The supervised classification resulted in 79.40% overall accuracy whilst the results improved by 8% with rule-based classification. 40 sample plots of trees and shrubs were measured to be compared to obtain the best classification results. The results showed a linear relationship between tree diameters and NDVI with a high Pearson correlation of 0.76 and coefficient of determination (r²) of 0.58. The canopy areas of shrubs were found to be representative spatially with an even higher Pearson correlation of 0.98 and r² of 0.95. The study concluded that the fusion of QuickBird image and low point density LIDAR in rule-based classification together with field data were useful in quantifying tropical trees and shrubs.

Keywords: Low point density LIDAR, QuickBird, OBIA, rule-based classification, tropical vegetated floodplain, vegetation parameter.

Introduction
Whilst very high resolution (VHR) satellite images may be sufficient for general mapping applications, it is often not the case when more details are required to make informed decisions. For instance, in hydraulic modelling, there have been many ongoing efforts in gaining better understanding of the uncertainties [Zahidi et al., 2014]; and floodplain surface roughness is among those that control the flood extents and levels [Van der Sande et al., 2003]. As the surface roughness relies heavily on the land cover, image classification becomes the first major procedure prior to assigning surface roughness values in hydraulic
models [Tymkow and Borkowski, 2008]. Moreover, a number of authors have reported that the surface roughness derived from the ecotope land cover classification can be significantly different from those measured based on field data; and the latter produced more accurate flow resistance [Van der Sande et al., 2003; Forzieri et al., 2011a, 2011b; Medeiros et al., 2012].

Quantifying vegetation is the first step in characterising vegetation roughness in floodplains [Forzieri et al., 2010] as hydraulic models require vegetation to be reasonably classified and a dataset may not be suitable for flood mapping even when the DTM accuracy is good, if the vegetation is poorly classified [NOAA, 2012]. Although conventional field survey would be the best estimate in quantifying vegetation, it is often not possible for a large area as it is time and cost consuming. Therefore, remote sensing technology has become a preferred tool for describing various vegetation properties [Cosh and Brutsaert, 2003; Straatsma, 2005; Straatsma et al., 2006; Straatsma and Baptist, 2008; Forzieri et al., 2010, 2011a, 2011b; Clementel et al., 2012; Corona et al., 2012; Pirotti et al., 2012]. Subsequently, object-based image analysis (OBIA) is often preferred for classification due to its better performance [Baatz and Schape, 2000; Blaschke, 2010; Forzieri et al., 2010; Li et al., 2011; Myint et al., 2011; Zhang et al, 2013; Blaschke et al., 2014; Hamedianfar and Shafri, 2014]. OBIA can be carried out as supervised or rule-based. The supervised technique can be performed by different supervised algorithms such as K-nearest neighbour or support vector machine (SVM). SVM has become a popular algorithm in remote sensing community due to its ability in providing good classification result with a small amount of training samples [Heumann, 2011; Mountrakis et al., 2011; Hamedianfar and Shafri, 2014]. This algorithm which was introduced by Boser et al. [1992] is then utilised for supervised classification based on the training samples defined by the user. The rule-based technique is based on human knowledge and reasoning about each feature class [ENVI, 2008] in which a rule-set can include one or several attributes to identify each class.

It is known that LIDAR data has a limited spectral information and it is almost impossible to interpret them without ancillary data such as satellite images. Likewise, satellite images do not contain height information and different vegetation classes require prior knowledge of the study area. Combining ancillary data with spectral bands can be considered for better characterisation and discrimination of the vegetation classes [Straatsma et al., 2006]. This integration is also recommended to reduce the spectral diversity in very high-resolution images due to variable reflections of vegetated classes [Stephens et al., 2012].

As VHR multispectral imagery is getting affordable and widely used, LIDAR data acquisition can be very expensive for vegetation studies alone and the readily available LIDAR data is often those below 4 points per square meter (PPSM). PPSM is measured directly as the ratio between the number of points and the covered area [Balsa-Barreiro and Lerma, 2014]; and it determines how well the estimations are. LIDAR data are still limited in Malaysia at the time of publication and the dataset used in this study contains 1.4 PPSM which is sufficient enough for DEM creation. However, it is recommended to have at least 4 PPSM for specific vegetation analysis [Watershed Sciences Inc., 2010]. This would give more accurate representation of the ground and vegetation. Therefore, many studies have mentioned the utilisation of high point density LIDAR data, but it is not easily obtained due to its cost. To address this, a number of recent studies have been focusing on the use of VHR spectral imagery with low point density LIDAR for land cover classification and vegetation
mapping with the help of object-based methodology [Geerling et al., 2007; Takahashi et al., 2010; Bujan et al., 2013; Alexander et al., 2014; Brubaker et al., 2014; Machala and Zejdova, 2014].

Although the majority of the previous studies were conducted for temperate vegetated floodplains or wetlands and mangroves, very little studies investigated the tropical vegetated floodplains [Li et al., 2011, 2012; Htun et al., 2011; Pouteau and Collin, 2013]. Tropical vegetation is often diverse in species with different patterns of distribution [Mueller-Dombois, 1984]. The challenges lie in the dense multi-storey tree canopies and weather conditions as they are often cloudy and rainy, thus obstructing the visibility of satellite images [Stibig et al., 2003; Razak et al., 2013]. Additionally, the field sampling is also hampered by the limited access [Li et al., 2012; Razak et al., 2013].

While supervised SVM classification can provide satisfactory results, tropical vegetation is largely dependent on subtle variations in elevation [Chadwick, 2010] which means that user-defined rule-sets might help in reducing the confusion between vegetation types. Htun et al. [2011] for instance, have reported rule-based classification to produce higher accuracy in tropical vegetation mapping using another algorithm, maximum likelihood classification (MLC) on fused Landsat image and elevation. Interestingly, the authors have discovered the highest accuracy of MLC approach was only slightly higher than the least accurate rule-based approach. However, Heumann [2011] found that SVM performed better than MLC in mapping mangroves at species level using Worldview-2. Similar to Chadwick [2010] who fused IKONOS image with LIDAR, Heumann [2011] also emphasised the need to distinguish subtle differences between vegetation species, but warned that achieving high accuracy using QuickBird imagery is very unlikely. Nevertheless, all studies point to the significance of multiple data sources for maximum accuracy in classification.

Therefore, the objectives of this study are (1) to use QuickBird image with low point density LIDAR to compare the performance of different OBIA approaches, namely supervised SVM and rule-based; (2) to quantify tropical trees and shrubs spatially using field measurements; and (3) to compare the field measurements against the best classification results. The relationships between important vegetation features and spatial attributes will allow low point density LIDAR to be a useful and cost-effective tool for characterising vegetation.

Methods

Study area

The study area of this research was Malacca River floodplain which is situated in Alor Gajah district in the state of Malacca, Malaysia. It lies approximately at longitude 104° 44’ 44.01” and latitude 2° 21’ 8.19” with an area of 14km². The location map is given in Figure 1.

The study area in particular does not vary greatly in topography, geology, and soil; but has sufficient vegetation cover for the study purposes. The total land area of the floodplain is 47km² while the vegetated area accounts for 36km² which is close to 77% of the whole area. Vegetation is composed of woody trees such as oil palm, rubber, shrubs, crops, and grassland.
Dataset and pre-processing

The 14km² imagery used in this investigation was a QuickBird image with the projection of Malaysian RSO and Kertau 1948 as its datum. The QuickBird image contained four bands in the visible and a near infrared (NIR) portion of the electromagnetic spectrum. The acquisition date of the image was 9 February 2011. The resolution was 0.60m (panchromatic) and 2.44m (multispectral). The classification was performed on a pan-sharpened QuickBird image for a better visualisation by using PANSHARP algorithm [Zhang, 2002].

The LIDAR data for the study area was acquired in 2009 with the same projection. The vertical and horizontal accuracies were +/-0.15m and +/-0.5m, respectively. The average PPSM was 1.4. The laser strikes were subsequently classified into ground and non-ground points. The last returns are often associated with ground measurement and although in reality these points can be lower-lying vegetation or rocks, they are still the closest approximation. The points were validated against ground checkpoints, acquired by an independent surveyor to evaluate the accuracy of the point data in addition to the manual checking and editing by the provider. The maximum mean difference was found to be -0.11m.

The DEM refers to the elevation point data representing the topography. The digital surface model (DSM) represents the surface land cover including the top of tree canopies and building roofs, whereas digital terrain model (DTM) was produced by only extracting the ground levels. Both were derived from the LIDAR point clouds using the triangulation algorithm. This technique has less smoothing effect which in return produces the best
representation of three nearest points [NOAA, 2012]. This is especially applicable in flat terrains such as the study area.

Subsequently, the height information from the LIDAR point clouds was extracted by subtracting the DTM values from DSM to produce normalised digital surface model (nDSM) as shown in Figure 2.

**Figure 2 - (A) QuickBird image and (B) nDSM.**

**Object-based image analysis (OBIA)**

Remote sensing classification conventionally implements pixel-based methodology in which the pixels are classified based on each spectral pattern; whereas the new method of object-based takes groups of pixels that are homogenous in colour, size, shape, and texture. Many studies have demonstrated the superiority of object-based classification over the traditional pixel-based technique [Li et al., 2011; Forzieri et al., 2010; Myint et al., 2011; Hamedianfar and Shafri, 2014a; Hamedianfar et al., 2014].

There are basically two ways of defining features as seen in the summarised workflow in Figure 3. The first one is supervised classification, based on the SVM algorithm, in which it allows the system to delineate individual land cover types based on statistical characterisation data derived from known samples in the image, or also known as training areas. The other technique is rule-based where it is based on user’s defined fuzzy rule-sets to reduce the uncertainty of data noise and ambiguous human knowledge in determining the degree of an object belongs to a land cover type [Jin and Paswaters, 2007].
Supervised OBIA

Supervised classifications rely greatly on the user’s knowledge of the area as the training samples selected by the user are used to train the algorithm to classify different land covers. Boser et al. [1992] first introduced the SVM algorithm which is used for supervised object-based classification. Essentially the groups of homogeneous pixels are used to define each land cover based on the closest spectral features of the training samples.

SVM is traditionally a binary (two-class) classifier. Its risk of misclassification is reduced by optimising the margin between the criterion of the classifier and the degree of points that are being misclassified [Gidudu et al., 2007]. The balance between the two is defined as classification probability threshold (C) which has to be optimised. A cross-validation was carried out to settle on the optimal parameters of gamma in the kernel function of 0.0078 and C of 0.5. Different values of gamma and C generate different transformations or classification results. The image was classified into the following seven classes:

**Table 1 - Land cover.**

| Class            | Description                                           |
|------------------|-------------------------------------------------------|
| Water            | Rivers, lakes, streams and other water bodies         |
| Built-up areas   | Buildings                                             |
| Paved surfaces   | Roads and tar surface                                 |
| Land             | Bare land or ground that is not covered by vegetation |
| Trees            | Vegetation higher than 2m                             |
| Shrubs           | Clusters of vegetation below 2m high                  |
| Grass and cropland | Agriculture land and grasses                           |
The three vegetation types were classified based on their distinctive surface roughness. The height of the trees was defined based on site observation. Additionally, the identity and location of the land cover types were known beforehand through a site visit and interpretation of satellite images and ecotope land cover map.

**Rule-based OBIA**

Rule-based classification basically means combining the best features of different data sources to extract land cover classes more accurately using certain rules to govern the attributes such as spectral, spatial, and texture as seen in Table 2. The user can create the rules based on human knowledge and reasoning on particular land cover types [ENVI, 2010]. Multiple rules can be defined to eliminate unwanted objects from targeted land cover types or to include the desired objects [Hamedianfar and Shafri, 2014].

Generally, the workflow starts with testing an attribute and gradually increase the conditions and attributes to filter out all other unwanted features. For a fair comparison, the same dataset and parameters used in the supervised OBIA previously were applied in the rule-based classification.

| Table 2 - List of attributes [ENVI, 2010]. |
|------------------------------------------|
| **Spectral Attributes**                  |
| Spectral (min, max, average, standard deviation) | The value of pixels comprising the region in band x. |
| **Texture Attributes**                   |
| Texture (range, average, variance, entropy) | Values that comprise the region inside the kernel. |
| **Spatial Attributes**                   |
| Area                                      | Total area of the polygon, minus the area of the holes. |
| Length                                    | The combined length of all boundaries of the polygon, including the boundaries of the holes. |
| Compactness                               | A shape measure that indicates the compactness of the polygon. |
| Convexity                                 | Measures the convexity or concavity of the polygon. |
| Solidity                                  | A shape measure that compares the area of the polygon to the area of a convex hull surrounding the polygon. |
| Roundness                                 | A shape measure that compares the area of the polygon to the square of the maximum diameter of the polygon. |
| Form_Factor                               | A shape measure that compares the area of the polygon to the square of the total perimeter. |
| Elongation                                | A shape measure that indicates the ratio of the major axis of the polygon to the minor axis of the polygon. |
| Rectangular_Fit                           | A shape measure that indicates how well the shape is described by a rectangle. |
| Main_Direction                            | The angle subtended by the major axis of the polygon and the x-axis in degrees. |
| Major_Length                              | The length of the major axis of an oriented bounding box enclosing the polygon. |
| Minor_Length                              | The length of the minor axis of an oriented bounding box enclosing the polygon. |
| Number_of_Holes                           | The number of holes in the polygon. |
| Hole_Area / Solid_Area                    | The ratio of the total area of the polygon to the area of the outer contour of the polygon. |
Based on the corresponding attributes, the rule-sets for each class are defined in Table 3. The spectral bands of 1 to 4 represented the QuickBird bands and the additional parameter of nDSM was added as band 5.

| Class               | Rules                                                                 | Description                                                                 |
|---------------------|----------------------------------------------------------------------|----------------------------------------------------------------------------|
| Water               | If band ratio < 0.3485 AND form factor < 0.4503 AND tx_range < 12.4049 AND avgband_4 < 469.4275  | Water has low values of NDVI, low reflectance in the NIR band and a small texture range. The ratio of water areas to the square of the total perimeter is also small. |
| Built-up areas      | If band ratio < 0.3645 AND avgband_1 < 365.5686 AND tx_range > 15.6191 AND tx_variance < 167.3810 AND avgband_5 > 2.8285 | Built-up areas have low values of NDVI and low reflectance in the blue band. The texture variance is small, but the range is big. Most buildings are higher than 2.8m. |
| Paved surfaces     | If band ratio < 0.3645 AND avgband_5 < 3.2389 AND avgband_1 < 351.6863 AND avgband_4 > 379.1530 | Paved surfaces have low values of NDVI, low reflectance in the blue band but a high reflectance in the NIR band. |
| Land                | If band ratio < 0.3284 AND avgband_4 > 532.6196 AND avgband_1 > 369.0000 | Land has low values of NDVI and high reflectance in both blue and NIR bands. |
| Trees               | If band ratio > 0.3871 AND tx_range > 24.1469 AND avgband_5 > 2.3696 | Trees have high values of NDVI and highly textured. They are generally higher than 2.3m. |
| Shrubs              | If band ratio > 0.3871 AND tx_range < 28.8729 AND avgband_5 > 0.2277 | Shrubs have high values of NDVI, but not highly textured. They are at least 0.2m high. |
| Grass and cropland  | If avgband_4 > 460.4000 AND avgband_3 < 372.9442 AND avgband_2 < 517.3961 AND avgband_1 < 351.6863 AND elongation < 6.1618 AND avgband_5 < 12.2165 AND tx_mean > 290.0000 | Grass and cropland have high reflectance in the NIR band, but low reflectance in the other bands. They are less elongated, but highly textured. |

Bujan et al. [2013] have reported that the classes of bare earth, pavement, low vegetation, and dirt road could be improved by using a vegetation index. In this study, the normalised difference vegetation index (NDVI) value, or band ratio in the rule-sets, is the primary attribute in discriminating vegetation from the rest of classes with a ratio lower than 0.36 represents no to little vegetation. This can be observed in the classes of water, built-up areas, paved surfaces, and land.

The NDVI measurement is done as a measure of vegetation density and homogeneity within an image pixel. The NDVI is calculated as the difference between the NIR and Red, whereby higher values equal to greater chlorophyll density. Based on the study area, values of 0.1 and below indicate barren areas of rock or sand. Moderate values of 0.2 to 0.4 correspond to shrubs and grassland, whereas higher values such as 0.5 to 0.7 correspond to tropical trees. Low NIR value is useful in refining the class water as well as low form factor and texture range. The built-up areas are characterised by both low NDVI and blue band. The classification is further refined with the rule of heights above 2.8m. The paved surfaces are singled out the same way as built-up areas minus the texture attributes. The high NIR band
is particularly helpful in refining the classification in addition to the rule of heights below 3.2m. The class land is differentiated using similar attributes as paved surfaces, with an exception of having higher blue band.

All three vegetation classes manipulate the texture attributes to segregate them primarily from the LIDAR elevation. Takahashi et al. [2010] for instance, have found that stand volume at various conditions could be estimated precisely through the relationship between diameter breast height (DBH) and crown area or the diameter derived from QuickBird panchromatic imagery when combined with tree heights derived from low point density LIDAR. Similarly, Bujan et al. [2013] have stated that the LIDAR point density does not affect the classification significantly. Whilst the low point density leads to losing the quality of the intensity image, the nDSM quality remains almost unchanged. Additionally, trees have a different texture than shrubs; therefore, the texture attribute is used to separate them. This has been demonstrated in the study by Tymkow and Borkowski [2008] where they found that the errors in classification were reduced through the texture features in addition to the inclusion of height. Li et al. [2011, 2012] have also reported the importance of textural images in land cover classification in tropical moist regions. Grass and cropland have more diverse attributes which utilised all four bands of QuickBird image to distinguish them.

**Accuracy assessment techniques**

In order to assess the accuracy of classification, a considerable amount of ground truth polygons was digitized on QuickBird image on the basis of field survey. The stratified random sampling technique was carried out to distribute the random point samples from the reference areas. The objective was to evaluate the classification results by comparing the known ground points to the points generated from each classification approach using the conventional confusion matrix. 100 ground truth points for each class were randomly picked for the accuracy assessment with a total of 700 points.

A more detailed accuracy assessment technique is the McNemar test. It is a non-parametric test based on the chi-squared statistic of $2 \times 2$ matrix [Foody, 2004] to determine the statistical reliability and significance of the classification with 95% of confidence level.

The formula is expressed in the equation [1] below:

$$x^2 = \frac{(f_{ij} - f_{ji})^2}{(f_{ij} + f_{ji})^2} \quad [1]$$

where the term $f_{ij}$ represents the number of ground truth pixels correctly classified in one set of classification but wrongly classified in the other.

**Site measurements**

Vegetation density is an important parameter in hydraulic modelling where the vegetation surface roughness is derived. This is defined as the total frontal area of vegetation in specific water volume [Petryk and Bosmajian, 1975] as in equation [2].
\[ Veg_d = \frac{\sum A_i}{AL} \quad [2] \]

A is the cross-sectional area of the flow and L is the length of channel reach considered. \( A_i \) is the frontal area which can be defined as the product of average vegetation diameter and the average height of the leaf mass that is submerged. While the density of shrubs can be calculated based on their canopy area as their width is generally uniform throughout their whole height, the tree density is based on its diameter which is hard to discriminate spatially. Therefore, the relationship between tree diameters and NDVI was thought to be the best indicator.

For validation, the field sampling was carried out and 40 square plots of 2.5m × 2.5m were sampled for trees and shrubs at various locations. Figure 4 below shows the different types of vegetation in the study area. The coordinates were recorded and inputted into geographic information systems (GIS). The GPS equipment used was GPSmap 60CSx with a field accuracy of 3m. Sketch maps and forms were used to guide the recording of vegetation parameters such as vegetation species, quantity, DBH, height, and percentage of ground cover or canopy area (0%, 25%, 50%, 75% or 100%).

Figure 4 - Different types of vegetation in the study area.
Results

Supervised object-based classification results

OBIA is known to provide a preferred alternative in land cover classification as it is based on image segments, and thus reduces the salt-and-pepper effects that are more common in pixel-based classification. The supervised SVM algorithm based on OBIA was subsequently used to classify the fused QuickBird image and nDSM as displayed in Figure 5 based on the training samples that the user has selected in prior.

Figure 5 - Result of SVM classification for QB imagery and nDSM image.
As seen in the confusion matrix below, the supervised classification results in Figure 5 shows an overall classification accuracy of 79.40%. While the classes of water and land recorded 100% producer’s accuracy, followed closely by shrubs at 97%, Table 4 shows that most of the uncertainty is due to the classes of paved surfaces and grass and cropland. This is due to their similar spectral signatures to built-up areas.

Table 4 - Confusion matrix for SVM classification.

| Class          | Water | Built-up areas | Paved surfaces | Land | Trees | Shrub | Grass and cropland | Total | Producer’s accuracy [percent] | User’s accuracy [percent] |
|----------------|-------|----------------|----------------|------|-------|-------|---------------------|-------|-----------------------------|--------------------------|
| Water          | 100   | 0              | 0              | 0    | 0     | 0     | 0                   | 100   | 100                         | 0                        |
| Built-up areas | 0     | 87             | 42             | 0    | 0     | 32    | 161                 | 87    | 54                          |                          |
| Paved surfaces | 0     | 13             | 58             | 0    | 0     | 0     | 71                  | 58    | 82                          |                          |
| Land           | 0     | 0              | 0              | 100  | 0     | 0     | 100                 | 100   | 0                          |                          |
| Trees          | 0     | 0              | 0              | 0    | 70    | 3     | 16                  | 89    | 70                          | 79                       |
| Shrubs         | 0     | 0              | 0              | 0    | 27    | 97    | 8                   | 132   | 97                          | 73                       |
| Grass and cropland | 0   | 0              | 0              | 0    | 3     | 0     | 44                  | 47    | 44                          | 94                       |
| Total          | 100   | 100            | 100            | 100  | 100   | 100   | 700                 |       |                             |                          |

Note: Overall accuracy = (556/700) 79.40%

**Rule-based classification results**

The aim of this paper was to see how well tropical vegetated floodplain land cover can be classified by the rule-based OBIA compared to the supervised SVM OBIA. Using the rule-sets described in the previous section, the fused data set of QuickBird image and LIDAR nDSM was classified and the accuracy was compared to the same ground truth samples used in the supervised classification accuracy assessment.

The accuracy assessment of the rule-based classification results (Fig. 6) was conducted in the same manner as the supervised classification. As seen in the confusion matrix below, the overall classification accuracy of rule-based classification had increased by more than 8% to 88.14%. While the same classes of water and land recorded the same maximum producer’s accuracy, the previously underperforming classes of paved surfaces and grass and cropland had improved by 19% and 50%, respectively.
Figure 6 - Result of rule-based classification for QB imagery and nDSM image.
Table 5 - Confusion matrix for rule-based classification.

| Class           | Ground Truth (pixels) | Water | Built-up areas | Paved surfaces | Land | Trees | Shrubs | Grass and cropland | Total | Producer’s accuracy [percent] | User’s accuracy [percent] |
|-----------------|-----------------------|-------|----------------|----------------|------|-------|--------|--------------------|-------|-----------------------------|-------------------------|
| Water           |                       | 100   | 0              | 0              | 0    | 0     | 0      | 100                | 100   | 100                        | 100                     |
| Built-up areas  |                       | 0     | 91             | 5              | 0    | 0     | 3      | 99                 | 91    | 92                         | 92                      |
| Paved surfaces  |                       | 0     | 2              | 77             | 0    | 0     | 0      | 79                 | 77    | 97                         | 97                      |
| Land            |                       | 0     | 0              | 3              | 100  | 0     | 0      | 103                | 100   | 97                         | 97                      |
| Trees           |                       | 0     | 0              | 0              | 72   | 12    | 0      | 84                 | 72    | 86                         | 86                      |
| Shrubs          |                       | 0     | 0              | 0              | 4    | 83    | 3      | 90                 | 83    | 92                         | 92                      |
| Grass and cropland |                   | 0     | 7              | 10             | 0    | 24    | 5      | 94                 | 140   | 94                         | 67                      |
| Total           |                       | 100   | 100            | 95             | 100  | 100   | 100    | 700                |                   |                             |                          |

Note: Overall accuracy = (617/700) 88.14%

Additionally, the McNemar test was useful in revealing how statistically significant the differences between two sets of results. Table 6 summarises the results of the McNemar test for the two classification techniques.

Table 6 - McNemar test results between supervised and rule-based classification.

| Rule-based | Supervised | x² | Significant? |
|------------|------------|----|--------------|
| Correct    | Correct    | 40.45 | Yes          |
| Incorrect  | Incorrect  |     |              |
| Total      | Total      |     |              |

The results indicated that the rule-based classification accuracy was highly significant compared to the supervised classification with 617 matches compared to 556 for supervised. Therefore, this confirms the reliability of rule-based classification as opposed to supervised classification for tropical vegetated floodplain.

Site validation
A field survey was carried out in March 2015 to collect 40 sample plots of 2.5m × 2.5m. The points were inputted into GIS where they were buffered as a 2.5m square. Using the rule-based classification results, the classes of trees and shrubs were extracted for each sample plot. Due to the wide variety of tree diameters and shrub canopy area percentages, they were grouped into a range or interval of 0.1m and 25%, respectively. The selected parameters, both measured and calculated, were plotted as scatter plot diagrams in Figure
7 and Figure 8 to visualise the trend and subsequently quantified using statistical tests such as Pearson correlation and coefficient of determination, $r^2$. 

Figure 7 - Relationship between the range of measured canopy area percentages and the range of calculated canopy area percentages.

Figure 8 - Relationship between mean NDVI and the range of measured diameters.
For the shrubs, the ground cover percentages were compared to the ranges of canopy area percentages calculated in the GIS whereas the trees were assessed by comparing the relationship between the ranges of diameters and the mean NDVI values as they represent the density better. The trees were located on the NDVI layer and the mean NDVI values corresponding to each tree plot were extracted.

The Pearson correlation coefficient can be used to measure the strength of a linear relationship between two variables, in which the value $r = 1$ means a perfect positive correlation and $-1$ means a perfect negative correlation. The $r^2$ can also be used as an indicator for linear correlation variability or goodness of fit. The values range between 0 and 1 with a higher value means a better fit. Table 7 summarises these coefficients for the trees and shrubs. The linear relationship between the measured and calculated canopy area of shrubs was very strong at 0.98 and 0.95 for the Pearson correlation coefficient and $r^2$, respectively. The correlation between the tree diameters and their corresponding mean NDVI values was also considered to be strong at 0.76 for Pearson correlation and 0.58 for $r^2$.

Table 7 - Coefficients of Pearson correlation and determination.

| Vegetation Type | Pearson | $r^2$ |
|-----------------|---------|-------|
| Shrubs          | 0.98    | 0.95  |
| Trees           | 0.76    | 0.58  |

**Discussion**

The first objective was to assess the accuracy of two OBIA classification techniques using a QuickBird image combined with low point density LIDAR elevation data. The SVM OBIA was carried out by selecting a number of training samples to define each land cover: water bodies, built-up areas, paved surfaces, land, trees for vegetation higher than 2m, shrubs, as well as grass and cropland. Most of the uncertainty were contributed by the classes of paved surfaces and grass and cropland. This is due to their similar spectral signatures with built-up areas. Van der Sande et al. [2003] equally achieved poor results in the supervised classification of residential areas and roads, whereas Dengsheng et al. [2010] found a high percentage of cropland and impervious surfaces was misclassified in their QuickBird image classification.

The overall classification accuracy of rule-based OBIA had increased by more than 8%. The previous underperforming classes of paved surfaces and grass and cropland had improved by 19% and 50%, respectively. The LIDAR data managed to minimise horizontal and vertical spatial variation, thus addressing the spectral resemblance issues. A comparable observation was reported by Tymkow and Borkowski [2008]. This is because the laser beam of LIDAR can penetrate dense vegetation which provides extra information on features that cannot be seen on satellite or aerial imagery even with a very high resolution. Despite the overall improvement, the class shrubs recorded a small decrease in accuracy from 97% to 83%. Such occurrence was expected as the change in probability of other classes can decrease or increase another class possibility [Geerling et al., 2007]. It is also the disadvantage of OBIA where the classification accuracy of some land covers can be improved while others are reduced, depending on the classification complexity and segmentation [Li et al., 2011].

The rule-based technique also showed the usefulness of NDVI and textures in discriminating vegetation areas from the rest of land covers. Even though the classification accuracy without
either parameter was not examined, the findings demonstrated a significant improvement when incorporating NDVI and textures from the satellite image with the LIDAR elevation. This finding is supported by Li et al. [2011] who found that both vegetation indices and textures can improve the overall classification accuracy, but the textures in particular improve vegetation classification. This underscores the advantage of rule-based classification where multiple data sources, including low point density LIDAR, can be derived to achieve a higher accuracy in classifying tropical vegetated floodplain. Additionally, Figure 9 verifies the capability of rule-based technique in distinguishing the classes of vegetation as the significant area of trees in the East that was previously misclassified as shrubs through the supervised methodology now belongs to the right class. Such a significant area of trees in the East that was misclassified as shrubs can cause a critical error in hydraulic modelling as the two have distinct surface roughness values.

![Figure 9](A) QB image against the classification results of (B) supervised and (C) rule-based.

From Figure 10, it was found that the classes of built-up areas and grass and cropland produced substantial differences between supervised and rule-based classification. This
echoes the supervised classification results by Dengsheng et al. [2010] who found spectral confusion between cropland and impervious surfaces such as built-up areas. It is due to the crop residues that remain in the fields after they have been harvested. This further demonstrates the variations between the two techniques.

![Figure 10 - Percentage areas of each class.](image)

Subsequently, the classes of trees and shrubs were validated against site measurements. While the canopy area of shrubs can be compared directly due to their consistent definition and direct calculation of density, the same cannot be done for trees. The density of trees is derived from the diameter and it was found that the vegetation index of NDVI is a better representation of density to validate against the diameters measured on the ground. This was demonstrated through site validation where 40 samples were compared to the GIS calculation. The tree diameters correlated positively with the mean NDVI values with Pearson correlation coefficient of 0.76 and $r^2$ of 0.58 which is in agreement with previous studies that found NDVI as a good indicator for forest volume estimate [Mohamedain et al., 2012; Santi et al., 2014]. The shrubs recorded an even stronger Pearson correlation coefficient at 0.98 and $r^2$ of 0.95 when the canopy areas were compared between site measurements and GIS calculation. There is a possibility that the good accuracy deduced from the low point density LIDAR is also due to the gentle slope of the study area. Slopes are known to have a considerable effect on the LIDAR heights in which areas with steep slopes have recorded slightly higher root mean square error [Brubaker et al., 2014]. This study highlighted the applicability of low point density LIDAR to reduce the spectral
confusion and generate more accurate land cover classification of tropical vegetated floodplain, particularly by using rule-based classification technique. By being able to quantify the trees and shrubs, vegetation can be more accurately represented in hydraulic models for an improved flood management. The methodology is also transferable to the policy makers and engineers in making sound decisions in terms of site-specific ideal land cover. We recommend the findings to be verified in real life 2D hydraulic model by applying the varying surface roughness values derived from the detailed land cover map of ecotope dataset to investigate if the model predictions are improved and to what extent.

**Conclusion**

In this paper, we fused together a QuickBird image and low point density LIDAR data of a tropical vegetated floodplain using two object-based classification techniques to investigate their performance. It has been demonstrated that the classification of tropical vegetated floodplain is more accurate by using the rule-based technique. The results showed an 8% improvement in the overall accuracy to 88.14% compared to the supervised classification. The McNemar results further demonstrated that the rule-based classification accuracy was highly significant compared to the supervised classification with 617 matches compared to 556 of supervised classification. Therefore, this confirms the reliability of rule-based classification as opposed to supervised classification for tropical vegetated floodplain. Furthermore, it was proven that even with low point density, the nDSM derived from LIDAR still retains good quality in order to improve the classification of paved surfaces and grass and cropland.

The vegetation classes of trees and shrubs were compared to 40 sample plots that were measured on site to be validated and quantified. The relationships between spectral data and field measurements of vegetation were assessed using scatter plots and correlation analysis. The tree diameters correlated positively with the NDVI values with a strong Pearson correlation of 0.76 and $r^2$ of 0.58. Furthermore, the canopy areas of shrubs can be directly extracted from the GIS as the measurements correlated strongly with the ground measurements at a Pearson correlation coefficient of 0.98 and $r^2$ of 0.95.

We conclude that the low point density LIDAR can improve the efficiency and accuracy of classifying tropical vegetated floodplain. This research could represent a potential application of less expensive and increasingly readily available LIDAR dataset with low point density for quantifying land cover and different vegetation types. This also presents the opportunities to extend the application to other tropical vegetated regions. While another potential extension of this study is to transfer the rule-sets to other tropical vegetated floodplains, it is worth noted that this study was limited to 0.6m QuickBird image and LIDAR dataset of 1.4 PPSM. If other multiple datasets are available, future studies can explore the transferability of the rule-sets.

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